Impact of Commitment, Information Sharing, and Information Usage on Supplier Performance: A Bayesian Belief Network Approach

Abstract

Due to the proliferation of information systems and technology, supply chains have the capability of acquiring an enormous amount of supplier data in their databases. However, much of the useful supplier-specific insights in terms of supplier performance metrics are mostly hidden and untouched. The current emphasis on supplier performance makes relationship commitment and information management functions an ideal application area to benefit from the use of data-mining tools for the decision-making process and improving supplier performance. By employing Bayesian belief networks (BBNs), this study investigates the role of the major variables of commitment, information sharing, quality of shared information, and information usage in relation to supplier performance in the U.S. aircraft manufacturing supply chain. The results provide insightful guidance to managers on how to enhance performance.

Keywords: Analytics, Data Mining, Relationship Commitment, Information Usage, Supplier Performance

1. Introduction

Companies are experiencing bursts of data with advancements in information technologies. The quality of decisions depends on how such big data is utilized via analytics. Hazen (2016) reports that successful companies have shifted their mind set towards quantitative decision making in order to capitalize on great outcomes. Leading companies such are Amazon, Walmart, Zara, UPS, Tesco, Proctor and Gamble, Deere & Company, and eBay have utilized data analytics extensively in supporting all decisions regarding order fulfillment, inventory management, warehousing, transportation and logistics, and reported significant savings (Sanders, 2014). The survey conducted among supply chain executives by Schoenherr & Speier-Pero (2015) reveals that improvement in efficiencies is among the top three benefits of big data analytics.

Data analytics possesses great potential for improving the return on investment (Perrey et al., 2013) and in revolutionizing existing theories in supply chain management (Wamba et al., 2018). Highly advanced information technologies synchronize lateral relationships across members of the supply chain, improve the visibility and quality of information (Srinivasan & Swink, 2018), and provide a vast amount of structured and unstructured data for managers to use it for effective decision-making pertaining to efficiency in the supply chain (Hazen et al., 2014). Using conventional modeling, Sener et al. (2019), adopting theories such as social exchange and organizational learning, identify constructs in relation to information sharing and usage, impacting retailer's performance. Data analytics techniques can help identify key variables among large sets of variables that are relevant and important for performance studies in supply chain management (Last et al., 2009; Choudhary et al., 2009; Waller & Fawcett, 2013; Kache & Seuring, 2017) and also uncover interrelations not observed in conventional models that are subject to limiting relational assumptions of linearity, multivariate normality, and independence of the predictive variable (Ravi et al., 2008; Chen et al., 2012).

Integrated efforts among the members of a supply chain entail both cooperation in setting collaborative goals and coordination in setting supply chain plans for designing, planning, and control activities, which include but are not limited to forecasting, demand, capacity, scheduling, and quality (Dubey et al., 2019). A large stream of research concludes that inter- and intra-collaboration and integration are important in contemplating improved operational, logistics, and organizational performance (Flynn et al., 2010; Johnson & Templar, 2011; Ramanathan, 2013). Wamba et al. (2018) suggest more attention to the outcomes of data analytics and its potential and emphasize the lack of research on contextual factors affecting performance of a supply chain. More specifically, Kaynak & Carr (2012) and Kembro & Näslund (2014) emphasize the need of research investigating the antecedents of information integration and their impact on suppliers' performances which is detrimental to the success of OEMs (Ireland & Webb, 1999; Modi & Mabert, 2007). The literature, however, reveals that research on supply chain performance is customer centric, focusing on OEM's perspective, and investigate hypothesized relationships utilizing models with limited relational assumptions (Last et al. (2009), Choudhary et al. (2009), and Chen et al. (2012).

On the other hand, while integration is offered as an inevitable prescription to improve performance (Cooper et al., 1997; Mentzer et al., 2001; Seggie et al., 2006), the scope of integration in supply chain management literature is very fragmented. Some research focuses on integration based on a supply chain tier involved such as customer integration versus supplier integration (Huo, 2012), others emphasizes external versus internal integration (Flynn et al., 2010). Regardless of the scope, information is considered ultimate power in achieving integration (Ding et al., 2011; Kocoglu et al., 2011). Conversely, based on Sener et al. (2019)'s snapshot of literature on aspects of information, literature shows no consensus on surrogate measurements or variables used for integration across the researchers, suggesting the need for a holistic approach to include all aspects of information integration in relation to performance.

This study is the first to use data-mining techniques in determining the most important variables and their relative importance, and to uncover interrelations between antecedents and supplier performance measures that are not observed in traditional conceptual models, considering a supplier-manufacturer dyadic relationship in the U.S. aircraft supply chain to the best of our knowledge. Our study contributes to the literature by doing the following: a) Utilizing a Bayesian belief networks (BBNs) tool for reasoning (Waller & Fawcett, 2013; Garvey et al., 2015; Sarkis & Dhavale, 2015) to relax the above-mentioned assumptions that exist in conventional modeling i.e. frequentist approach; (b) examining the data for all possible relationships among the variables of commitment, information sharing, information quality, and information usage relative to supplier operational performance; and (c) determining the most relevant variables managers should consider as information integration-related antecedents for their success, and providing insights into important variables.

In the remainder of this paper, section 2 provides a theoretical background covering issues related to information sharing, information usage, information quality, commitment, and performance. Section 3 is dedicated to research methods, including data acquisition, preparation, variable selection, and extraction of relations among variables. The results and discussion are presented in section 4, followed by theoretical and managerial contributions in section 5. The paper concludes with a summary and suggestions for future directions.

2. Theoretical Background

We categorize the current literature research efforts into five categories: information sharing, information usage, information quality, commitment, and performance. Following this categorization, we introduce our research methodology.

2.1 Information Sharing

Rai et al. (2006) and Kim (2009) report that information sharing among members of the supply chain have an affirmative impact on firm performance. According to the framework by Stevens (1989), companies go through four stages in order to achieve integration: baseline, functional, internal integration, and external integration. Huo (2012) breaks external integration into supplier integration and customer integration. While a vast amount of literature investigates the drivers of each type of integration, there is no consensus on surrogate measurements used for integration across the researchers (Zhao et al., 2011; Huo, 2012). Table 1 summarizes the variants in drivers.

Table 1. Drivers of Integration

Integration Type		Drivers	Source
External Integration	Customer	Information sharing, Integrated infrastructure, Partnership, Joint planning	Li et al., 2012; Yang, 2008; Swink et al., 2007
	Supplier	Information sharing, Degree of strategic partnership, Joint planning, Research and development with supplier	Zhao et al., 2013; Wong et al., 2013; Stank et al., 2001
		Information exchange, Strategic partnership, Sharing of production schedules, inventory and demand information	He & Xu, 2014; Danese & Romano, 2013; Flynn et al., 2010
Internal Integration		Data integration, Real-time data, Real-time searching	Flynn et al., 2010
		Integrated database, Operational information, Encouragement of integration	Stank et al., 2001
		Concurrent engineering/joint design, Standardization	Droge et al., 2004
		Responsiveness, Information flow, Psychical flow	Wong et al., 2013

A relational view by Dyer & Singh (1998) considers the information-sharing component of external integration as one of the major sources contributing to competitive advantages. Information sharing is often considered to be a general cure to supply chain and logistics problems (Gligor & Holcomb, 2014). Similarly, the resource-based view by Armstrong & Shimizu (2007); Newbert (2007);

Yu et al. (2013); and Huo et al. (2014) information is viewed as an essential ingredient for improving operational and organizational performances.

Many researchers focus on the theoretical impact of sharing specific information on a given operational performance measure, as summarized in Table 2. Among the specific types of information considered are demand forecast (Cachon & Lariviere, 2001; Özer & Wei, 2006), lead time (Dobson & Pinker, 2006), inventory (Ganeshan et al., 2001; Fleisch & Tellkamp, 2005), and quality (Tarí et al., 2014; Demeter et al., 2007). A few recent studies have expanded the scope of information sharing and investigated outcomes at either organizational-level performance or supply chain-level performance (Prajogo & Olhager, 2012; Hall & Saygin, 2012). Wu et al. (2014) investigate the relationship between performance, collaboration, information sharing, and drivers of information exchange.

Table 2 Scope of Information in Relations (T = Theoretical; E = Empirical)

Reference	Type	Relation Investigated: Information Type → Performance
Cachon & Lariviere, 2001	T	Sharing demand forecast → supply chain performance
Swaminathan et al., 1995	T	Sharing supplier capacity → supply chain performance
Demeter et al., 2007	E	Accessibility and quality of forecast information → supply chain performance
Özer & Wei, 2006	T	Impact of forecast information sharing → supply chain inefficiency
Ganeshan et al., 2001	T	Inventory and flow planning → supply chain performance
Yao et al., 2008	T	Vertical cost information → supply chain performance
Zhang et al., 2016	T	Shipment information → supply chain performance
Hariharan & Zipkin, 1995	T	Advance ordering information → supply chain performance
Karaesmen et al., 2004	T	Advance demand information → supply chain performance
Dobson & Pinker, 2006	T	Lead time information → organizational performance
Tarí et al., 2014	E	Quality management → operational performance
Williams & Naumann, 2011	E	Customer satisfaction → organizational performance
Carr & Kaynak, 2007	E	Information sharing → organizational performance
Fleisch & Tellkamp, 2005	T	Inventory information → Organizational performance
Randall & Ulrich, 2001	E	Product variety → firm performance
Lee & Whang, 2000	E	Sales forecast } Order status } → Organizational performance Inventory position } Shipment data }

Reference	Type	Relation Investigated: Information Type → Performance
Li et al., 2006	T	Demand } Inventory } → Firm performance Shipment }
Lin et al., 2002	T	Order information (inventory, demand) } Operational information } → Organizational performance Strategic information }
Hall & Saygin, 2012	T	Inventory level } Customer demand } → Organizational performance Reliability information }
Kulp et al, 2004	E	Consumer needs } Store inventory levels } → Organizational performance Warehouse inventory levels }
Prajogo & Olhager, 2012	E	Financial } Production } → Operational performance Design } Research }
Dubey et al., 2017	E	Supply chain connectivity } Information sharing } → Sustainable performance Visibility }

Min et al. (2005), Patnayakuni et al. (2006), Hsu et al. (2008), Gunasekaran & Kobu (2007), Olorunniwo & Li (2010), and Huo et al. (2014) articulate the concept that focusing on coordination without considering information sharing will not serve to improve the performance of firms in a supply chain. Carr & Kaynak (2007) integrate information sharing and supplier development theory and report positive impacts of intra-firm and inter-firm information sharing on operational performance. On the other hand, Van der Vaart & Van Donk (2008) suggest an examination of supply chain information integration and its impact on performance for a given specific industry or buyer-supplier relationship due to the lack of uniformity in factors compiled from 33 empirical research papers published during the last decade in ten major journals. The literature focusing on information integration, however, considers information sharing as synonymous with integration, without distinguishing usage of information from information sharing.

2.2. Information Usage

According to organizational learning theory, companies learn through three key processes: acquisition of information; analysis of information; and application of information in planning and execution Lichtenthaler, (2009). Hwang et al. (2013) report that proactive behavior of information usage leads to learning. Croson & Donohue (2005) conclude that suppliers perform better when they have access to information. While information sharing is about acquisition of information, the information usage is the process of analyzing and interpreting the information shared; and applying the processed information in decision making process (Sener et al., 2019). Srinivasan & Swink (2018), using organizational information processing theory, define supply chain information visibility, information sharing, as the source supporting data analytics capability.

Sanders (2007) argues collaboration in planning and control across the supply chain members has a direct impact on intra-level performance. According to Ramanathan (2013), the prerequisite for such success is the materialization of the information usage. Barut et al. (2002) develop a metric to measure the degree of information coupling, considering economies of scale and economies of scope for different types of information shared, and argue that the use of the information shared is critical in making a difference on operational performance; thus, the degree of information usage should be an indicator of active information sharing, assuming that companies will not deliberately preempt the use of information once it is provided. Similarly, Wowak et al. (2013) point out the importance of information usage among the partners in leading to superior performance. To have a sustainable and competitive supply chain, all three key processes of organizational learning must be coupled (Ellinger et al., 2015).

2.3. Information Quality

In this study, we focus on intrinsic or fundamental determinants of information quality where both academic and practitioner views overlaps. For details of both views, we refer to Lee et al., (2002). Among these overlapping determinants are accuracy, timeliness, adequacy and completeness, and reliability (Power & Sohal, 2001; Salaun & Flores, 2001). While the accuracy focuses on information to be free of mistakes or errors, any instability or frequent changes in the values of information shared may create nervousness in the upstream or downstream of a supply chain in relation to planning horizon and thus results in reliability impairment. While adequacy deals with the scale of information shared, completeness considers the details of the scope for the decision on hand. Timeliness determine whether the information shared is provided when needed and updated in timely fashion.

Ding et al. (2014) conclude that quality of information shared have direct impact on the efficiency measurements in supply chains and identify the efforts to improve information quality as innovative practices. Moreover, Nicolaou & McKnight (2006) indicate that the quality of information shared is highly predictive of trust and risks in information exchange, and directly affects the usage of information shared. Interestingly, Chiu et al. (2007) found that reciprocity among the supply chain members improved the magnitude of information shared rather than that of quality. Hartono et al. (2010) and Ding et al. (2014) suggest that in a manufacturing setting, special attention should be given to information quality in order to improve performance.

Nicolaou et al. (2013) highlight that information quality is an important factor affecting decision-making process. Vivek et al. (2011) explored the impact of information quality and found a clear relationship between improved information quality and better integration and organizational performance. The higher quality of information used leads to more effective decisions (Hazen et al, 2014). Wiengarten et al. (2010) report that collaborative decision making has significant impact on supply chain performance only when the information quality is high. Vivek et al. (2011) emphasize building partnerships with suppliers and investing to improve the information quality in order to increase supply chain agility and help members of supply chain to network benchmark capabilities of each other. Li & Lin (2006) state that commitment among the supply chain members is perceived as requisite for the quality of information shared.

2.4 Commitment

Hashim & Tan (2015) argue that commitment is a motivator for information sharing and involves risks. In supply chain context, commitment is seen as crucial element and requires voluntarily sharing information Min et al., (2005). As mentioned in information quality section above, without commitment information sharing cannot be in timely fashion and complete. Commitment has been a focal interest for many theories including organizational behavior (Hunt & Morgan, 1994), strategic management and marketing (Morgan & Hunt, 1994; Hunt, 1997), and social exchange (Eckerd & Hill, 2012). All studies reveal that commitment positively impacts outcomes of a system, weather it is a group, an organization, or a supply chain.

According to social exchange theory (SET), members of a group collaborate among themselves yielding to collective measurable benefits (rewards minus costs), assuming interactions can be quantified (Kale & Singh, 2009). Adoption of SET in context of supply chain by researchers focuses on development of interrelationships (Wei et al., 2012). Wu et al. (2014) argue that such relationships are based on information sharing and formed due to reciprocal benefits supply chain members offer to each other, and define the antecedents of information sharing as trust, commitment, reciprocity, and power. Ireland & Webb (2007) focus on how to develop and manage a portfolio of antecedents for a given inter-organizational relationships to improve outcomes. Kwon & Suh (2005) point out the relationships among these antecedents and conclude that the higher level of trust the higher level of commitment. Morgan & Hunt (1994) also observe that mediating impact of both trust and commitment between relationship practices and qualitative outcomes. Cropanzano & Mitchell (2005) further categorized transactions and relationships in social exchange theory whether they are social or an economic in nature; and conclude with that there is a match when both transaction and relationship are social or economic. Thus, when a social relationship is paired with an economic transaction there is a mismatch, offering both rewards and risks.

On the other hand, Zhao et al. (2008) benchmark the marketing and management practices of commitments and categorize them into normative and instrumental. Their study reveals the normative construct of a relationship positively impacting the relationship between customer power and dyadic information integration. The formation and continuity of a commitment based on mutual benefits (Wei et al., 2012) may be an essential antecedent that positively influences information sharing (Van den Hooff & De Ridder, 2004). Similarly, Vijayasarathy (2010) contemplates the relational commitment as an antecedent

Table 3. Relational Models Investigated in Literature

Author	Dimensions Investigated	Theory	Remarks
Huo et al., 2016	Strategic supply chain relationships, technology integration, internal and external integration, performance	Resource-based view	Supply chain relationship has a positive relationship with external information integration, and technology internalization has a positive relationship with internal integration.
Dubey et al., 2017	Behavioral uncertainty, information sharing, swift trust, commitment, coordination	Commitment trust theory	Commitment has mediating effect between swift trust and coordination in humanitarian relief supply chains and sharing information among organizations helps to build swift trust.
Huo et al., 2014	Relationship commitment, information technology (IT), coordination, supply chain performance	Socio-technical theory, configuration theory	Positive relationship among variables tested. Type of commitment has strong effect on coordination and performance.
Prajogo & Olhager, 2012	Long-term relationship, IT, information sharing, logistics integration, performance		Information sharing and technology capabilities have significant effects on logistics integration, which has a significant effect on operations performance considering long-term supplier relationships.
Cheng, 2011	Relational benefit, proclivity, power symmetry, connectedness, conflict, information sharing	Resource-based view	Relational commitment is critical for information sharing because it reinforces connectedness among supply chain members.
Vijayasarathy, 2010	Dependence asymmetry, trust, commitment, mutual dependence, information sharing	Transaction cost analysis, resource-based view	Trust, commitment, and mutual dependence are positively related to supply integration. No positive relation was found between dependence asymmetry and information sharing.
Brown et al., 1995	Supplier (mediated power, non-mediated power), power symmetry/asymmetry, retailer (instrumental and normative relationship commitment), performance	-	Relationship between supplier power and type of relational commitment partially supported.
Wu et al., 2014	Trust, commitment, reciprocity, power, information sharing, collaboration, performance	Social exchange theory	Social exchange theory-related issues are important to determine information sharing and collaboration, indicating partial mediation effect on supply chain performance.
Wang et al., 2014	Managerial ties, trust, information sharing, IT, quality, uncertainty, supplier opportunism	Social capital theory, transaction cost theory	Extent of information sharing, and quality of the information shared depends on managerial ties through trust but not on the quality of information shared. Quality of the information shared is more important than the extent of information sharing to reduce supplier opportunism.
Zhao et al., 2011	Relationship commitment to supplier and customer, internal integration, customer integration, supplier integration	Transaction cost theory	Relationship commitment to customers and suppliers has positive effect on external integration and internal integration.
Zhao et al., 2008	Customer power (expert, referent, legitimate, reward, coercive), relationship commitment (normative, instrumental), customer integration	Transaction cost theory, social exchange theory	Types of customer power have varying impact on manufacturers' relationship commitment. Normative commitment has more impact on customer integration than instrumental commitment.
Yang et al., 2008	Relational capital, relational commitment, trust of supplier, relational stability, alliance performance	Social exchange theory, goal interdependence theory	Alliance performance is positively affected by relational stability, which is also affected by relational commitment and trust of supplier.

Author	Dimensions Investigated	Theory	Remarks
Patnayakuni et al., 2006	Relational orientation, information sharing behavior	Resource-based view	Integration of information flow with supply chain partners is affected by tangible and intangible resources invested in supply chain relations.
Wu et al., 2014	Marketing determinants of SCM, behavioral determinants of SCM, SCM commitment, SCM business process integration	—	Positive relationship among business process integration and behavioral determinants of supply chain management.
Griffith et al., 2006	Justice, long-term orientation, relational behavior, conflict, satisfaction, performance	Social exchange theory	Under social exchange theory, there is a strong relation among relational commitment, duration of relationship, and performance.
Jap & Ganesan, 2000	Control mechanisms, relationship phase, retailer perception of supplier commitment to relationship, satisfaction, conflict, performance	Transaction cost analysis, transaction specific investment	Retailer's perceptions of commitment are positively related to supplier evaluation and satisfaction, and also negatively related to conflict.
Nyaga et al., 2010	Collaborative activities, key mediating variables, relationship outcomes	Transaction cost analysis, social exchange theory	Information sharing, joint relationship effort, and dedicated investments promote trust and commitment, in turn promoting improved satisfaction and performance.
Dubey et al., 2019	Swift trust, collaborative performance, flexible and control orientation, big data analytics	Organizational information processing theory	Big data analytics capability positively influences swift trust and collaborative performance. Other negative moderating effects and insignificant relationships are reported.
Hunt & Morgan, 1994	Consistency specific commitment types, global organizational commitment, organizational outcomes	—	Organizational commitment plays key mediation role between constituency-specific commitments and organizational outcomes.
Hunt, 1997	Resources, market positions, financial performance	Resource advantage theory	Companies should generate a relationship portfolio that involves relational resources such as parity, and comparative advantages and disadvantages.
Ireland & Webb, 2007	Cultural competitiveness, trust/power climate, authority, identity, boundary spanners, justice	Social capital theory, Transaction cost economics, Resource dependency theory	Balanced mixture of trust and power will lead to cultural competitiveness.
Kwon & Suh, 2005	IT share, mediating variables, trust, commitment	Social exchange theory	Information sharing has vital effect on trust through reduction of uncertainty, and commitment depends on level of trust.
Panayides & Lun, 2009	Trust, innovativeness, supply chain performance	Social exchange theory	Trust positively contributes to innovativeness and supply chain performance. Cooperation has significant impact on supply chain performance.

to supply chain integration. Following in their footsteps, Huo et al. (2016) consider mediating the impact of supply chain coordination on relationship commitment and technology relative to supply chain performance. Table 3 provides a comprehensive list of relational models investigated in the literature and hints on remarks.

Supply chain information visibility is achieved by acquiring interrelations among all members of a supply chain (Srinivasan & Swink, 2018). Integration among supply chain partners relies on commitment to their relationship and investing in such relationship yields to increased performance (Daugherty et al., 2006). Anderson & Weitz (1992) and Krause (1999) suggest that a relationship commitment of a company is a function of one's perception about partner commitment. In other words, commitment of manufacturer can be measured by the perception of suppliers.

2.5 Performance

An extensive line of research has focused on the categorization of performance measures by providing frameworks. Neely et al. (1995) classify performance measures using quality, cost, time, and flexibility dimensions. Beamon (1999) discusses the components of performance, and groups the measures under resources, outputs, and flexibility. Gunasekaran et al. (2001) consider decision-making levels and categorize performance measures into strategic, tactical, and operational. Chan (2003) uses a measurement-based approach to categorize measures in the literature and whether they are quantitative or qualitative in nature. Rafele (2004) emphasizes service-level aspects of performance and categorizes measures in relation to tangibility, ways of fulfillment, and informative action. Chan & Qi (2003) shift the focus and, using a performance activity approach, categorize measures into two groups—hard or soft—similar to tangible/intangible, quantitative/qualitative, or objective/subjective classifications. Aramyan et al. (2007) concentrate on agri-supply chain performance indicators and group them into efficiency, flexibility, responsiveness, and quality. In Table 4, we summarize our comprehensive review of performance measures by frameworks.

Table 4. Scope of Performance Measures by Framework

Framework by	Component	Performance Measures
Huo et al., 2016	Operational	Inventory turnover, productivity/asset utilization, production efficiency (use of resources and materials)
	Quality	Conformance of final products to design specification, performance of final products, on-time deliveries, accuracy of deliveries, delivery speed, and flexibility in delivery time
	Financial	Sales volume, profitability, return on assets, market share
Rafele, 2004	Tangible	Equipment productivity, surface utilization, volume utilization, fill rate, accident impact, personnel efficiency, inventory availability
	Ways of fulfillment	Flexibility, punctuality, completeness, correctness, harmfulness, delay, delivery frequency, shipping quantity, total order cycle time, lead time
	Informative actions	Range completeness, product information, documents management, backorders, claims management, web site completeness, ease of transactions
Zhang et al., 2016	Business improvement	Financial strength, reputation of industry, managing ability
	Extent of fitness	Flexible practices, sharing expertise, diversified customers
	Quality	Low defect rate, commitment to quality, improved process capacity
	Service	On-time delivery, quick responsiveness, supplier capacity
	Risk	Supply constraints, buyer supplier constraints, supplier profile
Gunasekaran et al., 2001	Strategic	Total cash flow time, rate of return on investment, flexibility to meet particular customer needs, delivery lead time, total cycle time, level and degree of buyer supplier partnership, customer query time
	Tactical	Extent of cooperation to improve quality, total transportation cost, truthfulness of demand predictability/forecasting methods, product development cycle time
	Operational	Manufacturing cost, capacity utilization, information carrying cost, inventory carrying cost
Chae, 2009	Sales and marketing	Forecast versus order, forecast volatility, inventory days of supply at sales subsidiaries
	Production	On-time departure from manufacturing, subsidiaries and ODM/OEM, production plan versus result, inventory days of (finished goods) supply at manufacturing subsidiaries, inventory days of raw material supply, on-time arrival to sales subsidiaries (or distribution centers) from manufacturing subsidiaries and ODM/OEM
	Purchasing	Supplier fill rate, automatic PO rate
	Operation strategy	Forecast accuracy, planning cycle, inventory days of supply, cash-to-case cycle
Poppo et al., 2016	Asset specificity	Product features, personnel, inventory and distribution, capital equipment, and tools
	Uncertainty	Pricing, product feature and specifications, vendor support services, technology used by suppliers, product supply
	Operational	Product quality, timeliness of delivery, sales/service/technical support

Framework by	Component	Performance Measures
Chan & Qi, 2003	Quantitative (hard)	Cost, time, capacity, productivity, utilization
	Qualitative (soft)	Quality, flexibility, visibility, trust, innovativeness, effectiveness, reliability, availability,
Bourne et al., 2000	Financial perspective	Profitability, value added, employee, order intake, invoiced sales
	Internal perspective	Order quality, forecast accuracy, on-time supplier, warranty returns, rework
	Innovation and learning	On-time appraisal, employee communication survey, on-time stage gates, training
	Customer perspective	Customer complaints, on-time delivery, new customer quotes, quotations, sales activity, order conversion rate
Soh et al., 2016	Engagement	Improving integration activities, communicating future strategic needs, creating a greater level of trust, compatible communication/information system
	Infrastructure	Testing capability, scope of resources, supplier's process capability, price of materials/parts and services
	Quality	Commitment to quality, ability to meet delivery due dates, commitment to continuous improvement
	Commitment	Company size, willingness to share confidential information, percentage of subcontracted work
	Relationship	Trust, business understanding, involvement, commitment, communication, information sharing
Kennerley & Neely, 2002	External drivers	Customers, market place, legislation, new industries, nature of work, future uncertainty
	Internal drivers	Actual performance, dysfunctional behavior, effective review/ monitoring systems
Neely et al., 2005	Quality	Performance, features, reliability, conformance, value, technical durability, serviceability, aesthetics, perceived quality, humanity
	Cost	Manufacturing cost, value added, selling price, running cost, service cost
	Time	Manufacturing lead time, rate of production introduction, delivery lead time, due-date performance, delivery frequency
	Flexibility	Material quality, output quality, new product, modified product, deliverability, volume, resource mix
Terpend & Ashenbaum, 2012 Terpend & Krause, 2015	Delivery	Ability to expedite rush order, fast delivery, time to develop a new part, ability to provide JIT delivery, delivery reliability
	Quality	Reliable items, durable items, conformity with specifications
	Cost	Total cost associated with item, sharing data cost, unit price
	Innovation	Technical capabilities, willingness to share key technological information, ability to design new products or make changes in existing items
	Flexibility	Ability to change order volumes or mix of order volumes
Kaplan & Norton, 1997	Financial	Return on investment, economic value added
	Internal process	Quality, response time, cost, new product introductions
	Learning/growth	Employee satisfaction, information system availability
	Customers	Satisfaction, retention, market, account share

Framework by	Component	Performance Measures
Beamon, 1999	Resource utilization	Total cost, distribution/manufacturing/cost, inventory, return on investment
	Output	Sales, profit, fill rate, on-time deliveries, backorder/stockout, customer response time, manufacturing lead time, shipping errors, customer complaints
	Flexibility	Backorders, lost sales, late orders, customer satisfaction
Aramyan et al., 2007	Efficiency	Costs, profit, return on investment
	Flexibility	Product scope and scale
	Responsiveness	Lead time, customer complaints
	Quality	Appearance, product safety
Li et al., 2006	Cost	Transportation/shipment cost, ordering cost, negotiation/ contracting cost, cost-reduction plan, total cost of ownership
	Quality	Total quality management processes and practice, defects/scraps/ nonconformance, six sigma quality, process capability efforts, product conformity (function, reliability)
	Service	Responsiveness to complaint/change, provision of training, perceived cooperativeness
	Corporate Metrics	Management and employee competence, leadership/business process and practices, financial strength/stability, market performance, future business plans
	Lower-tier management	Supplier's relationship with its lower tiers, supplier's lower-tier risks, supplier's lower-tier performance
Leuschner et al., 2013	Revenue	Sales, market share
	Customer-oriented	Customer satisfaction, customer loyalty
	Operational	Cost, quality, delivery, flexibility, innovation
Theeranuphattana & Tang, 2007	Reliability	Order fulfillment
	Responsiveness	Order fulfillment cycle time
	Flexibility	Upside supply chain flexibility, upside supply adaptability, downside supply chain adaptability
	Costs	Cost of supply management, cost of goods sold
	Assets	Cash-to-cash cycle time, return on supply chain fixed assets, return on working capital

The literature reveals a challenge in selecting the right performance measure for evaluation. Our suggestion is in line with Wisner & Fawcett (1991) that companies should develop performance measurement system based on their core competencies. While qualitative measures are considered important, Chen & Paulraj (2004), Kaplan & Norton (1997), Bourne et al. (2000), and Vickery et al. (2003) suggest focusing on quantitative measures, such as financial measures, serving shareholders' interests, productivity, and capacity improvement. Karaesement et al. (2004) identify the conditions that advanced information visibility creates significant quantitative benefits. Sener et al. (2019) report that the impact of information sharing, and information usage amplifies the interaction effect on operational efficiency measurements, which are quantitative, compared to that of operational effectiveness that are qualitative in nature.

Considering the higher impact of supply chain visibility on operational efficiencies and following the suggestion of creating manageable short list by Neely et al. (2005), in this study, we limit our research to operational performances that are tangible and quantitative.

3. Research Methods

In this study, we suggest a data analytics approach comprised of three main steps, as depicted in Figure 1. First, we start with data acquisition and preparation, whereby a questionnaire is designed, and data is collected from suppliers of aircraft manufacturers in the U.S. In the second step, we perform a variable selection approach using a Pearson product-moment correlation to generate candidate sets of predictors to be used in the Bayesian belief network at step 3.

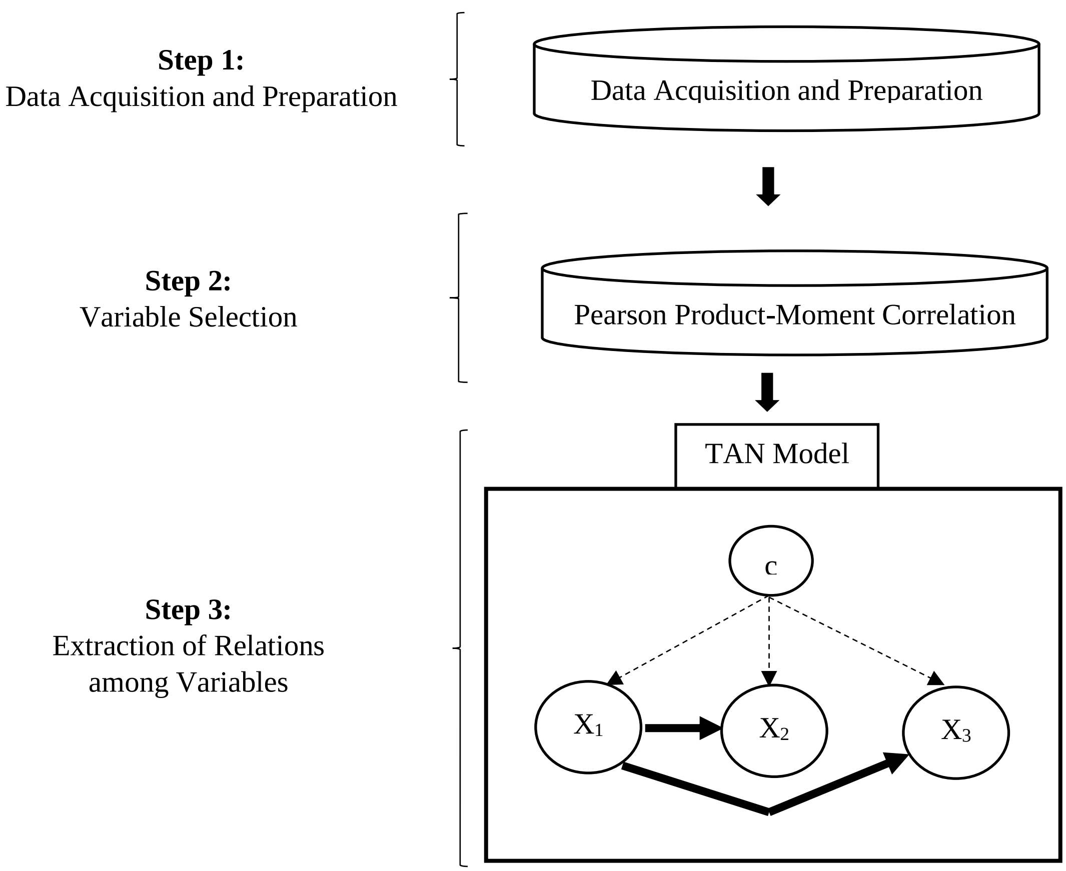

Figure 1. Data analytics approach.

3.1 Data Acquisition and Preparation

3.1.1 Questionnaire Design

In our survey instrument, all items (variables) in each category—information sharing, information usage, quality of information, commitment, and performance—were assessed using a seven-point Likert scale. The scope of suppliers, as dichotomous variable, weather they are domestic or international, is also considered per suggestion by Mawdlsey & Somaya (2018). Items were rigorously reviewed and evaluated for appropriateness, ambiguity, and redundancies by a team of four academicians and an executive manager who have years of professional experience in supply chain management in the aircraft industry to which the questionnaire was administered. The questionnaire was designed and administered in a way to eliminate common rate effects, item-priming effects, and acquiescence bias, as suggested by Podsakoff et al., (2003). Cohen's kappa coefficient of 76.9% is indicative of the minimal rater bias effect (Sim & Wright, 2005). The analysis of variance between the early and late respondent groups reveals no statistical differences between early and late respondent survey responses ($p > 0.1$), indicating lack of non-response bias. The variables used in the analyses are shown in Table 5.

Table 5. Description of Variables Used in Analysis

Variables Used in Analysis			
Relationship Commitment	Normative	NORM1	Our major customers view us as being an important ‘‘team member’’ rather than just another supplier.
		NORM2	We are proud to tell others that we are a supplier for these customers.
		NORM3	Our major customers would understand us when we have difficulty to meet their demand.
		NORM4	The reason we prefer our major customers to others is because of their values.
		NORM5	We will go the extra mile to please our major customers, even though we are not rewarded.
		NORM6	Our major customers are sincere.
	Instrumental	INST1	Unless we are rewarded for it in some way, we see no reason to spend extra effort on behalf of major customers.
		INST2	How hard we work for these major customers is directly linked to how much we are rewarded.
		INST3	Negotiation is necessary in order to obtain favorable terms of supply chain in dealing with these customers.
Information Sharing	Downstream	ISC1	Purchase order update
		ISC2	Planned order
		ISC3	Inventory level
		ISC4	Engineering requirements
		ISC5	Performance feedback
		ISC6	Future demand forecasting
		ISC7	Production schedule

	Upstream	ISS1	Production capacity
		ISS2	Production schedule
		ISS3	Order status
		ISS4	Delivery schedule
		ISS5	Product lead time
		ISS6	Research and development
		ISS7	Cost
Information Usage by Supplier		IU1	Purchase order update
		IU2	Planned order
		IU3	Inventory level
		IU4	Engineering requirements
		IU5	Performance feedback
		IU6	Future demand forecasting
		IU7	Production schedule
Quality of Information Exchanged		IQ1	Information exchange between the major customer and us is timely.
		IQ2	Information exchange between the major customer and us is accurate.
		IQ3	Information exchange between the major customer and us is complete.
		IQ4	Information exchange between the major customer and us is adequate.
		IQ5	Information exchange between the major customer and us is reliable.
Supplier Performance		PERF1	Line item fill rate
		PERF2	Service level
		PERF3	Logistics performance
		PERF4	Delivery reliability
		PERF5	Customer rejection rate

3.1.2 Data Collection

We randomly targeted 1,500 suppliers of the aircraft manufacturing industry in the United States. Manager contact information for suppliers of aircraft OEMs was obtained from DatabaseUSA.com, which has access to thousands of pieces of contact information for suppliers of aircraft OEMs. To ascertain data collection reliability, we followed the suggestion of Kull et al. (2018), Montabon et al. (2018), and Krause et al. (2018) and determined one key informant for each supplier who is knowledgeable content-wise and familiar with processes in their supply chain. We sent the survey to each key informant and followed up with four emails. Out of 366 responses received, 269 usable questionnaires were recorded.

3.2 Variable Selection

Variable selection aids in data comprehension and improves the performance of predictors by eliminating irrelevant variables from the data set (Chandrashekar & Sahin, 2014). We employed the variable selection method to select the opposite subset of existing variables. Current variable selection methods can be classified into two groups: filters and wrappers (Das, 2001; Kohavi & John, 1997). Filter methods entail agnostic models based on general characteristics of the training data to select some variables without relating to any learning algorithm. Filter methods rank variables based on their discrete predictive power, which can be assessed by several methods, such as the Fisher score, Pearson correlation, Kolmogorov-Smirnov test, or mutual information (Fleuret, 2004), On the other hand, wrapper methods are explicitly devoted to a specific type of prediction method to assess the quality of a set of variables. Both methods are affected by the number of variables, samples, and presence of complex nonlinear relations among the variables. In this study, we applied the Pearson product-moment correlation coefficient (PPMCC) in order to measure the strength and direction of the linear dependencies among random variables. The PPMCC value may range between –1 and 1, suggesting negative and positive linear correlations, respectively. While a PPMCC value of zero indicates linear independency among variables, it is possible to observe a non-linear relationship among the variables. Note that this coefficient is symmetric; thus, the correlation between x and y is the same as the correlation between y and x.

3.3 Variable Relations via Bayesian Belief Network

The Bayesian belief network is a powerful data-mining technique that is capable of quantifying and visualizing complex relationships among attributes (Anderson, 1986). The BBN is a directed acyclic graph or a probabilistic dependency model. It consists of a set of interrelated variables, where the nodes in the network correspond to variables (predictors), and the arcs reveal conditional dependencies and causal relations among these variables (Pearl, 1985), as shown previously in Figure 1, Step 3.

Let x_i be the i-th variable, and let Pa_{x_i} be the set of parents for each x_i. Then the Bayesian network chain rule can be expressed as (Koller & Friedman, 2009)

$$P(x_1, \ldots, x_n) = \prod_{i=1}^{n} P\left(x_i \middle| Pa_{x_i}\right). \tag{1}$$

The naive Bayes (NB) classification is a simple model that can help to determine the structure. It assumes conditional independence among all predictor variables with the given class/target. This classification is based on the Bayes rule, where the probability of the class/target value computed for each given attribute variables and then the highest prediction is chosen for the structure (Friedman et al., 1997). The treeaugmented naive Bayes (TAN) method is a relaxation of the NB classifiers, where the class variable (C) has no parents, but it is one of the parents of each predictor along with, at most, one other attribute. Thus, C is a parent for each predictor, and each predictor has at most one more parent along with C:

$$Pa_{x_i} = \{C, x_{\xi(i)}\}, \tag{2}$$

where $\xi(i)$ is the tree function over $x_1, \ldots, x_n$, and Pa_{x_i} is the set of parents for each x_i. The class variable has no parents and is defined as

$$Pa_c = \emptyset. \tag{3}$$

The arc between two predictors implies that the contribution of the child node in predicting the outcome (class node C) is dependent on the parent node value. For example, in predicting the class variable C_1, the contribution of X_3 is dependent on the value of X_1, and the contribution of X_2 is dependent on the value of X_1. Finding the best tree is an optimization problem, where the objectives are to maximize the log likelihood of $\xi(i)$ and to construct a maximum likelihood tree to find a maximal weighted spanning tree in a graph (Chow & Liu, 1968). Then, the TAN construction steps can be defined as follows (Chow & Liu, 1968):

- First, compute the conditional mutual information function for each (i, j) pair:

$$I_p(x_i : x_j | C) = \sum_{x_i, x_j, c} P(x_i, x_j, C) \log \frac{P(x_i, x_j | C)}{P(x_i | C) P(x_j | C)}, i \neq j.$$

  This function tells how much information x_j provides about x_i when the class variable is known.
- Then, build a complete undirected graph, and use the conditional mutual information function to annotate the weight of an edge connecting x_i to x_j.
- Finally, build a maximum weighted spanning tree.

3.4 Performance Criteria for Model Evaluation

In this study, two-thirds (67%) of the data was used for training purposes, and the remaining one-third (33%) was employed to test the model performance. This sampling procedure was completely randomized. There are two legitimate reasons for not employing a stratified ten-fold cross-validation approach, although based on empirical research, ten is the optimal number of folds that reduces the time it takes to complete the test while minimizing the bias and variance associated with the validation process (Breiman et al., 1984; Kohavi, 1995). The first reason involves the size of the dataset. Ten percent of the data for testing purposes would not be a large-enough sample to test the score in an unbiased way. Second, and perhaps the most important reason, the main goal here is to uncover the hidden interdependent relations among the independent variables. In other words, observing the interdependency network has critical importance in deciphering the relations. Therefore, only one representative model that would appropriately show the hidden relations among the predictors is needed. However, when applying a *k*-fold cross-validation, the entire data is divided into *k* mutually exclusive subsets (or folds) with an almost identical class distribution as the original dataset (stratified). Each fold is used once to test the performance of the classifier, which is generated from combined data of the remaining nine folds, leading to *k* independent predictive models.

3.4.1 Accuracy, Sensitivity, and Specificity

In order to compare the classification models, three performance criteria are adopted:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{5}$$

$$Specificity = \frac{TN}{TN+FP} \tag{6}$$

where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively. The accuracy, depicted in equation (4), measures the percentage of correctly classified test examples, thus predicting the overall probability of the correct classification. Sensitivity and specificity presented in equations (5) and (6), correspondingly, measure the model's ability to recognize the variables of a certain group.

Additionally, the area under the receiver operating characteristic curve, or area under the curve (AUC), is used to measure how well the parameters are differentiated from each other and the predictive ability of the learning algorithms.

3.5 Sensitivity Analysis

By using sensitivity analysis, the relative importance of the independent variables is measured after defining the performance of the different predictive models. The sensitivity of a specific predictor variable is calculated by taking the proportion of the error of the model that includes this variable to the error of the model when it does not include this specific variable (Saltelli, 2002). The importance of a variable is in direct proportion to the variance of the predictive error of the classification model in the absence of that specific variable. The same method is followed for all classification models and is used to rank the relative importance of the variables of each classification model according to the sensitivity measure defined by Saltelli (2002). Their measure is defined as

$$Si = \frac{Vi}{V(y)} = \frac{V(y|x_i))}{V(y)} \tag{7}$$

where y is the binary output variable (supplier performance), and V(y) is the unconditional output variance. The expectation operator is denoted by E, which calls for an integral over all predictor variables except x_i. A further integral operator is implied over x_i by the operator V_i. The importance of a specific variable is then computed as the normalized sensitivity, as described by Saltelli et al. (2004).

4. Results and Discussion

Among the 56 total variables, the PPMCC analysis resulted in 11 “important” variables, with a 95% confidence level: relationship commitment based on how much the supplier is rewarded (INST2), information usage of purchase order updates (IU1), engineering requirements (IU4), performance feedback (IU5), future demand forecasting (IU6), production schedules (IU7), information sharing of production capacity (ISS1), research and development (ISS6), quality of shared information measured as timely (IQ1) and complete (IQ3), and scope.

These selected variables were then fed into the BBN to analyze their importance towards supplier performance. Based on the distribution of answers received for the supplier performance construct, answers received were encoded as a categorical binary dependent variable with values 0 and 1, representing unsuccessful and successful, respectively. Accuracy measures provided in section 3.4.1 were utilized to evaluate our results. The BBN model achieved a classification accuracy of 0.6346 with a sensitivity of 0.6865 and specificity of 0.5652 (see Table 6). Recall that 67% of the entire data was used for training, and 33% was used in the testing phase of the study. Therefore, 52 out of 156 cases were tested. As shown in Table 6, 30 and 22 of these firms were successful and unsuccessful, respectively. Among those that were successful (30 of them), our BBN model was able to predict 20 of them correctly, which provides a specificity score of 0.66. In addition, the model was able to predict 13 out of 22 unsuccessful companies, which provides a sensitivity score of 0.59. Overall, 33 out of 52 cases were predicted correctly, which shows that overall score for accuracy is 0.64.The BBN model achieved an AUC score of 0.636, as shown in Table 6, indicating that probabilities from successful suppliers were satisfactorily separated from those of unsuccessful suppliers. Expectedly, the specificity was lower than sensitivity. Thus, our model accurately distinguished suppliers who met their goals in relation to operational performance of those who were not able to meet their goals.

Table 6. BBN Classification Results

	Successful	**Unsuccessful**	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
Successful	20	10	0.6346	0.6865	0.5652	**0.636**
Unsuccessful	9	13				

The TAN network showing an understanding of the interrelations among each decision variable and the dependent variable, and the degree of intervariable relations to the probability of each outcome is given in Figure 2.

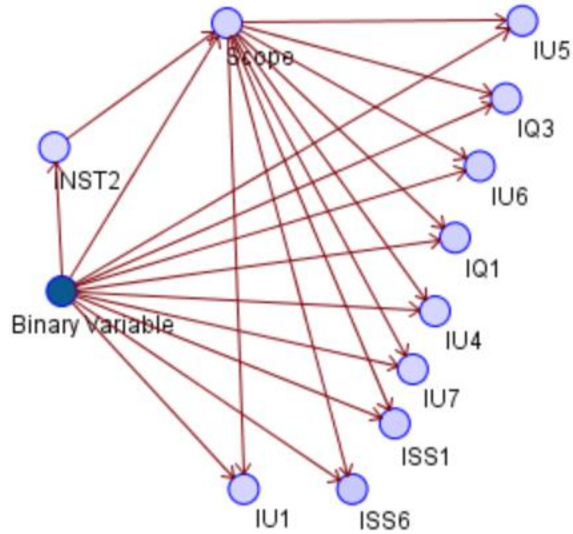

Figure 2. TAN Network

In further explanatory assessment, sensitivity analysis shed light on the relative importance of contributing variables to the value of the supplier's performance measure. Figure 3 lists results of the sensitivity analysis for contributing variables in descending order per their percentage impact on the dependent variable: the higher the x-value, the higher the dominancy of the independent variable to the dependent variable.

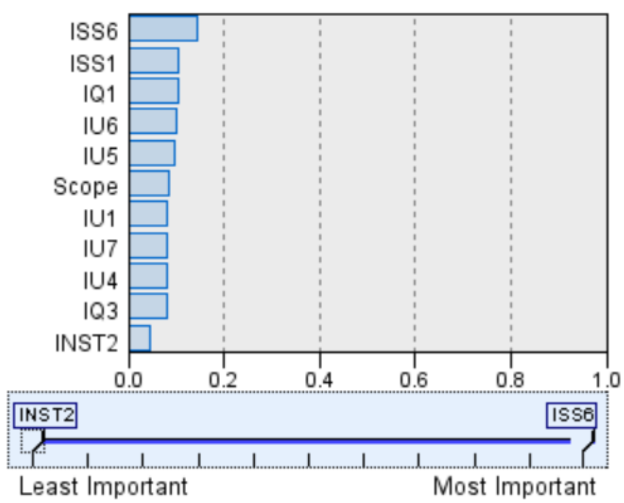

Figure 3. Sensitivity Analysis Results

Recall that an arrow from a predictor (parent) to another (child) infers that the impact of the child predictor on the binary variable depends on the value of the parent. Figure 2 shows that the effects of IU1, IU4, IU5, IU6, IU7, ISS1, ISS6, IQ1, and IQ3 on the supplier performance variable depends on the value of the scope of operations. In other words, the magnitude of impact by using purchase order update information, for example, is directly related to the value of scope. It is interesting that the impact of all the variables (except reward power) on the outcome depends on the scope of operations. It is also interesting to observe the potential impact of reward power on the relationship between the scope and dependent variable.

Observing the significant impact of reward power (INST2) on supplier performance is consistent with the findings of Chae et al. (2017) and Poppo et al. (2016). It is inevitable that reward power is important, but it also essential to keep it at a certain level so that it does not hamper the integration efforts among other members. As discussed in the work of Chae et al. (2017), we suggest using rewards as a gauge for positive feedback to improve the motivation to relationship commitment. Our study also adds to the literature by showing that the power of reward not only offers significant impact but also, if its magnitude is strong, overshadows other variables and reduces their importance. While such a strong relationship commitment may provide a competitive advantage in the current fast-changing market environment, it may also increase dependency to a smaller supply base, thus making customers more vulnerable to failure (Mawdsley & Somaya 2018).

Similarly, the effect of scope in predicting the dependent variable depends also on the degree of relationship commitment based on how much the supplier is rewarded. The magnitude of the scope of operations is also important while investigating the effects of variables on the dependent variable, which in our case is supplier performance. Whether the supplier operates for a domestic market, an international market, or both at the same time is important. This could be the result of differences in the target market in terms of business culture and possible requirements that can affect the level of importance for the variables.

The significance of information sharing in supply chain management and performance relations is apparent (Gligor & Holcomb, 2014; Hsu et al., 2008). As shown in Figure 3, decision variable ISS6 is the most important variable in the prediction of supplier performance. This variable is concerned with suppliers sharing research and development activities with their major customers. The second most important decision variable in the prediction of supplier performance is ISS1, which is concerned with sharing production capacity. In the current literature, sharing both of these information are found to be important in evaluating supplier performance (Zsidisin & Smith, 2005; Wang et al., 2009; Gunasekaran et al., 2004). For manufacturers in the aircraft industry, it is critical for them to aid their suppliers by sharing their production plans in order to better manage their resources. The two significant variables referring to the quality of information shared are found to be timely information (IQ1) and complete information (IQ3), which are considered impactful on supplier performance (Gorla et al., 2012).

According to McAfee et al. (2012), companies using available data in the decision-making process are better at achieving financial and operational performance measures, and companies in the top third of their industry that use available information in the decision-making process are on average 5% more productive and 6% more profitable than their rivals. Sener et al. (2019) indicated that the benefits of information sharing may not be materialized if information shared is not used. Our study reveals that using the information regarding purchase order updates (IU1), engineering requirements (IU4), performance feedback (IU5), future demand forecasting (IU6), and production schedule (IU7) is critical for the success of suppliers in the aircraft industry. In contrast to the study by Walton & Marucheck (1997), our study interestingly found that using demand forecast information is more critical than using production schedule information. This suggests that while suppliers value the production schedules of customers, they base their plans on demand forecast information. Although forecasts are considered inaccurate and unreliable in the upstream (Shockley & Fetter, 2015), such emphasis may be due to timely sharing of forecast information as well as current dynamics of the aircraft industry requiring effective use of forecasting information in guiding other processes in order to be sustainable and competitive. Another explanation could be supplier lead times are shorter than expected yielding to minimum level of safety stock, making the demand forecast information usage more important. When lead times are significantly longer production schedules by the manufacturer may reflect substantial safety stock. In such cases, production schedules will be more important. It is however our recommendation to future researchers to examine the impact of lead times that is not considered in our study. Sharing information on these specific variables allows suppliers to be flexible and responsive to changes. Our study also reveals positive impact of the feedback loop on supplier performance. Feedback is considered the motivator for supplier commitment, and it positively impacts supplier perception towards manufacturer cooperation and collaboration (Prahinski and Benton, 2004).

5. Theoretical and Managerial Contributions

Availability of information and its usage have become essential in decision making regarding supply chain functions such as order fulfillment, inventory management, warehousing, transportation and logistics in order to achieve efficiencies (Sanders, 2014). This study sheds light on the role of information usage in relation to performance measures that refer to efficiency (reducing costs by utilizing resources) and effectiveness (achieving given objectives) that its impact is rarely investigated in literature. We argue that having access to information may not necessarily be used when a partner makes planning and control decisions. Segregation of "information usage" from "information sharing" is one of the significant contributions for researchers to consider in developing theoretical modeling.

It is noteworthy to mention that the model TAN used in this study combines Bayesian approach with random forest-like optimization in order to find a probabilistic interrelation (not interaction) among the predictors, which also has not been studied in the frequentist approach Markot & Pennman, (2019). As described in Friedman et al. (1997), for a frequentist, limiting the frequency of occurrence of an event is defined as probability, assuming that there are true values of the parameters of the model to compute the point estimates of the parameters. With the Bayesian approach, on the other hand, probability is defined as the extent of (dis)belief on the occurrence of an event, claiming that only data are real, and treats the model parameters as probability distributions (i.e., in a dynamic nature rather than stationary as in the frequentist), which are to be inferred. Frequentists are reluctant to use any a-priori information; thus, they perform worse when existing information is useful, and perform better when existing information is systematically biased. The model we developed updates its belief on supplier success in accordance with the prior knowledge provided, which fits well the changing nature of supply chain management, thereby enhancing the model performance and its level of plausibility. Further, the posterior probability provided for each supplier considers the prior knowledge that takes place before the prediction is produced, which allows the supplier companies to receive the information they need for success in the timeliest and most effective fashion.

This study offers insightful hints for practicing supply chain managers to zero in on important sharing, usage, commitment, and quality variables affecting operational performance, and to benchmark their performance to those of successful counterparts. Companies should focus on improving their information-processing capabilities in order to effectively obtain, analyze, and act upon timely and complete information. Papadopoulos et al. (2017) point out that building information processing capability may reduce uncertainty in highly complex operational tasks. By utilizing data analytics, managers may determine the most important variables affecting their performance. Understanding the interrelation between variables and quantitative operational performances offers motivation to identify strengths and weaknesses of capabilities. Managers, for example, may focus on information usage-related initiatives to obtain sustainable results relative to customer satisfaction. Considering commitment and quality of information, we recommend that managers investigate whether their organizational culture and infrastructure offer the motivation to use the information shared available and ensure its practice. It allows them to focus on whether and how the information available is utilized in developing alternative decisions in their planning and execution. It is nonetheless important for managers to carefully consider the enhancing and hampering impacts of the relationship commitment with their partners in a supply chain.

6. Conclusion and Future Directions

This study tries to first identify variables, among a pool of variables that have a significant impact on supplier performance. Despite an enormous number of variables affecting operational performance, which are identified in the literature, it is impossible for practicing managers to cope with all of them at once. This necessitates the identification of the most important set of variables in order for practitioners to focus on them to create value and make the decision-making process more efficient. Additionally, the effects of interaction among the explanatory variables and supplier performance are investigated in order to make useful assumptions by both practitioners and researchers.

Using the data obtained through a survey from upper managers of the suppliers working with OEM aircraft manufacturers in the U.S., results of the Bayesian belief network revealed that the effect of purchase order update (IU1), engineering requirements (IU4), performance feedback (IU5), future demand forecasting (IU6), production schedules (IU7), production capacity (ISS1), research and development (ISS6), timely information exchange between supplier and customer (IQ1), and complete information exchange between supplier and customer (IQ3) on the dependent variable depends on the value of the scope of operations, and how hard suppliers work for these major customers is directly linked to how much they are rewarded (INST2).

This study encourages other researchers to further investigate the effective management of relationships, especially the reward power between supplier and customer in order to promote a positive commitment that leads to information sharing, information usage, and operational performance. It would also be interesting to investigate how competition among suppliers affects the outcome. One limitation of our study is that the data were collected from suppliers only, thus reflecting only their perspective. Future research may collect data from both suppliers and customers in order to create a more complex model and understand both constituents' perceptions towards each other holistically.

Our study considered suppliers in the aircraft industry operated in the U.S. Future research might also consider replication of this work to other industries and map important variables common across different industries. Further, suppliers across different continents may be considered for benchmarking as well as for strengthening the generalization of the results obtained from our study.

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