The Impact of Supply Chain Analytics on Operational Supply Chain Transparency: An Information Processing View

Full Paper

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Abstract

For many firms, implementing business analytics in supply chain management has become a key element of strategic success. Drawing on organizational information processing theory, this paper uses a sample of 114 survey respondents to investigate the role supply chain analytics play in operational supply chain transparency under turbulent supply environment. Three areas of analytics are involved: supply chain analytics in *plan*, *source*, and *make*. We find that supply chain analytics capability in all the three areas positively affects operational supply chain transparency. In addition, supply uncertainty positively moderates the relationship between supply chain analytics in make and transparency. This paper contributes to the supply chain transparency literature and provides managers with insights on the importance of supply chain analytics in building transparent supply chains, especially the role of supply chain analytics in make in turbulent supply environment.

Keywords

Supply chain analytics, operational supply chain transparency, organizational information processing theory, supply chain management

Introduction

Today's increasing supply chain risks require firms to be able to monitor, visualize, and track their upstream and downstream supply chain operations so that they can make better decisions on supply chain practices (i.e. demand forecast, supplier selection, production scheduling, routing choices) (Carter and Easton 2011). This request gives rise to the notion of *operational supply chain transparency* which is defined as "proactively engaging in communication with stakeholders and having traceability into upstream and downstream supply chain operations" (Morgan et al. working paper).

The achievement of transparent supply chains relies heavily on information about products as they move through the chain. Moreover, such information need to be in a form that is usable to supply chain partners for decision-making (Spekman et al. 1998). However, today's corporate world faces high-volume, high-variety, and high-velocity of both structured and unstructured data, or big data, generated from supply chain operations (Brown et al. 2011). The required processing capability of these data exceed the processing capability of traditional data management approaches used for decision-making (Chen and Zhang 2014), which creates a barrier to operational supply chain transparency among partner firms. In response to this challenge, *supply chain analytics* (SCA) has been proposed as a promising approach to improve the capability of information processing, which enables the enhanced visibility of operations for better decision-making (McAfee et al. 2012). SCA refers to a group of approaches, organizational procedures and tools used in combination with one another to collect information, analyze information, and gain insights to solve problems and improve performance in supply chain management (Trkman et al. 2010).

Research on SCA is still in its infancy. Scholars have emphasized that more research is needed to better understand the value creation of SCA in supply chain management. One of the aspects related to value creation via SCA that deserve more academic attention is the transparency of supply chain operations (Brown et al. 2011; Richey et al. 2016; Wamba et al. 2015). Extant research on the relationship between SCA and supply chain transparency is conducted with qualitative explorations (Richey et al. 2016; Wamba et al. 2015). No empirical study, however, has been conducted to assess the impact of SCA on the transparency of supply chain operations. To bridge this gap, we conduct an empirical study with the aims to advance the understating of SCA's influence on operational supply chain transparency. Furthermore, previous research suggest that context factors can influence the effect of SCA on its value creation in supply chain management (Chen et al. 2015). Therefore, our study also includes a context factor (supply uncertainty) and addresses the following research questions:

RQ1: How does supply chain analytics influence operational supply chain transparency?

RQ2: How does supply uncertainty affect the relationship between supply chain analytics and operational supply chain transparency?

To obtain a comprehensive understanding of the role SCA plays in affecting operational supply chain transparency, we conceptualized SCA in terms of its use in different supply chain processes based on the Supply Chain Operations Reference (SCOR) model. The theoretical lens through which we developed the research model is *organizational information processing theory* (OIPT) (Galbraith 1977; Tushman & Nadler 1978). We expect that the use of SCA in different function areas (e.g., SCA in plan, source, and make) enables greater information process capability, which in turn facilitates the provision of useful insights that supply chain participants need for better decision-making. It follows the formation of transparent supply chains where large amounts of valuable information regarding product movement are disseminated. Furthermore, the improved information processing capability is likely to be especially valuable when the uncertainty embedded in the supply market increases.

The remaining of the paper will proceed as follows. We start with a discussion of theoretical backgrounds and the resulting hypotheses of this research. Next, we describe the construct measurements and the data collection process, followed by data analysis and results. We then conclude the study with theoretical and practical implications, limitations, and future research.

Backgrounds and Hypotheses Development

Operational Supply Chain Transparency

Operational supply chain transparency lies in the traceability of products as they move through the supply chain. It refers to the extent to which supply chain partners can track the current and historical activities of products throughout the entire chain (Morgan et al. working paper). The traceability of product activities provides specifics including "batch sizes, run quantity, transfer quantity, buffer stock sizes, throughput time, available machines, number of operators and engineers, resource utilization, transport time, level of work in progress and so on" (Cheng and Simmons 1994, pp.11). Transparent supply chains can lower the complexity of supply chain processes by ensuring the visibility of upstream and downstream supply chain operations (Gunasekaran et al. 2015).

Organizational Information Processing Theory

This research is grounded in the organizational information processing theory in which organizations are characterized as open social systems possessing both requirements and capabilities to process information and mitigate business-related uncertainty (Galbraith 1977; Tushman & Nadler 1978). OIPT consists of three components: information processing capabilities (IPC), information processing requirements (IPR), and the fit between IPR and IPC (Tushman & Nadler 1978). Drawing upon OIPT, we present the research model composed of six testable hypotheses (Figure 1).

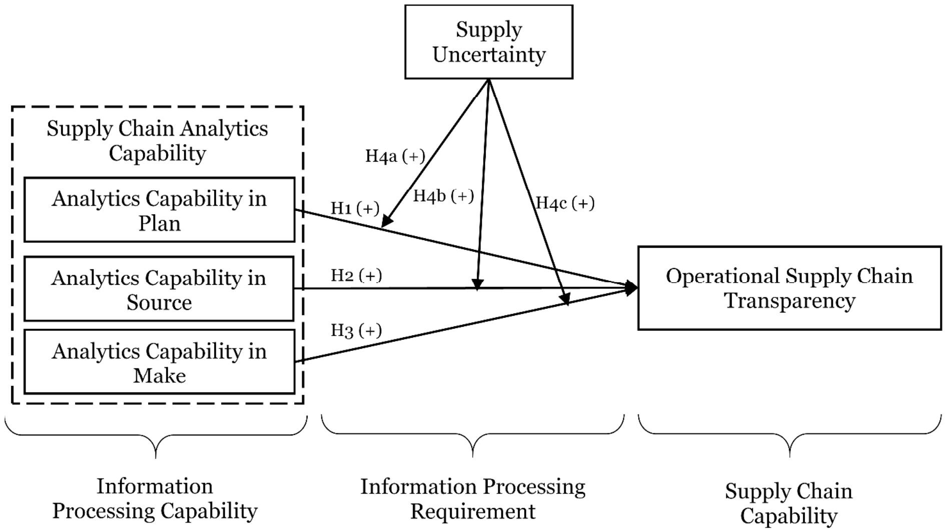

Figure 1. Research Model

Information Processing Capabilities

IPC refers to an organization's ability to gather, interpret, synthesize, and distribute information (Tushman and Nadler 1978). In this study, we conceptualize the use of SCA in supply chain management as a vital information processing capability which organizations can count on to transform information into a form that can benefit business partners across a supply chain. To have a comprehensive understanding of the role of SCA in supply chain management, we adopted Turkman et al. (2010)'s work that selected SCOR model as a framework to structure SCA based on its use in main supply chain processes. As such, SCA includes four aspects–*analytics capability in plan, source, make, and deliver*.

Analytics capability in plan focuses on demand planning that aims to analyzing data to forecast market demands of products and services (Trkman et al. 2010) and supply planning that focuses on developing supply plans to match market demands with resources in a profitable way (Chae and Olson 2013). The analytics capability in source lies in "improving inbound supply chain consolidation and optimization" (Stefanovic and Stefanovic 2009). Analytics capability in make can provide useful insights to production-related issues such as production scheduling, order sequence adjustment, machine failures, and any anomalies occurred in the production process (Turban et al. 2011). We do not include SCA in deliver in the research model because many companies choose to fully or partly outsource the "deliver" process to logistics service providers (Chu and Wang 2012; Huo et al. 2016), and thereby the impact of SCA in this area may be limited (Trkman et al. 2010). Now, we discuss the influence of SCA on operational supply chain transparency from the aforementioned three dimensions below.

Through the analysis of large amounts of historical and current sales and customer data, organizations are able to sense market signals (e.g. customer purchase patterns), translate them into demand signals, and utilize demand signals to shape future demand, which allows companies to improve their demand forecast accuracy, and reduce demand variability (Chase 2013). The accurate predictions of product demand provide visibility of the supply chain planning operations from customers back to suppliers, so that the company's upstream suppliers can use this information to generate more accurate production and procurement plans. Therefore, we propose that:

H1: Analytics capability in plan process is positively related to operational supply chain transparency.

SCA allows companies to assess supplier performance from both quantitative and qualitative perspectives, thus presenting a comprehensive view of what suppliers actually delivered now, in the past, and what they may deliver in the future (Wang et al. 2016). For example, predictive analytics can integrate supplier performance data with other critical information (e.g. current and emerging market trends) to provide insights on supplier responsiveness to customer needs and the potential for continuous improvements in the future (Agarwal et al. 2014). The past and current performance of suppliers, in combination with future performance, form a holistic picture of each supplier, thus improving focal companies' decision making on supplier selection. This leads us to hypothesize that:

H2: Analytics capability in source is positively related to operational supply chain transparency.

Supply chain managers use analytics to dive deeply into historical machinery and process data which usually comes from manufacturing execution systems, identifying anomalies in production processes, predicting machinery failures, and discovering hidden relationships and potential problems (Auschitzky et al. 2014). For example, prescriptive analytical techniques such as association rule mining can help identify potential reasons for machine failures and estimate the effects of such failures on product quality and production efficiency. Through the disclosure of the problems (e.g. process anomalies, machine failures) in making, organizations are able to obtain the right information to determine an objective estimation of their manufacturing capabilities and readiness of each product, thereby adding transparency into production process. We propose that

H3. Analytics capability in make is positively related to operation supply chain transparency.

Information Processing Requirements

Information processing requirements (IPR) is defined as the gap between information needed and information available to a firm for decision making (Premkumar et al. 2005; Tushman and Nadler 1978). This gap creates uncertainty which is the source of IPR. One example of uncertainty in the context of supply chain management is the *supply uncertainty* that refers to the extent of unpredictability and uncontrollability of suppliers' product quality and delivery performance (Davis 1993; Li and Lin 2006). Within supply chains, supply uncertainty can raise the complexity of decision making and subsequently increase organizations' need for new and additional information (Cegielski et al. 2012; Premkumar et al. 2005). Hence, from OIPT point of view, supply uncertainty can be seen as a source of IPR that stimulates organizations to acquire new knowledge to support decision making along the chains.

The "Fit" between Information Processing Requirements and Capabilities

OIPT emphasizes the importance of the "fit" between information processing requirements and information processing capabilities: the greater the uncertainty is, the greater the amount of information must be processed among decision makers to achieve a given level of outcomes (Galbraith 1977). When organizations employ certain organizational practices to achieve their performance, work-related uncertainties may weaken the effectiveness of such practices. This is due to the lack of fit between the organizational practices and contextual conditions–the information processing requirements exceed information processing capabilities. Under this condition, organizations need to raise their information processing capabilities with an aim to obtain more information for better outcomes.

In the context of supply chain management, a rapidly changing supply market creates a need to scan the supply market, collect information, and transform the information into useful insights that can mitigate the unpredictability and unreliability of the supply market (Wong et al. 2011). According to OIPT, the information processing capability of organizations should be improved to fit the increasing information processing requirements in order to achieve the expected outcome. When companies are operating in an uncertain supply environment, the application of SCA brings companies the information processing power to continuously monitor the conditions in the supply market via automated processes and to track suppliers with a more holistic, 360-degree view (PwC 2016). This enables firms to infuse insights derived from the suppliers with operations of plan, source and make processes, generating a more comprehensive and holistic view of how to plan supply chain operations as well as where and when to buy and make products through the supply chain network.

In contrast, when supply uncertainty decreases, suppliers can provide reliable quality, quantity, and delivery performance. There is no need for SCA to scan, analyze, and foresee the unknowns related to the supply market and suppliers' activities, as well as to incorporate them into executions in plan, source, and make. Therefore, SCA produces less value for responsive organizations in a stable supply environment than in an uncertain supply environment. Accordingly, we propose:

H4a: The greater the level of supply uncertainty, the stronger the relationship between analytics capability in plan and operational supply chain transparency.

H4b: The greater the level of supply uncertainty, the stronger the relationship between analytics capability in source and operational supply chain transparency.

H4c: The greater the level of supply uncertainty, the stronger the relationship between analytics capability in make and operational supply chain transparency.

Research Methodology

Measurement Items

Five constructs were measured in this study: analytics capability in plan, analytics capability in source, analytics capability in make, supply uncertainty, and operational supply chain transparency. The items measuring each construct were adapted from validated measurements in previous studies. Analytics capability in plan, analytics capability in source, and analytics capability in make constructs were measured respectively by 11-item, 4-item, and 7-item scale developed by Trkman et al. (2010), with minor modifications. These three constructs were operationalized as formative constructs because respondents were expected to report what practices companies should have in place to have analytics capabilities in plan, source, and make processes. The items of these three constructs were assessed with a 5-point Likert scale measuring the frequency of practices consisting of: 1–never, or does not exit; 2–sometimes; 3–frequently; 4–mostly; and 5–always, or definitely exists. Supply uncertainty measurements were adopted from Chen and Paulraj (2004) to evaluate the degree to which suppliers' deliveries meet the organization's requirements. Eight items developed by Morgan, Richey, and Ellinger (working paper) were used to measure operational supply chain transparency. The items of supply uncertainty and operational supply chain transparency were assessed with seven-point Likert scales, with 1 representing "strongly disagree" and 7 representing "strongly agree". A complete list of measurements is displayed in Appendix A1.

Data collection

Empirical data was collected via a field survey. We selected 208 adults who had supply chain background as our sample. The sampling was conducted within the U.S. and contained U.S. citizens only. An invitation e-mail with the survey link was sent to each individual in fall 2016. Among the selected contacts, 143 individuals responded to our survey with 114 usable observations after excluding straight-line responses and responses with unusually short durations. The effective response rate from the data collection was 54.81 percent.

Data Analysis and Results

Partial least squares (PLS) approach is employed to analyze the data. We used PLS rather than Amos or other covariance-based methods, because it is able to handle both reflective and formative constructs in the analysis and it allows us to analyze moderating effects effectively (Chin et al. 2003). The software used for analysis is SmartPLS, version 3.0.

Measurement Model Assessment

We initially analyzed the measurement properties of the reflective constructs–supply uncertainty and operational supply chain transparency. The constructs of reliability were examined using Cronbach's alpha and composite reliability (CR). As summarized in Table 1, Cronbach's alphas for reflective constructs, specifically, supply uncertainty and operational supply chain transparency, all exceed the prescribed thresholds 0.7 (Cronbach and Thorndike 1971). Composite reliability for reflective constructs are all greater than 0.8 (Chin 1998). These statistics indicate adequate reliability of the measurement scales. We then assessed convergent validity by using factor loadings and average variance extracted (AVE). All indicators of reflective constructs have statistically significant ($p<0.05$) factor loadings from 0.63 to 0.90, which reflect convergent validity of theoretical constructs (Anderson and Gerbing 1988). Furthermore, the AVE of each reflective construct is greater than the recommended minimum value 0.5 (Fornell and Larcker 1981), which also suggest strong convergent validity. Last, the square root of AVE of all the reflective constructs is greater than the correlation between any pair of them, indicating no discriminant validity issues among reflective constructs (Fornell and Larcker 1981).

Formative constructs–analytics capability in plan, source, and make–need to be assessed in a different manner from that for reflective constructs (Diamantopoulos and Winklhofer 2001; Petter et al. 2007). Specifically, factor loadings, Cronbach's alphas, CR, and AVE are not an appropriate criterion, because formative indicators are not reflections of the latent construct and are not necessarily correlated. Instead, multicollinearity among formative items is an issue and need to checked by computing variance inflation factor (VIF) because the formative model is based on multiple regression (Diamantopoulos and Winklhofer 2001). The results of multicollinearity diagnostics showed that all VIF were well below the maximum acceptable cut-off value 10.0, demonstrating that multicollinearity is not an issue (Petter et al. 2007).

Structural Model Assessment

The PLS analysis suggests that analytics capability in plan has a significant positive effect on operational supply chain transparency (β=0.258, $p<0.01$), supporting H1. Analytics capability in source also positively influences operational supply chain transparency (β=0.244, $p<0.05$), which provides support for H2. Analytics capability in make is positively associated with operational supply chain transparency (β=0.278, $p<0.001$), which lends support for H3. In testing the moderating effects, supply uncertainty positively moderates the relationship between analytics capability in make and operational supply chain transparency (β=0.254, $p<0.05$), supporting H4c. However, our analysis finds no support for H4a and H4b, the moderating effect of supply uncertainty on the relationships between analytics capability in plan/source and operational supply chain transparency. Findings for H1, H2, H3, and H4c explain 55.7% of the variance of operational supply transparency.

	Cronbach's α	CR	AVE	VIF	ACP	ACS	ACM	SU	OPSCT
ACP	Formative	Formative	Formative	2.144	**N/A**				
ACS	Formative	Formative	Formative	1.683	0.56	**N/A**			
ACM	Formative	Formative	Formative	2.182	0.672	0.568	**N/A**		
SU	0.749	0.889	0.8	1.25	0.301	0.325	0.364	**0.894**	
OPSCT	0.873	0.901	0.535		0.612	0.569	0.649	0.366	**0.731**

Note: Bolded numbers are square roots of AVEs; ACP–Analytics Capability in Plan, ACS–Analytics Capability in Source, ACM–Analytics Capability in Make, SU–Supply Uncertainty, OPSCT–Operational Supply Chain Transparency

Table 1. Construct Reliability and Validity

Discussion

The results of analytics capability–transparency relationships (H1-H3) support our expectations: the use of supply chain analytics in key process areas can improve operational supply chain transparency. More importantly, the use of SCA in different supply chain areas contributes differently to operational supply chain transparency. Our results indicate that investment in SCA in the make process can bring the most significant improvement in operational supply chain transparency, followed by investment of SCA in plan and in source. One possible explanation is that companies may not be able to make simultaneous efforts in each of the SCOR areas (plan, source, and make) since investment in SCA to gather and process large amount of data can be difficult and time consuming (Davenport 2009).

The results provide partial support for the moderating effects of supply uncertainty. The results show that supply uncertainty exerts a positive effect on the relationship between analytics capability in make and operational supply chain transparency, but has no significant moderating effects on the relationship between analytics capability in the other areas (source and plan) and operational supply chain transparency. One possible explanation is that the harm resulting from supply uncertainty first takes place in a focal firm's production process, which makes it difficult for production to correspond with on-time delivery to the market.

Implications

Theoretical and Practical Implications

Our research provides important theoretical contributions. First, this research contributes to the supply chain transparency literature. Previous studies implied that one of the major contributions supply chain analytics can make to businesses is to create transparency (Brown et al. 2011; Richey et al. 2016; Wamba et al. 2015). To our best knowledge, this paper is the first empirical study to develop and test a novel theoretical model to demonstrate the relationship between SCA and transparency as well as the moderating effects of context factor (supply uncertainty) on SCA-transparency relationships. Second, our research focuses on SCA use as an information processing capability, and demonstrates its positive influence on operational supply chain transparency, thus confirming the potential benefit of SCA for organizational value creation in supply chain management. We also provide more insights into the nature of relationship between SCA and operation supply chain transparency as dictated by information processing requirements–supply uncertainty. These findings are consistent with existing literature that information processing capability is critical for organizational management, especially within the domain of supply chain management (Premkumar et al. 2005; Trautmann et al. 2009).

This study also provides implications for managerial practices. First, this study can provide guidance on the investment sequence of SCA in different areas. Investment in supply chain analytics is difficult and time consuming. Organizations are likely unable to put simultaneous efforts on SCA in the four SCOR areas (Trkman et al. 2010). Our results show a preliminary indication that SCA investment in make process may bring the most improvement in OPSCT. Therefore, companies aiming to improve OPSCT can first focus their limited resources on enhancing analytics capabilities in the make area rather than put equal efforts in each of the four SCOR areas. Furthermore, our findings also provide insights for managers on how to evaluate the potential impacts of context factors (i.e. supply uncertainty) on operational supply chain transparency. We find that SCA use positively influences operational supply chain transparency, but only the influence of SCA in the make process is amplified in an uncertain supply environment. As such, organizations may want to focus on SCA investment in the make process when supply uncertainty is high as the transparency outcome is more sensitive to SCA input in make in an uncertain supply environment.

Limitations and Future Research

The survey respondents for this study do not have very long work experience in the supply chain domain. Although we affirmed that the respondents have sufficient knowledge background in supply chain and analytics, we cannot generalize the findings from this sample to those who have more experience in supply chain area. For future study, we have already started our data collection from supply managers or above to get a generalized sample. In addition, this is a pilot test of the research model and we did not include control variables at this stage. The future study mentioned above has included firm size, industry sector, annual revenue, country, and IT department size as control variables. Last, although we justified the reasons for not including "Deliver" portion of the SCOR model, the future study has included "Analytics Capability in Deliver" to contrast its effects with effects resulted from other processes.

Conclusion

Drawing on organizational information processing theory, this study aims to understand the influence of SCA use in three supply chain domains on operational supply chain transparency. It also examines the moderating effects of supply uncertainty on the relationship between SCA and operational supply chain transparency. 114 surveys were collected and PLS approach was used to test the research model. Our findings suggested that SCA plays a salient role in improving operational supply chain transparency, with analytics capability in plan, source, and make all significantly contributing to operational supply chain transparency. Furthermore, supply uncertainty positively strengthens the relationship between analytics capability in make and operational supply chain transparency. However, it does not show any moderating effect on the relationships between analytics capability in plan/source and operational supply chain transparency.

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Appendix A1. Construct Measurements

Code	**Construct and Items**
ACP	***Analytics Capability in Plan*** *(adapted from Trkman et al. 2010)*
ACP1	Has your organization established supply chain performance measures (e.g. product quality, order-to-delivery lead time, supply chain response time, resource utilization, etc.)?
ACP2	Does your organization look the impact of its strategies on supply chain performance (e.g. order-to-delivery lead time, supply chain response time, resource utilization, etc.)?
ACP3	Does your organization use adequate analysis tools to examine the impact before a decision is made?

ACP4	Does your organization look at customer profitability?
ACP5	Does your organization look at product profitability?
ACP6	Does your organization analyze the variability of demand for your products or services?
ACP7	Do you use mathematical methods (statistics such as time series analysis) for forecasting demand?
ACP8	Is a forecast developed for each product or service in your organization?
ACP9	Is a forecast developed for each customer in your organization?
ACP10	Does your demand management process make use of customer information?
ACP11	Is the demand forecast accuracy measured in your organization?
ACS	***Analytics Capability in Source*** *(adapted from Trkman et al. 2010)*
ACS1	Are the supplier inter-relationships (variability, metrics) understood and documented?
ACS2	Do you "collaborate" with your suppliers to develop a plan?
ACS3	Do you measure and feedback supplier performance?
ACS4	Do you share planning and scheduling information with suppliers?
ACM	***Analytics Capability in Make (****adapted from Trkman et al. 2010)*
ACM1	Are your planning processes integrated and coordinated across divisions?
ACM2	Does your organization update supplier lead times monthly?
ACM3	Does your organization use constraint-based planning methodologies?
ACM4	Does your organization measure the degree of production planning adherence?
ACM5	Do the sales, manufacturing and distribution organizations collaborate in the planning and scheduling process?
ACM6	Is your customers' planning and scheduling information included in yours?
ACM7	Are plans developed at the "item" level of detail?
SU	***Supply Uncertainty*** *(adopted from Chen and Paulraj 2004)*
SU1	Our suppliers consistently meet our requirements.
SU2	Our suppliers produce materials with consistent quality.
OPSCT	***Operational Supply Chain Transparency*** *(adopted from Morgan et al. working paper)*
OPSCT1	Our suppliers provide us with operational plans (e.g. distribution plan, production plan) regarding the products they produce for us.
OPSCT2	Our major suppliers provide us with detailed product design information.
OPSCT3	Our major suppliers collect operations information (for example: batch size, run quality, transfer quality, buffer stock, available machines, machine breakdown time).
OPSCT4	Our major suppliers share their operations information with us.
OPSCT5	Our major suppliers collect planning and design information (for example: current performances of operations level, resource utilization, rework and scrap level, level of work progress).
OPSCT6	Our major suppliers share their planning and design information with us.
OPSCT7	Our major suppliers collect strategic information (for example: current performances of planning and design level, new order, product demand, internal and external expertise, teachability, culture, government regulations).
OPSCT8	Our major suppliers share their strategic information with us.