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# The role of information usage in a retail supply chain: A causal data mining and analytical modeling approach

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ABSTRACT

This study utilizes both a resource-based view and organizational learning theory to present the need to distinguish information sharing from information usage. Our main research aim was to investigate the mediating role of information usage between information sharing, and operational efficiency and effectiveness. We tested the hypotheses in our relational model using empirical data obtained from food retailers in Turkey. The analysis of results from structural equation modeling reveal that the separation of information sharing from information usage is valid, and the mediating role of usage is significant in improving operational effectiveness and efficiency. We further utilized a Bayesian neural networks-based causal analytic model, i.e., universal structure modeling methodology to reveal non-trivial, implicit, previously unknown, and potentially useful relationships among the constructs.

## 1. Introduction

Supply chain management (SCM) is the effective coordination of the flow of materials, products, and information, not only within a company but also among other members of a supply chain in order to improve the performance of the company (Mentzer et al., 2001) and received the full interest of researchers (Autry, Rose, & Bell, 2014; Frohlich & Westbrook, 2001; Prajogo & Olhager, 2012; Stevens, 1989; Tan, Kannan, & Handfield, 1998). Globalization and amplified competition among supply chains have magnified the importance of effective SCM for which "integration" is offered as an inevitable prescription for successful performance (Cooper, Lambert, & Pagh, 1997; Mentzer et al., 2001; Seggie, Kim, & Cavusgil, 2006). Schoemaker (1993) indicates how difficult it is to achieve such coordinative integration efficiency given the asymmetry and complexity of information. Information asymmetry due to strong reluctance of demand and supply related information sharing increases the uncertainty in planning and thus in meeting customer demand. The size of supply and customer base, the length of the supply chain tiers, information technology invested by supply chain members, and communication styles among members of supply chain defines the complexity across different industries such as food, aircraft, healthcare, automotive, etc., and defines the magnitude of uncertainty.

The scope of integration in SCM, however, is very fragmented, and the theoretical development in relational studies is lacking (Huo, 2012; Zhao, Huo, Selen, & Yeung, 2011) or limited (Jiménez-Jiménez & Sanz-Valle, 2011; Narasimhan & Kim, 2002; Yu, Jacobs, Salisbury, & Enns, 2013). Understanding supply chain integration would be incomplete if the impact of information usage is not investigated (Boon-itt & Paul, 2006; Childerhouse & Towill, 2000).

This study focuses on the role of information usage and proposes a relational model considering information sharing (IS) as an antecedent to information usage (IU). The objective here is to enhance theory development by integrating a resource-based view and organizational learning theory, especially under absorptive capacity, as introduced by Cohen and Levinthal (1990), and by obtaining empirical evidence to fill the gap in the literature. Moreover, we go beyond proving cause-and-effect relations and employ the universal structural model (USM), with its predictive causal analytics capability, to uncover unhypothesized patterns in our data.

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The remainder of this paper is organized as follows. Section 2 provides a theoretical background and hypotheses development. Section 3 is dedicated to research methodology, including questionnaire design and sampling. Section 4 presents the results and discussion. In section 5, we conclude with a summary and suggestions for future directions.

## 2. Literature review and hypotheses development

### *2.1. Role of information in supply chain integration*

In supply chain management, integration is viewed as a way of connecting (Frohlich & Westbrook, 2001), coordinating (Carr, Kaynak, & Muthusamy, 2008), and collaborating (Katunzi, 2011; Stank, Keller, & Daugherty, 2001) among partners. In the literature, different dimensions of supply chain integration are proposed, based on the involved supply chain tiers, such as customer integration, supplier integration, external integration, and internal integration (Droge, Jayaram, & Vickery, 2004; Flynn, Huo, & Zhao, 2010; Vickery, Jayaram, Droge, & Calantone, 2003; Zhao et al., 2011). Ideally, complete integration is achieved when all members or actors of the supply chain share the same objective ("goal congruency") with high coordinative integration efforts, acting as if the whole supply chain is a monolithic entity, mirroring the "unitary actor model" in a conceptual quadrant framework, as presented by Schoemaker (1993). In reality, with the current technology and resistance to share certain information, however, integration efforts are at a level of that in an organizational model where optimality is desired but not absolutely necessary. Lee and Whang (2000) consider three dimensions based on the types of stages involved in integration: information integration, coordination and resource sharing, and organizational relationship linkage. Very similar to the work of Barut, Faisst, and Kanet (2002), Huo (2012) reports overlapping aspects among these dimensions and suggests three major dimensions in relation to the supply chain operations reference (SCOR) model: internal integration, customer integration, and supplier integration.

As pointed out by Zhao et al. (2011) and Huo (2012), there are no widely accepted drivers for each of these dimensions. For example, Flynn et al. (2010) use infrastructure drivers such as data integration, real-time data, and real-time searching for internal integration, and Stank et al. (2001) use an integrated database, operational information, and encouragement of integration as drivers. For Droge et al. (2004), internal integration indicators are concurrent engineering/joint design and standardization. On the other hand, Wong, Wong, and Boon-itt (2013) introduce responsiveness, information flow, and psychical flow as drivers for internal integration.

Similarly, supplier integration is achieved by information sharing, degree of strategic partnership, joint planning, and research and development with the supplier (Stank et al., 2001; Wong et al., 2013; Zhao, Huo, Sun, & Zhao, 2013), and by information exchange, strategic partnership, and sharing of production schedule inventory and demand information (Danese & Romano, 2013; Flynn et al., 2010; He & Da Xu, 2014).

Customer integration is characterized in general by information sharing, integrated infrastructure, partnership, and joint planning (Li, Tarafdar, & Subba Rao, 2012; Swink, Narasimhan, & Wang, 2007; Yang, Sun, Sohal, Li, & Zhao, 2009). In summary, Table 1 provides a snapshot of literature that has appeared in top journals in the field along with the above-mentioned dimensions. A closer investigation reveals that no consensus on surrogate measurements used for integration currently exists in the literature, and that most of the measurements are related to sharing of a specific aspect or type of information.

According to the resource-based view, information is an essential factor for achieving and improving performance (Armstrong & Shimizu, 2007; Benton & Maloni, 2005; Huo, Qi, Wang, & Zhao, 2014; Newbert, 2007; Vickery et al., 2003; Yu et al., 2013). Information sharing is defined as the mutual process of distributing important implicit and explicit information among supply chain members (Narasimhan & Kim, 2002; Van den Hooff & De Ridder, 2004). Many researchers have focused on specific information aspects in relation to their impact on performance. For example, Cachon and Lariviere (2001) and Özer and Wei (2006) investigate the impact of sharing demand-forecast information on supply chain profitability. Dobson and Pinker (2006) report that sharing lead-time information results in better organizational performance.

Ganeshan, Boone, and Stenger (2001) and Fleisch and Tellkamp (2005) focus on inventory information sharing and its impact on performance. Recent studies have expanded the scope of IS and investigated the outcomes on either organizational or supply chain performance (Hall & Saygin, 2012; Prajogo & Olhager, 2012). Table 2 is a list of the scope of information considered in the literature. In general, the benefits of sharing information have been exemplified by a reduction in inventory, a reduction in cost and cycle time, and improvement in resource utilization, productivity, and uncertainty about the changes in customer demand and supply capability. Despite such prolific research indicating the importance of information integration in contemplating improved operational or organizational performance, Kaynak and Carr (2012) indicate a continuing lack of empirical research on supply chain IS.

### *2.2. Information sharing versus information usage*

The literature of organizational learning theory focuses on information processing and defines it as a firm's ability to recognize and interpret the value of new information and use it towards innovative capabilities. Lichtenthaler (2009) describes the three key learning processes as follows: information acquisition; analyzing, interpreting, and understanding of information; and application of information in decision making. According to Fiol and Lyles (1985), organizational learning theory defines learning as the process of improving organizational practices through increased knowledge. Organizations learn through the process of acquisition and distribution of information as well as the interpretation of information. Jayachandran, Sharma, Kaufman, and Raman (2005) analyze learning processes under four constructs: reciprocity to ensure effective communication; capture and integration to prevent information loss; access to limit information overload; and usage related to developing and offering product and services (action-oriented), and understanding the need and behaviors (knowledge enhancing). Hwang, Kettinger, and Mun (2013) suggest being proactive, transparent, and formal in such processes.

While organizational learning theory has been applied in a range of fields from economics to management science to psychology to sociology to anthropology (Jain & Moreno, 2015), the academic research in supply chain integration is in its infant stage when it comes to incorporating organizational learning theory (Yu et al., 2013). Yu et al. (2013) argue that the exchange of information and its usage are prerequisites for achieving organizational learning. The dilemma for retailers, however, is how much information to share with food suppliers and what information to protect against opportunism. Organizational learning promotes empowerment that may motivate members of a supply chain to continuously learn from the exchange of information (Bryson, Crosby, & Stone, 2006).

Croson and Donohue (2005) conclude that retailers and suppliers are better off when they have access to more information. However, having access to or sharing information does not necessarily mean that a firm will use the information in its planning and control decisions. According to the information management motivation framework presented by Hwang et al. (2013), the more proactive behavior of information usage, the higher motivation for learning. Similarly, Ali, Pascoe, and Warne (2002) and Van den Hooff and De Ridder (2004) argue that information sharing leads to organizational learning if usage of the information is materialized. Barut et al. (2002) consider the degree of information usage as an indicator of active IS, assuming that

**Table 1**
Snapshot of literature on aspects of information relative to integration types.

| | Customer integration | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Information sharing | Demand/sales visibility | Involvement in R&D | Inventory visibility/ Information | IT usage/ Integrated database | Operational information | Encouragement of integration | Linkage/ Partnership with customers | Production/ Schedule information | Joint production/ Capacity planning |
| Danese (2013) | | | | | | | | | | |
| Danese and Romano (2013) | x | x | | | | | | | | |
| Devaraj, Krajewski, and Wei (2007) | | x | | x | | | | | x | x |
| Droge et al. (2004) | | | | | | | | x | | |
| Flynn et al. (2010) | | x | | x | x | | | x | x | |
| Germain and Iyer (2006) | | | | | | | | | | |
| Gimenez and Ventura (2005) | | | | | | | | | | |
| He and Da Xu (2014) | | x | | x | | | | | x | x |
| Huo, Zhao, and Zhou (2014) | | | | | | | | | | |
| Koufteros, Vonderembse, and Jayaram (2005) | | | x | | | | | x | | x |
| Li et al. (2012) | | | | | x | | | x | | x |
| Mollenkopf & Dapiran (2005) | | | | | | | | | | |
| Quesada, Rachamadugu, Gonzalez, and Luis Martinez (2008) | | | | x | x | | | | x | x |
| Ragatz, Handfield, and Petersen (2002) | | | | | | | | | | |
| Rodrigues, Stank, and Lynch (2004) | | | | | | | | | | |
| Salvador and Villena (2013) | | | | | | | | | | |
| Sanders and Premus (2005) | | | | | | | | | | |
| Stank et al. (2001) | | | | | x | x | x | | | |
| Swink et al. (2007) | x | | | | | | x | x | | |
| Vachon and Klassen (2006) | | | | | | | | | | x |
| Vickery et al. (2003) | | | | | | | x | | | |
| Won Lee, Kwon, and Severance (2007) | | x | | | x | | | | x | |
| Wong, Boon-Itt, and Wong (2011) | x | x | x | | | | | | | |
| Yang et al. (2009) | x | | | | x | x | x | | | |
| Zhao et al. (2013) | | | x | | | | | x | | |

| | Customer integration | | | Supplier integration | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Market/ Segmental focus | Customer satisfaction/ Feedback | Flexibility/ Responsiveness | Partnership | Information sharing/ Exchange | Joint planning with suppliers | Joint product development | Production \schedule information | Inventory information | Demand information |
| Danese (2013) | | | | x | x | | | x | | |
| Danese and Romano (2013) | | x | | | | | | | | |
| Devaraj, Krajewski, and Wei (2007) | | | | | | x | | x | x | x |
| Droge et al. (2004) | | | | x | | | | | | |
| Flynn et al. (2010) | | | | | x | | | x | x | x |
| Germain and Iyer (2006) | | | | | | | | | | |
| Gimenez and Ventura (2005) | | | | | | | | | | |
| He and Da Xu (2014) | | | | | | x | | x | x | x |
| Huo, Zhao, and Zhou (2014) | | | | | | | | | | |
| Koufteros, Vonderembse, and Jayaram (2005) | | | | | x | | x | | | |
| Li et al. (2012) | x | x | | | x | x | | | | |
| Mollenkopf & Dapiran (2005) | x | | x | x | | | | | | |
| Quesada, Rachamadugu, Gonzalez, and Luis Martinez (2008) | | | | | | x | | | x | |
| Ragatz, Handfield, and Petersen (2002) | | | | | x | | x | | | |
| Rodrigues, Stank, and Lynch (2004) | | | | | | | | | | |

(continued on next page)

**Table 1** (*continued*)

| | Customer integration | | | Supplier integration | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Market/ Segmental focus | Customer satisfaction/ Feedback | Flexibility/ Responsiveness | Partnership | Information sharing/ Exchange | Joint planning with suppliers | Joint product development | Production \schedule information | Inventory information | Demand information |
| Salvador and Villena (2013) | | | | | x | | x | | | |
| Sanders and Premus (2005) | | | | | | x | | | | |
| Stank et al. (2001) | | | | | x | | | | | |
| Swink et al. (2007) | | x | | x | | | x | x | | |
| Vachon and Klassen (2006) | x | | | x | | | | | | |
| Vickery et al. (2003) | | x | x | x | | | | | | |
| Won Lee, Kwon, and Severance (2007) | | | | x | x | x | x | | | |
| Wong, Boon-Itt, and Wong (2011) | | | | x | x | x | x | | | |
| Yang et al. (2009) | | x | x | | x | | | | | |
| Zhao et al. (2013) | | x | x | x | | x | x | | | |

| | Supplier integration | | | | | | | | Customer integration | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Sharing cost information | Operational integration | Supplier development | Logistics planning | Joint EDI/ Networks/ Automated systems | Joint cost improvements | Supplier input/ Contribution | Standardization establishment | Interdepartmen-tal integration | Joint design decisions |
| Danese (2013) | | | | | | x | | | | |
| Danese and Romano (2013) | | | | | | | | | | |
| Devaraj, Krajewski, and Wei (2007) | | | | | | | | | | |
| Droge et al. (2004) | | | x | | | | | | | x |
| Flynn et al. (2010) | | | | | | | | | | |
| Germain and Iyer (2006) | | | | | | | | | x | |
| Gimenez and Ventura (2005) | | | | | | | | | | |
| He and Da Xu (2014) | | x | | | | | | | | |
| Huo, Zhao, and Zhou (2014) | | | | | | | | | x | x |
| Koufteros, Vonderembse, and Jayaram (2005) | | | | | | | x | | | |
| Li et al. (2012) | | | | | x | | | | x | |
| Mollenkopf & Dapiran (2005) | | x | x | | | x | | | | |
| Quesada, Rachamadugu, Gonzalez, and Luis Martinez (2008) | | | | x | x | | | | | |
| Ragatz, Handfield, and Petersen (2002) | | | | | | | x | | | |
| Rodrigues, Stank, and Lynch (2004) | | x | | | | | | | | |
| Salvador and Villena (2013) | | | | | | | | | | |
| Sanders and Premus (2005) | x | x | | | | | | | | |
| Stank et al. (2001) | | x | | | | | | | | |
| Swink et al. (2007) | x | | | | | x | | | | |
| Vachon and Klassen (2006) | | | x | | | | | | | |
| Vickery et al. (2003) | | | | | | | | | | |
| Won Lee, Kwon, and Severance (2007) | | | | x | | | | | x | |
| Wong, Boon-Itt, and Wong (2011) | | | | | | | | | | x |
| Yang et al. (2009) | | x | x | | | | | x | x | |
| Zhao et al. (2013) | | | | | | x | | | x | |

(continued on next page)

**Table 1** (*continued*)

| | Customer integration | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Responsiveness | Information flow | Physical flow | Operations integration | Standardization | Cross-functional collaboration/ Joint teamwork | Joint operational planning and decision | Infrastructure for information sharing | Standardization | Compliance | Simplification/ Structural adaptation |
| Danese (2013) | | | | | | | | | | | |
| Danese and Romano (2013) | | | | | | | | | | | |
| Devaraj, Krajewski, and Wei (2007) | | | | | | | | | | | |
| Droge et al. (2004) | | | | | x | | x | | | | |
| Flynn et al. (2010) | | | | | | | | x | | | |
| Germain and Iyer (2006) | | | | x | | | | | | | |
| Gimenez and Ventura (2005) | | | | | | x | x | | | | |
| He and Da Xu (2014) | | | | | | | | | | | |
| Huo, Zhao, and Zhou (2014) | | | | | | x | | | | | |
| Koufteros, Vonderembse, and Jayaram (2005) | | | | | | | | | | | |
| Li et al. (2012) | | x | | | | x | x | x | | | |
| Mollenkopf & Dapiran (2005) | | | | | | x | | | x | x | x |
| Quesada, Rachamadugu, Gonzalez, and Luis Martinez (2008) | | | | | | | | | | | |
| Ragatz, Handfield, and Petersen (2002) | | | | | | | | | | | |
| Rodrigues, Stank, and Lynch (2004) | | | | x | | | | | | | |
| Salvador and Villena (2013) | | | | | | | | | | | |
| Sanders and Premus (2005) | | x | | | | x | | x | | | |
| Stank et al. (2001) | | | | | | | | | | | |
| Swink et al. (2007) | | | | | | | | | | | |
| Vachon and Klassen (2006) | | | | | | | | | | | |
| Vickery et al. (2003) | | | | | | | | | | | |
| Won Lee, Kwon, and Severance (2007) | | | | | | | | x | | | |
| Wong, Boon-Itt, and Wong (2011) | x | x | x | | | | | | | | |
| Yang et al. (2009) | | | | | | x | | x | | | |
| Zhao et al. (2013) | | | | x | | x | | | | | |

**Table 2**
Scope of information used in relations (T = Theoretical; E: Empirical).

| Reference | Type | Relation investigated: Information type → Performance |
|---|---|---|
| Cachon and Lariviere (2001) | T | Sharing demand forecast → Supply chain performance |
| Swaminathan, Sadeh-Koniecpol, and Smith (1995) | T | Sharing supplier capacity → Supply chain performance |
| Yan and Pei (2011) | E | Demand Information → Firm performance |
| Özer and Wei (2006) | T | Impact of forecast information sharing → Supply chain inefficiency |
| Ganeshan et al. (2001) | T | Inventory and flow planning → Supply chain performance |
| Yao, Yue, and Liu (2008) | T | Vertical cost information → Supply chain performance |
| Zhang, Tan, Robb, and Zheng (2006) | T | Shipment information → Supply chain performance |
| Devaraj et al. (2007) | E | Production information → Supply chain performance |
| Hariharan and Zipkin (1995) | T | Advance ordering information → Supply chain performance |
| Karaesmen, Liberopoulos, and Dallery (2004), | T | Advance demand information → Supply chain performance |
| Dobson and Pinker (2006) | T | Lead time information → Organizational performance |
| Tarí, Molina-Azorín, Pereira-Moliner, López-Gamero, and Pertusa-Ortega (2014) | E | Quality management → Operational performance |
| Williams and Naumann (2011) | E | Customer satisfaction → Organizational performance |
| Carr and Kaynak (2007) | E | Information sharing → Organizational performance |
| Fleisch and Tellkamp (2005) | T | Inventory information → Organizational performance |
| Randall and Ulrich (2001) | E | Product variety → Firm performance |
| Lee and Whang (2000) | E | Sales forecast } |
| | | Order status } → Organizational performance |
| | | Inventory position } |
| | | Shipment data } |
| Li, Ragu-Nathan, Ragu-Nathan, and Rao (2006) | T | Demand } |
| | | Inventory } → Firm performance |
| | | Shipment } |
| Lin, Huang, and Lin (2002) | T | Order information (inventory, demand) } |
| | | Operational information } → Organizational performance |
| | | Strategic information } |
| Hall and Saygin (2012) | T | Inventory level } |
| | | Customer demand } → Organizational performance |
| | | Reliability information } |
| Kulp, Lee, and Ofek (2004) | E | Consumer needs } |
| | | Store inventory levels } → Organizational performance |
| | | Warehouse inventory levels } |
| Prajogo and Olhager (2012) | E | Financial } |
| | | Production } → Operational performance |
| | | Design } |
| | | Research } |

companies will deliberately not preempt the use of information once it is provided. The benefits may not materialize if information is made available but not used by upstream or downstream members. Thus, we propose the distinction of information sharing from information usage, and to use IS as an antecedent to IU, leading to the following hypothesis:

**H1.** Information sharing has a positive direct impact on the information used.

### *2.3. Impact of information usage on operational performance*

Ellinger, Chen, Tian, and Armstrong (2015), Flores, Zheng, Rau, and Thomas (2012), and Cheng (2011) perceive organizational learning theory as an effective and sustainable approach for supply chains to improve their performance and to be competitive. Wowak, Craighead, Ketchen, and Hult (2013) point out the importance of supply chain information usage among partners in leading to superior performance. In fact, Mohtadi (2008) indicates that information shared by the food retailer to suppliers may lead to ex-post opportunism in developing cash flow strategy in order to improve their performance. In the supply chain integration literature, no empirical research has been done to explore the role of information usage between the information sharing and performance relationship. The extant literature on supply chain integration reveals categorical performance measures, such as operational efficiency and effectiveness (Prajogo & Olhager, 2012; Ramanathan, 2012; Vereecke & Muylle, 2006), organizational performance (Danese & Romano, 2013; Sanders & Premus, 2005; Zhao et al., 2013), financial performance (Narasimhan & Nair, 2005; Zhang et al., 2006), and logistics performance (Chinniah, Sundram, & Bhatti, 2013; Salema & Buvik, 2016). Since the literature includes an abundant amount of research investigating the impact of operational performance on organizational performance (Green Jr, Whitten, & Inman, 2008; Lambert & Burduroglu, 2000), the focus here is on the role of information usage between information sharing and operational performance that refers to efficiency (reducing costs by utilizing resources) and effectiveness (achieving given objectives) to consequently better serve customers.

Huo, Zhao, and Zhou (2014), Lai, Hsu, Lin, Chen, and Lin (2014), Klein and Rai (2009), Hsu, Kannan, Tan, and Keong Leong (2008), Gunasekaran and Kobu (2007), and Frohlich and Westbrook (2001) all highlight the importance of information sharing in order to achieve operational-level efficiency and effectiveness among supply chain members. Sahin and Robinson (2002), Gligor and Holcomb (2014), and Esper, Fugate, and Davis-Sramek (2007) argue that information sharing is often introduced as a universal antidote to purge problems faced by the supply chain and problems in logistics. The literature seems to indicate that empirical studies focus on direct relationships between information sharing and performance measures. Schroeder and Flynn (2002) argue that the way information is used makes a difference in a firm's performance. Ramdas and Spekman (2000) report a significant gap in the performance of outstanding and mediocre supply chains as a result of the company's ability to share and use information. Thus, we develop a theoretical model, as visualized in Fig. 1, that considers the direct and indirect effects of information sharing and usage among supply chain members on performance, and we propose the following

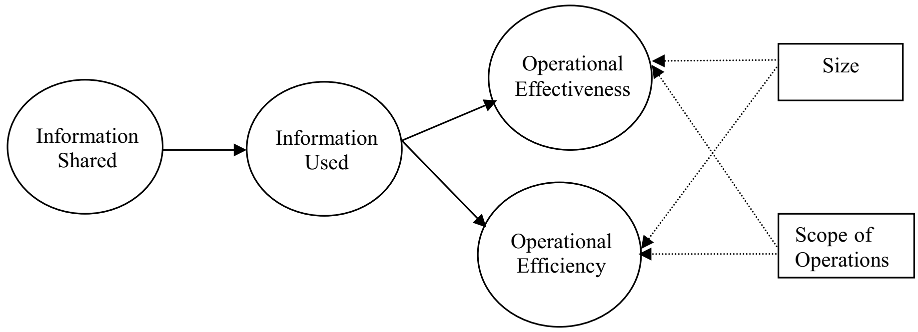


**Fig. 1.** Complete conceptual model.

hypotheses:

**H2.** Information usage has a positive direct impact on retailer's operational efficiency.

**H3.** Information usage has a positive direct impact on retailer's operational effectiveness.

We also hypothesize whether the usage of information has a mediating impact on information sharing and operational performance in terms efficiency and effectiveness:

**H4.** Information usage has a positive mediating role between information sharing and operational efficiency.

**H5.** Information usage has a positive mediating role between information sharing and operational effectiveness.

Note that we also introduce firm size (number of people employed) and scope of operations (whether company operates locally, regionally, nationally, or internationally) as control variables. It is expected that larger companies and geographically expanded companies are more likely to realize performance improvement. Larger food retailers in size and scope are expected to have larger supplier base and thus they are less concerned with the opportunistic behavior of their suppliers due to increased competition.

## 3. Research methodology

### *3.1. Questionnaire design and measures*

In our questionnaire, all items were assessed using a five-point Likert scale. We specifically focused on items used for the following: (a) operational performance constructs by Mentzer and Konrad (1991), Bobbitt (2004), Krauth, Moonen, Popova, and Schut (2005), Fugate, Mentzer, and Stank (2010), and Huo, Zhao, and Zhou (2014); and (b) upstream and downstream information sharing and usage constructs by Zhao, Xie, and Zhang (2002), Barut et al. (2002), Hui and Lingrong (2012), and Huo, Zhao, and Zhou (2014). The items in our study were reviewed by a team of four academicians with a combined experience of 36 years in the supply chain management profession. They evaluated the appropriateness of the items to the constructs in consultation with practitioner managers in the food retailer industry to which the questionnaire was administered. Through a rigorous process, items with a high degree of ambiguity were clarified, and redundancies were eliminated. As a result of the high degree of inter-team agreement in opinions and consistency with the literature, the questionnaire items were finalized. The questionnaire was designed and administered in a way to eliminate common rate effects, item priming effects, and acquiescence bias, as suggested by Podsakoff, MacKenzie, Lee, and Podsakoff (2003). Cohen's kappa coefficient of 77.9% is indicative of the minimal rater bias effect (Sim & Wright, 2005).

### *3.2. Sampling and data collection*

Our designated country was Turkey, the seventh and tenth largest retail market in Europe and in the world, respectively, according to a 2015 U.S Department of Agriculture (USDA) report. Turkey is also categorized as an emerging market, and hence the findings from this study can be extended to such settings. We concentrate on the food retail sector representing 60% of the total retail sector in Turkey, which is expected to grow 8% annually from 2014 to 2018. The Turkish retail sector has promptly responded to recent global economic struggles by streamlining their supply chain structure as much as possible to reduce the cost of inefficiencies (USDA, 2015).

Data for this study was collected using a self-administered direct-mail survey distributed to all 763 registered retailers of the Turkish Food Retailers Association. In this study, the key respondent was chosen to be knowledgeable content-wise and familiar with processes in their supply chain, as suggested by Zhao et al. (2011). In order to ascertain the collection of reliable data and to determine respondent's contact information for our survey, we had research assistants call each company and ask for the name of the person in charge of supply chain activities and having the highest degree of knowledge competency related to retailer supply chain processes including logistics, information exchanges, and performance rating. Out of 245 responses received, 209 usable questionnaire results were recorded, yielding a response rate of 27.4%.

The results of the Harman's (1976) single factor test, as suggested by Podsakoff and Organ (1986), revealed that among the twelve distinct factors, the first factor accounts for only 32.8% of the total variance, thus suggesting a low likelihood of the common method bias impact due to single respondents. We also utilized an extended partial least squares algorithm (Lohmoeller, 1989) with several marker variables to estimate the loadings on every item in the path model. A comparison of the estimated path model relationships with and without each of the additional marker variables shows no notable differences, and all theorized paths maintain their level of statistical significance. Neither the traditional Harman's single factor test nor the marker variable approach suggests a substantial threat of common method bias in our results.

We further performed an endogeneity test using Warp PLS 6.0 software by Kock (2017). By introducing instrumental variables, iCs and iCy, into the model, one for each operational performance, the test results revealed no evidence of endogeneity. The $\beta$ and $P$-values are 0.04 and 0.29 for iCs and 0.09 and 0.11 for iCy, respectively. Thus, the path coefficient-biased estimation via PLS is statistically not significant.

Table 3 provides a profile of respondents emerging from the survey, 42% of which indicated their current job title as logistics manager, followed by 29% as line manager, and 20% as department manager. Of the 209 usable responses, 33% of respondents indicated their scope of operation as the national level, followed by 30% as the international level, 30% as the local level, and the remaining 7% as the regional level. More than half of respondents (54%) indicated a firm size

**Table 3**
Profile of Respondents.

| Job title | N = 209 | % | Scope of operations | N = 209 | % | Firm size | N = 209 | % |
|---|---|---|---|---|---|---|---|---|
| Director | 7 | 3.3 | National | 68 | 32.6 | 1–25 | 34 | 16.3 |
| Senior manager | 13 | 6.2 | International | 63 | 30.1 | 26–50 | 12 | 5.7 |
| Logistics manager | 87 | 41.6 | Local | 63 | 30.1 | 51–100 | 16 | 7.7 |
| Department manager | 41 | 19.6 | Regional | 15 | 7.2 | 101–250 | 21 | 10 |
| Line manager | 61 | 29.3 | | | | 251–500 | 13 | 6.2 |
| | | | | | | 501–More | 113 | 54.1 |

of > 501 employees, about 24% indicated a firm size between 51 and 500 employees, and the remaining 22% indicated a firm size < 50 employees.

### 3.3. Structural equation modeling

To assess the measurement and our structural model, we utilized partial least squares structural equation modeling (PLS-SEM), which is a component-based estimation method using two sets of linear equations: an inner model that examines the relationships between unobserved or latent variables, and an outer model that examines the relationships between a latent variable and its observed or manifest variables (Tenenhaus, 2008). Reliable and valid outer model estimations permit an evaluation of inner path model estimates (Henseler, Ringle, & Sinkovics, 2009). PLS-SEM uses available data to estimate the path relationships in a given model, with the objective of minimizing error in terms of endogenous constructs (Chin, 1998; Henseler et al., 2009), and provides accurate estimates of mediation effects (Hair, Ringle, & Sarstedt, 2013).

#### 3.3.1. Assessment of convergent validity, collinearity, and significance and relevance

Following the procedure by Hair Jr, Hult, Ringle, and Sarstedt (2016), pp. 137–138), as illustrated in Fig. 2, we first assessed our model's convergent validity by checking whether the formative measures of a construct were highly correlated with the reflective measures of the same construct. Considering both measures, redundancy analysis reveals strong path coefficients above 0.70 and $R^2$ values above 0.5 for all latent variables, thereby supporting the convergence validity of the four constructs in our model.

Second, we assessed the collinearity between indicators by utilizing variance inflation factors (VIFs). High levels of collinearity between indicators have an impact on the estimation of weights and their statistical significance. Collinearity may boost the standard error and thus reduce the ability to demonstrate that the estimated weights are significantly different from zero. Since all VIF values provided in Table 4 are all less than the suggested threshold value of five (Hair Jr et al., 2016, p. 143), we conclude that there is a lack of collinearity between indicators.

Third, we assessed the significance and relevance of indicators. As summarized in Table 4, the estimated weights of indicators for all constructs are statistically significant ($p < 0.01$) and positively relevant in their present constructs. Analysis results provide the support for the general quality of our constructs and indicate that our data and measurement model are suitable for the structural model evaluation and hypothesis testing process.

### 3.4. Universal structure modeling

The essential assumption of PLS-SEM is that the relation between observed data sets is linear and that similar linearity holds between latent variables. However, it is possible that significant relationships are due to variables not taken into consideration. True causal effects may also be hidden and difficult to observe, due to mediating and moderating relationships. Buckler and Hennig-Thurau (2008) released the force-fitted linearity assumption and presented the universal structural model that allows more exclusive nonlinear causalities between latent variables. While PLS-SEM is intended to test the "truth" of a given structural model (Joreskog & Yang, 1996), under the USM, the proposed model inherently must compete with an array of alternative model specifications, excluding illogical paths. Thus, USM is capable of quantifying and visualizing non-linear relationships, including potential undefined paths with interaction effects, by utilizing both the iterative component-based approach and Bayesian neural network technique. Such features have rendered USM methodology as an enhancement if not superior to conventional linearly structured equation models in the literature. USM has recently become a credible model in the literature (Henseler, Hubona, & Ray, 2016; McIntosh, Edwards, & Antonakis, 2014; Rigdon, & Ringle, & C. M., Sarstedt, M., 2010) and stands as a good benchmark to traditional PLS-SEM (Garbe & Richter, 2009; Turkyilmaz, Oztekin, Zaim, & Demirel, 2013; Turkyilmaz, Temizer, & Oztekin, 2017). Fig. 3 illustrates the three steps involved in universal structure modeling.

The first step in USM involves determining both the specification matrix and measurement model. In the second step, both structural and measurement models are iteratively and simultaneously estimated in such a way as to compare them to the PLS. The estimation begins with determining values from the linear principal component analysis for latent variables and then estimating the paths between the model constructs using a Bayesian neural network with multi-layer perceptron (MLP) architecture (Ripley, 1996). The enhanced scores for the unobserved variables obtained from the neural network process are then used as input to compute the weights of the measurement model. The iterative calculation of inner and outer model estimates is continued until the difference between the unobservable variable scores calculated by the inner model and those by the outer model is minimal. Once the final scores of the latent variables are obtained, the last step is to determine the strength, significance, and shape of the relationships among the latent variables of the structural model. Apart from the SEM approach, path coefficients (metric of the strength between the two latent variables) are determined by utilizing an "Overall Explained Absolute Deviation" (OEAD) criterion (Zimmermann, 1994) as a measure of the latent construct's share of variance in the structural model.

On the other hand, the value effect of the independent variable is measured by the leverage factor, demonstrating either a progressive or digressive nonlinear relationship. In a digressive relationship, low values of the independent variables have more impact than its high values. The reverse is characterized as a progressive relationship (Buckler & Hennig-Thurau, 2008). Thus, a leverage factor higher than one indicates a progressive relationship. Similarly, a leverage factor lower than one indicates a digressive relationship. Note that a negative leverage factor value means a U-shape relationship.

During the last step, both the coefficient of determination ($R^2$) and the goodness of fit (GoF) are also employed to assess and compare the performance of USM to that of SEM. The GoF is an overall standardized fit index measuring how well the relationships embedded in the data are explained (Henseler & Sarstedt, 2013; Joreskog, 1993; Joreskog & Yang, 1996; Tenenhaus, Vinzi, Chatelin, & L. C., 2005). For theoretical details we refer the reader to Albashrawi, Kartal, Oztekin, and Motiwalla (2019) and Oztekin, Kong, and Delen (2011).

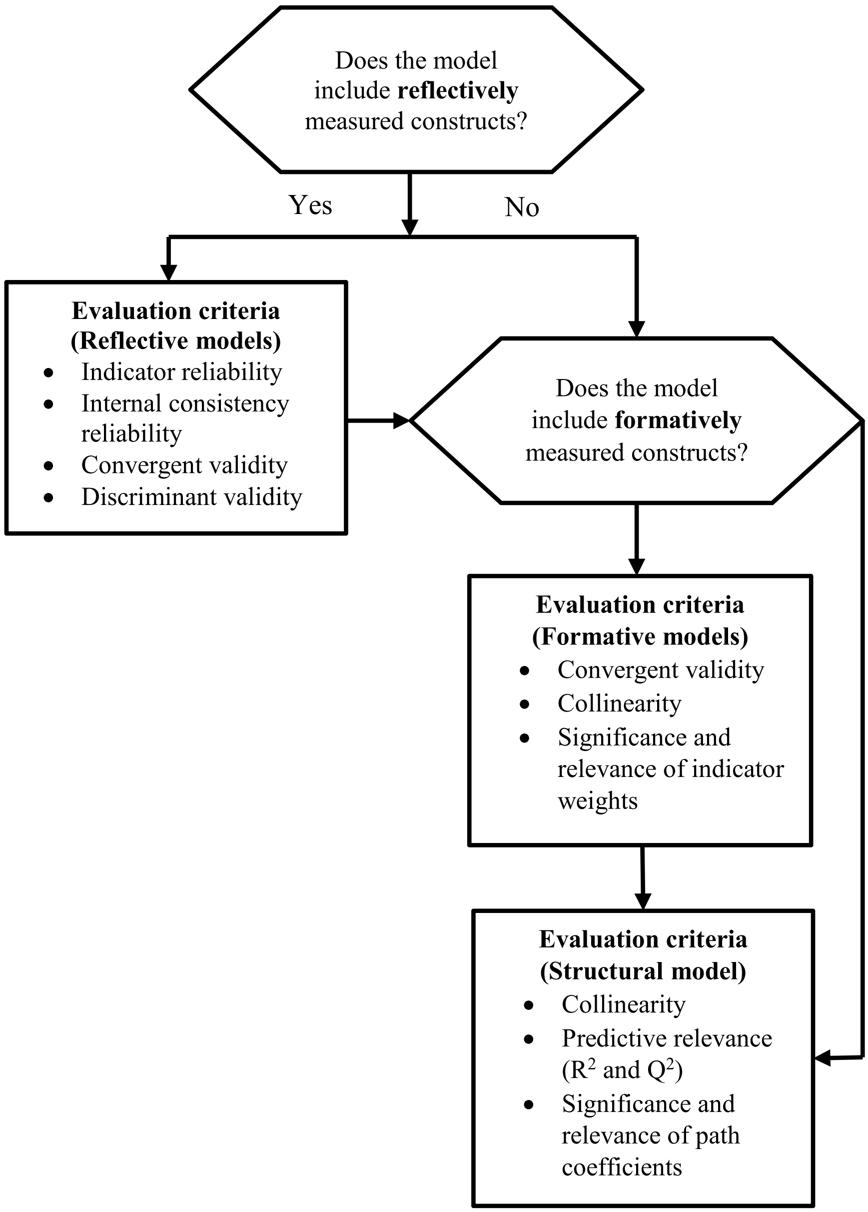


**Fig. 2.** Illustration of PLS-SEM methodology steps
**Source:** Sarstedt, M., Ringle, C. M., Smith, D., Reams, R., & Hair Jr., J. F. (2014). Partial least squares structural equation modeling (PLS-SEM): A useful tool for family business researchers. *Journal of Family Business Strategy*, *5*(1), 105–115.

## 4. Results and discussion

### 4.1. Assessment of structural model

Fig. 4 shows the hypothesized relationships between the constructs and presents PLS-SEM results for the structural path coefficient significance and relevance of the structural model.

The statistical significance of the path coefficients ($\beta$) was obtained using bootstrapping (4999 re-samples and 209 cases). Table 5 summarizes the results for coefficients of determination ($R^2$ values) and the Stone-Geisser's ($Q^2$) values for our latent variables. The $R^2$ values of latent variables range from 0.40 to 0.77, which indicates the model's predictive accuracy. Performing blindfolding procedures, the $Q^2$ values of latent variables were all above zero, ranging from 0.05 to 0.28, thus supporting the model's predictive relevance. While the significant effect of firm size on operational efficiency and effectiveness ($p < 0.05$) suggest that larger firms are more likely to realize performance improvement, interestingly, the scope of operations does not have a significant impact on operational efficiency and effectiveness.

### 4.2. Discussion of direct impacts

Table 6 provides support for our hypotheses with direct impacts. Information sharing between supplier and retailer is likely to increase the retailer's information usage level. This effect is positive and statistically significant ($\beta = 0.882$, t-value = 45.867, STDV = 0.019, $p < 0.01$), supporting our hypothesis $H_1$. The model explains 77% of the variance in the retailer's information usage level which consequently has a positive and statistically significant effect on the retailer's operational efficiency with statistical results ($\beta = 0.487$, t-value = 6.182, STDV = 0.079, and $p < 0.01$), supporting our hypothesis $H_2$. The model explains 58% of the variance in the retailer's operational efficiency level. Moreover, a retailer's usage level of information has a positive and statistically significant effect on the

**Table 4**
Item description and VIF.

| Construct | | Item | | Weight | STD | T-statistic | *P* value | VIF |
|---|---|---|---|---|---|---|---|---|
| Information sharing (IS) | Information provided to supplier | IPS1 | New product specifications | 0.159 | 0.012 | 13.140 | 0.000 | 2.604 |
| | | IPS2 | Customer value | 0.100 | 0.013 | 7.519 | 0.000 | 3.041 |
| | | IPS3 | Retail price changes | 0.245 | 0.041 | 5.932 | 0.000 | 2.933 |
| | | IPS4 | Order status | 0.126 | 0.011 | 11.351 | 0.000 | 2.975 |
| | | IPS5 | Promotional events | 0.065 | 0.016 | 4.063 | 0.000 | 3.264 |
| | | IPS6 | Inventory holding costs | 0.068 | 0.014 | 4.928 | 0.000 | 3.206 |
| | | IPS7 | Delivery schedules | 0.083 | 0.013 | 6.194 | 0.000 | 3.175 |
| | | IPS8 | Customer information | 0.154 | 0.014 | 11.407 | 0.000 | 3.189 |
| | | IPS9 | Real-time demand | 0.111 | 0.015 | 7.303 | 0.000 | 2.714 |
| | | IPS10 | Point-of-sale data | 0.362 | 0.020 | 18.469 | 0.000 | 3.029 |
| | | IPS11 | Demand forecast | 0.042 | 0.012 | 3.409 | 0.000 | 2.955 |
| | | IPS12 | Inventory level information | 0.136 | 0.020 | 6.733 | 0.000 | 2.718 |
| | Information received from supplier | IRS1 | Lead times | 0.307 | 0.02 | 12.634 | 0.000 | 3.175 |
| | | IRS2 | Response time | 0.289 | 0.03 | 11.031 | 0.000 | 2.999 |
| | | IRS3 | Production schedules | 0.033 | 0.02 | 2.813 | 0.000 | 2.977 |
| | | IRS4 | Service level | 0.328 | 0.03 | 11.884 | 0.000 | 2.667 |
| | | IRS5 | Availability level | 0.084 | 0.02 | 4.468 | 0.000 | 3.163 |
| | | IRS6 | Forthcoming promotion | 0.216 | 0.02 | 11.077 | 0.000 | 2.447 |
| | | IRS7 | Production capacity | 0.210 | 0.02 | 13.636 | 0.000 | 3.022 |
| | | IRS8 | Product design | 0.162 | 0.02 | 10.318 | 0.000 | 3.165 |
| | | IRS9 | Inventory level | 0.162 | 0.02 | 10.318 | 0.000 | 3.204 |
| | | IRS10 | Order status | 0.222 | 0.01 | 16.567 | 0.000 | 2.156 |
| | | IRS11 | Supply price changes | 0.548 | 0.02 | 26.602 | 0.000 | 3.072 |
| | | IRS12 | Supply disruptions | 0.148 | 0.02 | 8.409 | 0.000 | 2.988 |
| Information used (IU) | | IUR1 | Response time | 0.297 | 0.02 | 13.624 | 0.000 | 2.812 |
| | | IUR2 | Service level | 0.171 | 0.02 | 9.194 | 0.000 | 3.261 |
| | | IUR3 | Availability level | 0.325 | 0.03 | 13.000 | 0.000 | 2.640 |
| | | IUR4 | Lead times | 0.405 | 0.03 | 16.135 | 0.000 | 3.217 |
| | | IUR5 | Production schedules | 0.266 | 0.03 | 9.301 | 0.000 | 3.084 |
| | | IUR6 | Forthcoming promotion | 0.144 | 0.02 | 7.826 | 0.000 | 3.187 |
| | | IUR7 | Product design | 0.310 | 0.01 | 23.846 | 0.000 | 2.683 |
| | | IUR8 | Order status | 0.127 | 0.01 | 10.325 | 0.000 | 2.727 |
| | | IUR9 | Production capacity | 0.450 | 0.01 | 37.815 | 0.000 | 2.803 |
| | | IUR10 | Supply price changes | 0.196 | 0.01 | 15.680 | 0.000 | 2.615 |
| | | IUR11 | Inventory level | 0.238 | 0.02 | 15.455 | 0.000 | 3.283 |
| | | IUR12 | Supply disruptions | 0.070 | 0.02 | 4.192 | 0.000 | 3.285 |
| Operational efficiency (OEFy) | | EFFIY1 | Inventory costs | 0.191 | 0.01 | 17.364 | 0.000 | 3.197 |
| | | EFFIY2 | Warehousing costs | 0.178 | 0.01 | 16.182 | 0.000 | 2.758 |
| | | EFFIY3 | Safety stock costs | 0.138 | 0.02 | 8.118 | 0.000 | 2.643 |
| | | EFFIY4 | Purchasing costs | 0.162 | 0.01 | 16.200 | 0.000 | 3.129 |
| | | EFFIY5 | Transportation costs | 0.184 | 0.01 | 15.333 | 0.000 | 2.617 |
| | | EFFIY6 | Ordering costs | 0.169 | 0.01 | 15.364 | 0.000 | 3.243 |
| | | EFFIY7 | Sales level | 0.171 | 0.01 | 15.545 | 0.000 | 3.286 |
| Operational effectiveness (OEFs) | | EFFES1 | Inventory turns per year | 0.309 | 0.06 | 4.828 | 0.000 | 2.746 |
| | | EFFES2 | Time between order receipt and delivery | 0.312 | 0.06 | 5.288 | 0.000 | 3.055 |
| | | EFFES3 | Percent of orders shipped on time | 0.236 | 0.06 | 4.000 | 0.000 | 3.305 |
| | | EFFES4 | Line item fill rate | 0.273 | 0.04 | 7.583 | 0.000 | 2.641 |
| | | EFFES5 | Providing desired quantities on consistent basis | 0.188 | 0.04 | 4.947 | 0.000 | 2.841 |
| | | EFFES6 | Percent of damage-free deliveries | 0.113 | 0.03 | 3.767 | 0.000 | 2.733 |
| | | EFFES7 | Percent of shipments requiring expediting | 0.184 | 0.02 | 7.965 | 0.000 | 3.056 |

retailer's operational effectiveness, as hypothesized in $H_3$. This relationship is supported by the statistical results ($\beta = 0.688$, t-value = 13.932, STDV = 0.049, and $p < 0.01$). The model explains 40% of the variance in the retailer's operational effectiveness level.

The issue of one member having more knowledge or information than another member may partially be explained by the challenge of preserving competitive identity. This challenge has been a critical issue from the perspective of information sharing. We know from Cachon and Zipkin (1999) that competition reduces efficiency. In order to keep the competitive identity of collaboration and sustainable collaboration among members of the supply chain, Nidumolu, Ellison, Whalen, and Billman (2014) suggest building a structured competition and nurturing a culture of trust. Luckily, new developments in blockchain technology seem to offer avenues to both create such a trust culture and preserve competitive identity.

In order to test the mediating effect of information usage between information sharing and operational performance (effectiveness and efficiency), hypotheses 4 and 5, respectively, we used the bootstrapping test as suggested (Hair Jr et al., 2016; Preacher & Hayes, 2008). The results of bootstrapping the indirect effect analysis, using PLS-SEM's bias corrected and accelerated (BCA) bootstrap two-tailed testing, with 4999 bootstrap sample, no sign changes, and a significance level of 0.05, are presented in Table 7.

PLS-SEM's BCA bootstrapping results reveal that both indirect effects are significant since none of the 95% confidence intervals includes zero. The empirical t-value of the indirect effect (0.280) for the information sharing to operational efficiency relationship is 2.616, yielding a *p*-value of 0.008. Similarly, for the indirect effect (0.212) of the information sharing to operational effectiveness relationship, we obtain a t-value of 2.269, indicating a p-value of < 0.05. In the next step, considering the magnitude and significance of the direct effects in the mediation analysis procedure, the relationship from information sharing to operational efficiency is relatively weak (0.196) and statistically significant ($t = 0.096$; $p = 0.000$). Following the mediation analysis procedure, we can conclude that information usage partially mediates the information sharing to an operational efficiency relationship, since both the direct and indirect effects are significant. Also, the direct and indirect effects are both positive, and the sign of

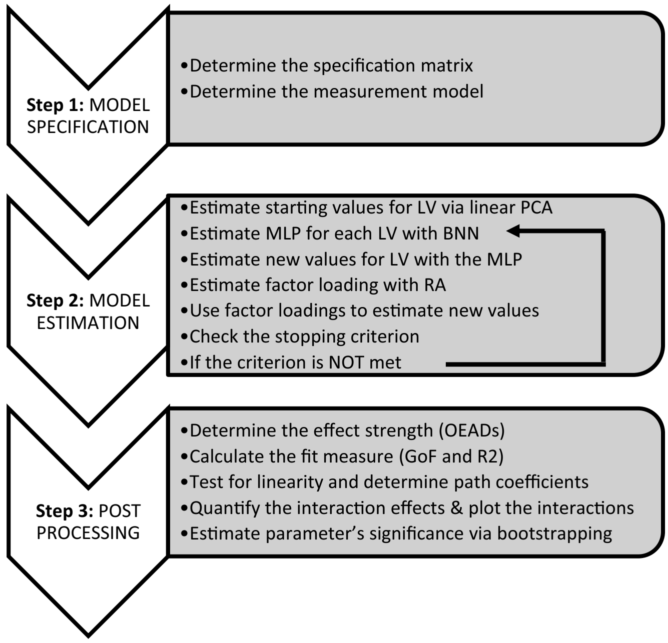


**Fig. 3.** Illustration of universal structure model (USM) methodology steps (PCA = Principal Component Analysis; LV = Latent variables; BNN = Bayesian Neural Networks; RA = Regression Analysis; MLP = Multi-Layer Perceptron; IE = Interaction Effect) Adopted from Buckler and Hennig-Thurau (2008).

their product is also positive. Hence, we conclude that information usage represents complementary mediation of the relationship from information sharing to operational efficiency. Similarly, the relationship from information sharing to operational effectiveness is relatively high (0.527) and statistically significant ($t = 3.438$; $p = 0.000$). Also, the direct and indirect effects are both positive, and the sign of their product is also positive. Hence, we can conclude that information usage represents complementary mediation of the relationship from information sharing to operational effectiveness. Thus, both hypotheses 4 and 5 are supported.

### 4.3. Importance-performance matrix analysis

We implemented the Importance-Performance Matrix Analysis (IPMA) (Hair Jr, Sarstedt, Ringle, & Gudergan, 2017) to further analyze the PLS-SEM results by accounting for the performance of each construct. For a specific construct-operational efficiency, and operational

**Table 5**
PLS-SEM results for endogenous latent constructs $R^2$ and $Q^2$.

| Endogenous latent constructs | $R^2$ | $Q^2$ |
|---|---|---|
| Information used by retailer (IUR) | 0.778 | 0.054 |
| Operational effectiveness (OEFs) | 0.589 | 0.288 |
| Operational efficiency (OEFy) | 0.408 | 0.080 |

effectiveness, the IPMA contrasts the structural model importance (total effect) and the average values of the performance (latent variable scores) to emphasize important factors with a relatively high or low importance and performance. While executing an IPMA, we determined both operational efficiency and operational effectiveness as target constructs in our model.

The IPMA process requires the latent variable scores to be re-scaled on a range from 0 to 100. This necessitates all indicators in the PLS path model to use a quasi-metric or metric scale, so that the minimum value of an indicator represents the worst outcome, and the maximum value represents the best value of an indicator. Regardless of whether the measurement model is formative or reflective, IPMA considers positive outer weight estimates. Further information on dealing with unexpected negative outer weights can be found in the work of Hair Jr et al. (2017).

A latent variable's total effect on predicting another variable is referred to as the importance of a latent variable. Also, the sum of the direct and all indirect effects in the structural model provides a total effect. As shown in Table 8, information usage is the most important factor for both operational efficiency and effectiveness. Additionally, Table 9 provides the top five most important variables in terms of operational efficiency and effectiveness. In addition, we also performed a conditional query using Warp PLS 6.0 software (Kock, 2017) to determine the increase in conditional probability of performance given low and high levels of information sharing and usage. These results are populated into Table 10. Thus, the higher the information usage for a given shared information, the better conditional probability of both efficiency and effectiveness performances.

### 4.4. Analyzing hidden structures via universal structure modeling

The coefficient of determination and goodness of fit were used to assess the results of PLS-SEM and USM, which are provided in Table 11. While USM confirms the predictive strength of our model, the higher $R^2$ and GoF values under USM may suggest some nonlinear and interaction effects among the latent variables.

To enlighten these relationships not set as a priori, the overall explained absolute deviation and leverage factor values were calculated

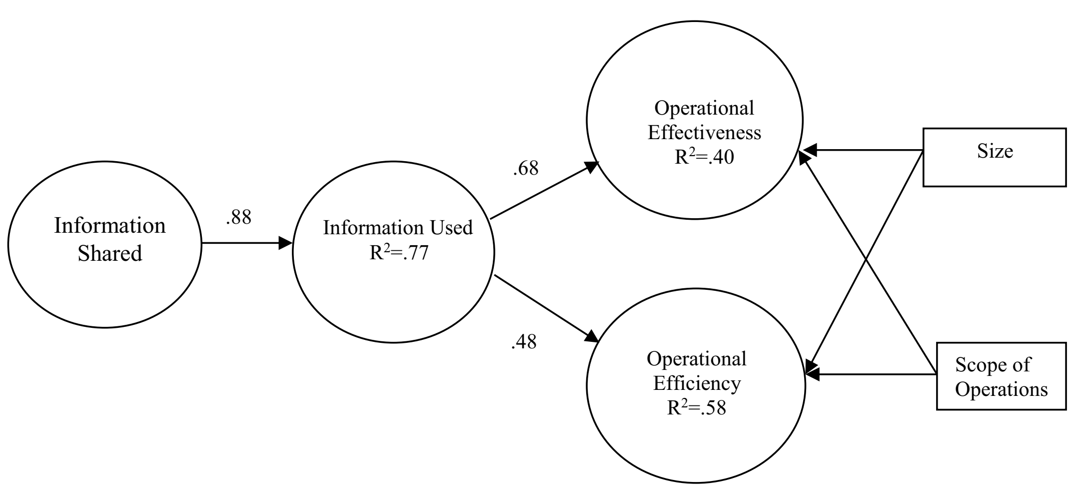


**Fig. 4.** Results summary of general conceptual model.

**Table 6**
PLS-SEM results for structural model and hypothesis testing on direct effects.

| Path | Path coefficient ($\beta$) | Standard deviation | T-statistic | P-values | Hypothesis | Decision |
|---|---|---|---|---|---|---|
| IS → IU | 0.882 | 0.019 | 45.867*** | 0.000 | H1 | Supported |
| IU → OEFy | 0.487 | 0.079 | 6.182*** | 0.000 | H2 | Supported |
| IU → OEFs | 0.688 | 0.049 | 13.932*** | 0.000 | H3 | Supported |

t-Values for two-tailed test: *1.65 (sig. level 10%), **1.96 (sig. level 5%), ***2.58 (sig. level 1%).

**Table 7**
Analysis of mediation effects.

| | Path coefficient | Standard deviation | T-Statistic | 5.0% | 95.0% | P-values |
|---|---|---|---|---|---|---|
| Total effects | | | | | | |
| Information sharing → Operational efficiency | 0.476 | 0.076 | 6.275* | 0.418 | 0.662 | 0.000 |
| Information sharing → Operational effectiveness | 0.739 | 0.045 | 16.582* | 0.703 | 0.847 | 0.000 |
| Indirect effects | | | | | | |
| Information sharing → Operational efficiency | 0.280 | 0.107 | 2.616* | 0.071 | 0.489 | 0.0086 |
| Information sharing → Operational effectiveness | 0.212 | 0.092 | 2.296** | 0.046 | 0.363 | 0.0217 |
| Direct effects | | | | | | |
| Information sharing → Operational efficiency | 0.196 | 0.057 | 3.438* | 0.085 | 0.287 | 0.000 |
| Information sharing → Operational effectiveness | 0.527 | 0.129 | 4.096** | 0.275 | 0.779 | 0.000 |

*$p < 0.001$, **$p < 0.01$, ***$p < 0.05$.

**Table 8**
IPMA results of constructs for efficiency and effectiveness.

| Target constructs | Indicator | Total effect | Performance |
|---|---|---|---|
| Operational efficiency | Information shared | 0.404 | 64.080 |
| | Information used | 0.527 | 65.948 |
| Operational effectiveness | Information shared | 0.579 | 64.080 |
| | Information used | 0.756 | 65.948 |

**Table 10**
Probabilistic query results.

| Conditions | Increase in conditional probability of performance | |
|---|---|---|
| | OEFs | OEFy |
| Low shared, Less used | 0.039 | 0.071 |
| High shared, Less used | 0.176 | 0.118 |
| High shared, High used | 0.462 | 0.577 |

and are shown in Table 12, and their relationships were pictorially depicted in Fig. 5, using the USM technique. USM was also computed using the same constructs along with their corresponding indicators as in the PLS model for comparison purposes. Comparison of the results for PLS and USM, shown previously in Table 11, reveal the superiority of USM in terms of both individual $R^2$ values of the constructs and the overall GoF score of the entire model The performance superiorities of USM over PLS can be attributed to the fact that PLS can only capture and handle the hypothesized linear relationships, whereas USM can reveal nonlinear and interaction effects among the constructs. Table 12 presents the effect of nonlinearity among the latent variables and how much it contributes to the OEAD. To illustrate, USM results revealed two significant (at alpha level of 0.05) nonlinear relationships that had not been present in the original conceptual model presented in Fig. 1: a nonlinear relationship between the operational effectiveness and operational efficiency, and a U-shaped cubic relationship between the information shared and the operational efficiency. These relationships are numerically tabulated in Table 12 and pictorially shown in Fig. 5.

In order to determine the extent of the interaction effects explaining the observed variance of a dependent latent variable, we captured interaction effect values and tabulated the results in Table 13 and visualized the relations in Fig. 6.

Fig. 6 reveals the three-dimensional interaction effects not captured by conventional SEM techniques. To illustrate, the top plot in Fig. 6 indicates that "information shared" and "information used" have an amplifying effect on "operational effectiveness." Strong operational

**Table 9**
IPMA results of variables for efficiency and effectiveness.

| Constructs | Variables | Total effect | Performance | Standardized outer weights | Rescaled outer weights |
|---|---|---|---|---|---|
| Efficiency | IUR9 - Production capacity | 0.228 | 69.378 | 0.441 | 0.433 |
| | IRS11- Supply price changes | 0.170 | 59.330 | 0.573 | 0.421 |
| | IUR3 - Availability level | 0.125 | 62.919 | 0.366 | 0.237 |
| | IUR10 - Supply price changes | 0.105 | 74.163 | 0.212 | 0.198 |
| | IUR7 - Product design | 0.104 | 65.191 | 0.274 | 0.196 |
| Effectiveness | IUR9 - Production capacity | 0.327 | 69.378 | 0.441 | 0.433 |
| | IRS11 - Supply price changes | 0.244 | 59.330 | 0.573 | 0.421 |
| | IUR3 - Availability level | 0.179 | 62.919 | 0.366 | 0.237 |
| | IUR10 - Supply price changes | 0.150 | 74.163 | 0.212 | 0.198 |
| | IUR7 - Product design | 0.148 | 65.191 | 0.274 | 0.196 |

Note: For each construct, top five variables with highest total effects are included in table.

**Table 11**
USM vs. PLS-SEM results comparison.

| Model Performance | Method | Information Used | Operational Effectiveness | Operational Efficiency |
|---|---|---|---|---|
| $R^2$ | USM | 0.778 | 0.645 | 0.668 |
| | SEM | 0.778 | 0.589 | 0.408 |
| Overall model | USM | − 0.622 | | |
| GoF | SEM | − 0.573 | | |

effectiveness can only be achieved when both the information shared and information used receive high values. Interestingly, the interaction plot depicts that a plateau is reached when the effect of information used on operational effectiveness is stabilized (after a threshold value of information used), where an increase in information used does not lead to higher operational effectiveness. As can be derived from the interaction plot, this saturation level is lower when the information shared is low, and it is higher when the information shared is high.

The strength of such an interaction effect between information shared and information used on the operational effectiveness is found to be 0.41 (Plate, 1998). This measures how much of the total explained variance of the latent variable operational effectiveness (0.645 in Table 8) can be attributed to the interaction effects caused by the two latent variables: "information shared" and "information used." Similar conclusions can concurrently be drawn from Table 13 and Fig. 6 in comparison to Table 11 for the other two significant interaction effects

**Table 12**
Nonlinear relationships via leverage factors and OEADs.

| Construct relationships | Leverage factor | Relationship type | Total OEAD | OEAD* by nonlinear relations |
|---|---|---|---|---|
| OEFs-OEFy | 7.71 | Progressive nonlinear | 0.55 | 0.55 |
| IU-OEFy | −4.83 | U-shaped cubic | 0.64 | 0.36 |
| IS-OEFy | −986.07 | U-shaped cubic | 0.66 | 0.16 |
| IU-OEFs | −0.98 | U-shaped quadratic | 0.50 | 0.50 |

*Significant at 0.05.

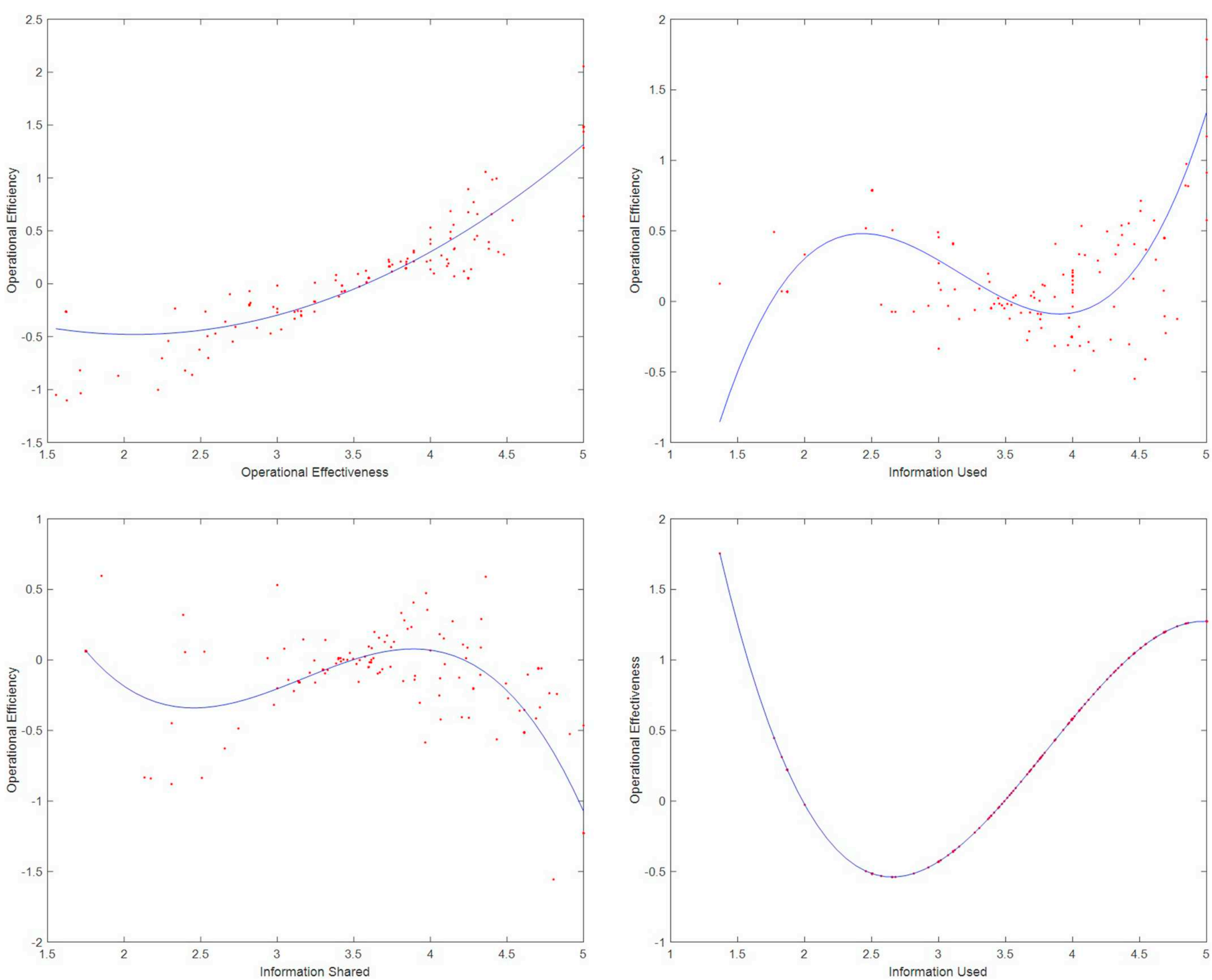


**Fig. 5.** Nonlinear relationships captured by USM technique.

**Table 13**
Interaction effects captured via USM.

| Interaction effect of | On | IE values* |
|---|---|---|
| IS and IU | OEFs | $IE_{IS\&IU}{}^{OEFs} = 0.41$ |
| IS and OEFs | OEFy | $IE_{IS\&OEFs}{}^{OEFy} = 0.17$ |
| IU and OEFs | OEFy | $IE_{IU\&OEFs}{}^{OEFs} = 0.26$ |

*Significant at 0.05; IE: interaction effect.

observed at the 0.05 significance level.

## 5. Conclusion, limits, and future research

This study demonstrates the need to extract the information usage component from the information sharing component that is commonly used in the literature. Following the organizational learning theory, we conceptualize and illuminate how learning is materialized at the organizational level. Investigating the role of information usage allows us to uncover its important relationship as a post-requisite to information sharing.

Using the empirical data obtained from upper managers in the food retail industry via a survey, results from both PLS-SEM and USM revealed that information usage is an absolutely important, critical, and significant component in studies focusing on the relationship among factors affecting supply chain performance. Information usage is found to have a strong mediating impact between information sharing, and operational efficiency and effectiveness. Moreover, the deployment of the USM extracted interesting information, such as a direct nonlinear effect of operational effectiveness on operational efficiency. Similarly, information shared was also found to be nonlinearly related to operational efficiency. More strikingly, the study revealed the fact that information shared and information used collectively have an amplifying interaction effect on operational efficiency, whereas they hit a plateau at a certain level. This is a critical finding for decision-makers in developing policies about information sharing and usage in order to improve their operational performance. This study presents interesting but unique results that rectify, and in a way correct, a common linear belief that assuming an increase in one driving factor would always monotonously increase the expected outcome in an exogenous factor.

For the first time in empirical study in information integration, we explicitly separate the information sharing from information usage and investigated direct impacts. Consistent with organizational learning theory, our study also reveals that retailers are better off when they utilize the information by suppliers, and information usage plays a critical mediating role between information shared and operational performance achieved. Results suggest that the higher the information usage the higher the probability that performance will be significantly better. Among the benefits are reduced costs in supply chain drivers such as inventory, transportation, warehousing, and communication. More studies with different datasets are expected to be conducted to reveal potential relationships at various settings. We suggest our fellow researchers to further utilize additional techniques to confirm such relationships.

This study also provides important hints to practicing supply chain managers. We share with managers the similar warning by Zhou and Benton Jr (2007): while hardware and software are important to information sharing, the essence in making a difference in performance is directly related to how the information is used. Our study helps managers to understand the role of information usage in improving effectiveness and efficiency of an organization. It allows them to focus on whether and how the information available is utilized in developing alternative decisions in their planning and execution. It may also allow them to juxtapose their performance to those of successful companies within an industry. Similar to the Whole Foods Market, a supermarket chain that is considered a sustainable business because of its full

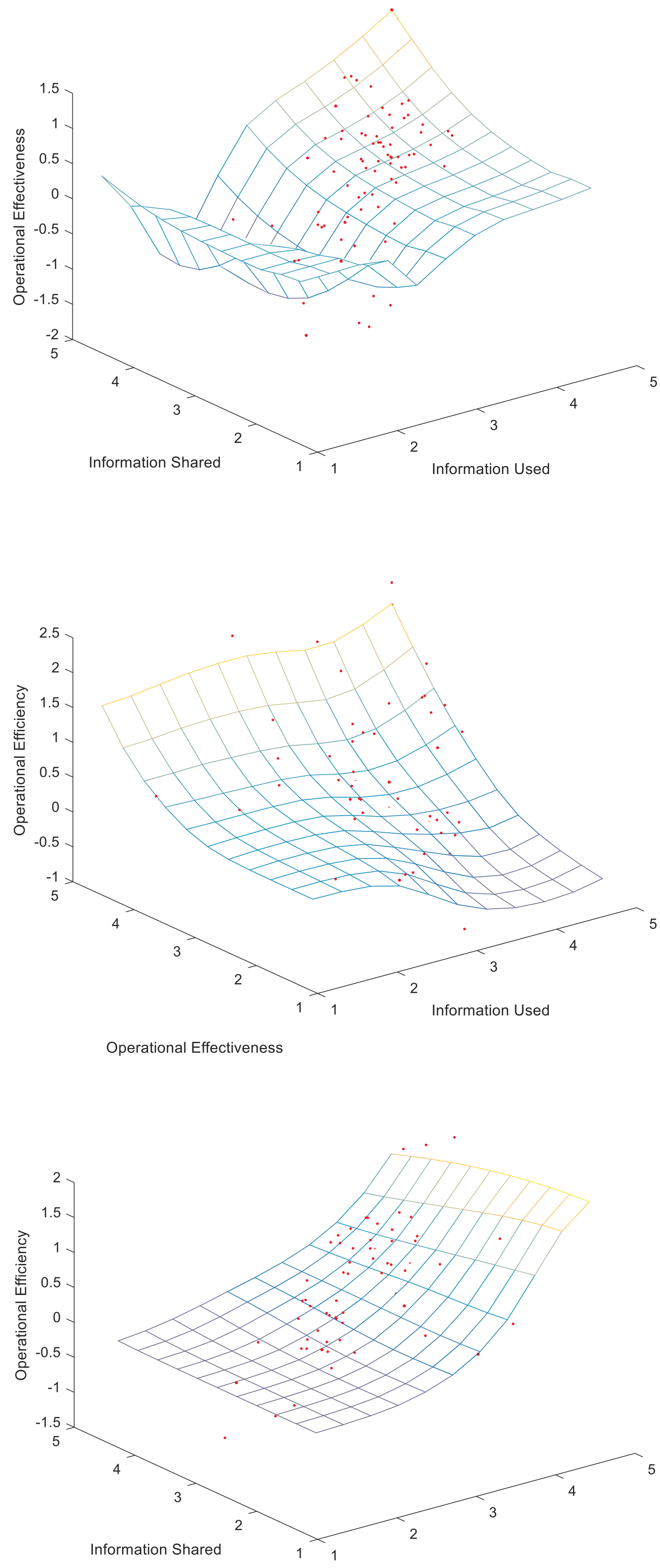


**Fig. 6.** Interaction effect plots captured via USM technique.

information transparency to customers (Busse, Meinlschmidt, & Foerstl, 2017), managers can focus on information usage-related benefits to better serve their customers with sustainable results. From a managerial standpoint, understanding the impact of information usage on operational-level performances offers the motivation to investigate strengths

**Table 14**
Implications of factors on information sharing.

| Factors | Implication/Decision options |
|---|---|
| Initial and operating costs | Managers should be aware of costs involved in sharing, maintaining, and utilizing the information. Effective use of information should be considered to avoid hazardous results. Accurate and timely utilization of information is a must to improve the performance. |
| Supply chain culture | Degree of engagement by supply chain members and communication strategy followed by managers makes a big difference in sharing and utilizing information. Literature show significant willingness to share information under an organizational culture exemplified by fairness, affiliation, innovation, solidarity, mutual interests, and shared goals (Bock, Zmud, Kim, & Lee, 2005). Managers must be sure that efforts to share information are valued and do not clash with organizational culture. |
| Organizational structure | Where an organization positions itself on a continuum of centralization to decentralization structure impacts the type and degree of information sharing. The more the managers formalize coordination among the members of supply chain the more unfriendly environment they create for information sharing. Creating a balanced coordination mechanism is critical to promote information sharing. |
| Commitment/Trust | Supply chain members are usually reluctant to share certain strategic and tactical level information and willing to share operational level information. When it comes to determine decision options for information sharing, supply chain must proactively formulate a strategy incorporating the degree of willingness or commitment to share information. Such willingness determines the confidence and trust among the supply chain members. On the other hands, informal efforts rather than strict contract-based efforts may naturally lead to healthier sustainable confidence and trust in sharing information. Type of commitment seems to have an impact on motivating information sharing. |
| Infrastructure security | Lack of common database or information technologies across the supply chain members contribute to insecurity and thus to lack of willingness to share information. Responsibility to secure safe operation of information sharing is the responsibility of all supply chain members. The role of top managers in a supply chain is critical in creating an effective information security policy. Managers need to create security awareness and training programs and assess security risks related to data privacy and unintended use of information. Outsourcing supply chain information system can be an option, but it requires consideration of technological capabilities of each member. |

and weaknesses of their enabling capabilities. While this study does not provide conceptual insights on motivators for information usage, we advise managers to investigate whether the organizational culture and infrastructure create the motivation to use the information available, and to develop a set of gauges to ensure that the usage of information is in place.

Based on findings and the literature, such as Schoemaker (1993), organizations should have a desire for organizational reconfiguration of their processes to more effectively acquire relevant information and use this information during the decision-making process, considering the different dynamics within the organization. The issue of not having widely accepted drivers in internal, customer, and supplier integration suggests the need to focus on sustainable supply chain management best practices.

We suggest that future researchers consider the moderating impact of motivators between information sharing and usage. In addition, considering the complexity of supply chains, researchers may develop a unified measurement of information sharing and usage, in the hope of obtaining global optimization, and compare that to the use of a selected type of information that may lead to local solutions.

An interesting study could be the investigation of whether inter-coordination efforts across different information types help the sum of local optimums approach to global optimum. This approach allows supply chain members to aim for the same goal congruency with a much lower level of coordination efficiency, thereby suggesting the "organizational model" of Schoemaker (1993). Attention, however, should be given to dysfunctional behavior among members of supply chains towards achieving the shared goal.

An interesting future study could be the investigation of the impact of sources of dysfunctionalities, such as incentive or reward misalignments, resistance to sharing certain types of information, the presence of conflicting objectives, and differing commitment motivations. Also, the issue of monitoring asymmetric access to information or knowledge considering the challenge of preserving competitive identity would definitely add to the literature. In Table 14, we also summarize some factors that may hinder or promote information sharing, along with their managerial implications and options managers may follow. Some of these factors may be considered as antecedents to information sharing, and some may play a moderating impact between information sharing and information usage. Future research would help better understand creating a sustainable structure for information management.

Results from this study have also indicated that larger food retailers benefit more in terms of operational performance than smaller retailers. In fact, food supply chains may possess different structures depending on the size of retailers. For example, the supply chains of smaller retailers may tend to be short and have many small suppliers that provide only the basic commodities. Future research may consider this setting obvious or unique in order to test a general model.

When developing policies about information sharing and usage to improve their operational performance, it is critical for supply chain members to jointly identify the dynamics among themselves and to be involved in the development of reciprocal solutions, which is necessary for knowledge co-creation. The knowledge co-creation process focuses on the dynamic coordination of a micro-level set of implicit expertise of each heterogeneous supply chain member and joint actions taken by supply chain (Prahalad & Ramaswamy, 2004). Thus, to become efficient and compete effectively, supply chains must invest in infrastructure and managerial capabilities centered on co-creation where the direct interaction among members is critical.

The predictive causal analytics capability of USM helped to generalize the hypothesized relationships. While Turkey may represent other emerging markets since it is the seventh largest emerging retail market in Europe (larger than that of Greece, Czech Republic, and Portugal markets combined) and tenth in the world based on a report by the USDA (2015), to justify the generalization of these results and conclude the enhanced results, it may be worth replicating a similar study across different countries or continents that are categorized as emerging markets. We believe that such a study would provide insight to and a benchmark for where companies stand relative to performance or integration. While emergent markets are the best candidates for investigating supply chain dynamics, we agree and understand the fragmentation across markets. As pointed out by Sudhir et al. (2015), differences are very wide and span every metric defined by the United Nation. The metric includes multifaceted measures from education, income, religion, governmental regulations, infrastructure, and logistics as well as needs and solutions, and growth and opportunities in each market. Most of the traceability related analysis focuses on the importance of the information flow aspect of the integration and offers approaches to meet legal requirements in the food supply chain. However, the focal point of our research is to empirically observe the impact of sharing and usage of information on performance, assuming that traceability is an integral part of supply chain management. On the other hand, it is evident that some food corporations in emergent markets can be very co-dependent on market links. While we believe that macro-level measures of efficiency and effectiveness can be labeled by similar antecedents, the micro-level measures of information types shared and used may not be generalized.

Since our study does not deal with measurement development, another research opportunity would be to consider psychometric-based measurements for both information sharing and information usage that are evolving at the exploratory stage.

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