Supply chain learning and firm performance:
A meta-analysis

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Abstract

Purpose: This paper aims to provide a comprehensive understanding of the supply chain learning (SCL)–performance relationship based on the existing empirical evidence.

Design/methodology/approach: We sampled 54 empirical studies on the SCL–performance relationship. We proposed a conceptual research framework and adopted a meta-analytical approach to analyse the SCL–performance relationship.

Findings: The results of the meta-analysis confirm the positive effects of SCL on the performance of both firms and supply chains. In addition, building on the knowledge-based view, we found that learning from customers has a stronger positive effect on performance than does learning from suppliers, while joint learning has a stronger positive effect on performance than does absorptive learning. Business knowledge had a greater effect on performance than did general knowledge, process knowledge or technical knowledge, while explicit knowledge had a stronger effect than tacit knowledge. Moreover, the SCL–performance relationship is moderated by performance measure and industry type but not by regional economic development, highlighting the broad applicability of SCL.

Originality: This study is the first meta-analysis on the SCL–performance relationship. It differentiates between learning from customers and learning from suppliers, examines a more comprehensive list of performance measures and tests five moderators to the main effect, significantly contributing to the SCL literature.

Keywords: Meta-analysis, supply chain learning, firm performance, supply chain performance

Paper type: Literature review/meta-analysis

1. Introduction

Amid increasingly fierce competition, learning capability and knowledge accumulation have become even more important for firm survival (Hult *et al.*, 2003). Scholars have demonstrated that organisational learning is influenced by both learning capacity and supply and demand (Hult *et al.*, 2000). Spekman *et al.* (2002) further propose that learning capacity is a critical factor affecting a firm's supply chain (SC) capabilities and that SCs can be viewed as 'a vehicle for gathering knowledge and learning' (p. 42). As a result, scholars have studied the learning behaviours of organisations at the SC level and proposed the concept of SC learning (SCL), defined as 'multiple supply chain partners engaged in interaction where learning occurs and is focused on supply chain issues and solutions' (Flint *et al.*, 2008, p. 274).

Given that SCL can improve the competitiveness of firms, its effects on organisational performance have been investigated. Some studies have confirmed the benefits of SCL on organisational performance. For instance, Flint *et al.* (2008) found that learning from customers or suppliers can improve a firm's innovation processes, improving its overall performance. In their study on Taiwanese electronics suppliers, Jean *et al.* (2016) found that joint learning with customers led to radical innovations. When firms and customers collaborate and learn from each other, it can lead to groundbreaking concepts and innovative breakthroughs.

In contrast, other studies have found that SCL has a non-significant effect on firm performance. For example, Nguyen and Harrison (2019) found that the effect of customer knowledge on the financial performance of manufacturers in 10 countries (both developed and developing) was unclear, reasoning that companies in mature markets tend to focus on improving their existing processes rather than their financial growth or market share. Moreover, Suh *et al.* (2019) proposed that the transfer of institutionalised knowledge can cause conflicts among SC partners, in turn damaging relationships and firm performance. Meanwhile, scholars have found that the effects of SCL may vary because of differences in performance measures. For instance, Sáenz *et al.* (2018) found that learning from suppliers has a more significant effect on manufacturing flexibility than on customer satisfaction. Meanwhile, there is a lack of evidence for the effect of SCL on SC-level performance. Given that SCL implies learning behaviours that transcend organisational boundaries, this may affect performance not only at the firm level but also at the SC level.

After conducting a systematic literature review, we found no existing review on the effects of SCL on firm performance, adding to the lack of clarity in the SCL–performance relationship debate. Moreover, the effects of potential moderators (such as regional economic development and industry) on the SCL–performance relationship remain unclear. These mixed findings motivated us to explore the SCL–performance relationship. We posed the following two research questions:

RQ1. *What is the relationship between SCL and performance in firms and supply chains?*

RQ2. *What factors affect the SCL–performance relationship?*

To answer the proposed research questions, we adopted a meta-analytical approach (Hunter and Schmidt, 2004) to aggregate all relevant empirical studies. A meta-analysis is an objective, quantitative and systematic means of collating all previous studies on a specific topic, conducted in different regions, at different times and using different data and analytical methods, and statistically analysing the relationships between the independent and dependent variables (Hunter and Schmidt, 2004). In our case, a meta-analysis was conducted to identify how SCL affects performance and the factors affecting this relationship. By conducting a meta-analysis, we were able to resolve previous discordance. Our results are valuable because they can assist future SCL researchers to evaluate effect size and explore the potential factors affecting the SCL–performance relationship.

The remainder of the paper is arranged as follows. Section 2 presents the literature review. Section 3 discusses the research framework and develops the hypotheses. Section 4 presents the methodology. Section 5 presents the results of the meta-analysis. Section 6 discusses the contributions, implications and limitations of the study as well as future research directions.

2. Literature review and sampling

2.1. Conceptual development of SCL

The concept of SCL originated from interorganisational learning, which relates to how different organisations cooperate to develop collective knowledge (Mariotti, 2012). Interorganisational learning has been studied at various sublevels, such as alliance learning or mutual learning (Jia and Lamming, 2013). These learning concepts emphasize the interactions between two organisations, thus may be termed 'dyadic learning' (Jia and Lamming, 2013). The concept of SCL arose when scholars extended dyadic learning to the SC network level. The literature provides a range of definitions, characteristics and practical applications of SCL. Y. Yang *et al.* (2019) reviewed 123 journal articles on SCL antecedents, consequences and barriers and developed an organisation-level conceptual framework to guide future research. Gosling *et al.* (2016) undertook a content-based literature review to explore how key firms can assume a leadership role and use SCL to spread sustainable philosophies and practices throughout SC networks. Further, Gong *et al.* (2018) argue that SCL is an antecedent to a firm's resource orchestration and leads to a shift in the SC relationship. Silvestre *et al.* (2020) developed a theoretical framework demonstrating that SCL is an essential procedure for developing, adapting and enhancing SC competencies, further promoting SC sustainability. The definitions of SCL in the literature have emerged from multiple perspectives (see Table I).

[Insert Table I about here]

As shown in Table I, some scholars (e.g. Bessant *et al.*, 2003) define SCL as a type of dyadic learning behaviour between buyers and suppliers, while others (e.g. Flint *et al.*, 2008) focus on SC partners to solve SC problems, which goes beyond the traditional dyadic relationship. In addition, scholars have defined SCL from different perspectives. For example, some (e.g. Gosling *et al.*, 2016) focus on the process of learning or the creation of fresh knowledge that could alter how businesses behave (Huber, 1991), while others adopt a structural view, defining SCL according to its components and how it takes place. For example, Theodorakopoulos *et* *al.* (2005) describe SCL as an interorganisational learning process that occurs between suppliers and customers. The final perspective focuses on outcomes, which is the ultimate goal of learning, such as boosting competitiveness and overall performance (e.g., Zhang, H.-Y. and Lv, 2015). While the dimensions of SCL definitions differ, they all reflect the interactions between two or more organisations in the SC network through learning.

2.2. Antecedents of SCL

As a type of organisational learning, SCL is critical to an organisation's ability to adjustment and innovation (Flores *et al.*, 2012). Flores *et al.* (2012) quantify the influence of four cultural antecedents—participative decision-making, openness, learning orientation and transformational leadership—on the acquisition of information in the learning process. Scholten *et al.* (2019) find different antecedents for different types of learning; for example, SC disruption is an antecedent of situational learning, while the reflection of existing knowledge is an antecedent of experiential learning. Given that most scholars regard learning as a risk management strategy (Braunscheidel and Suresh, 2009; Jia and Lamming, 2013; Graham, 2018; Scholten *et al.*, 2014, 2019), antecedents involving risk management elements cannot be ignored. Similar to Flores *et al.* (2012), Braunscheidel and Suresh (2009) state that the antecedents of learning should be discussed from a cultural perspective.

2.3. Outcomes of SCL

Scholars have proposed that learning at the SC level can produce positive outcomes at both the organisational and SC levels. For example, Hult *et al.* (2003) argue that SCL is crucial to improve SC performance, with 10 possible positive outcomes, including improved SC efficiency and overall organisational performance. Lambrechts *et al.* (2012) propose five possible consequences of SCL: improved product quality, improved ability of the SC to adapt to complexity, the creation of unique knowledge, mutual understanding among SC members and the emergence of new business models. Finally, Yang *et al.* (2019) divide SCL outcomes into two categories: SC capabilities (i.e. innovation, relationship and collaboration, integration, agility and process improvement capabilities) (Flint *et al.*, 2008; Jean and Sinkovics, 2010; Ojha *et al.*, 2016) and sustainable SC performance, (i.e. economic, environmental and social performance) (Hernández-Espallardo *et al.*, 2010; Leal-Millán *et al.*, 2016; Silvestre *et al.*, 2020; Spekman *et al.*, 2002). Therefore, the existing literature indicates that SCL can promote interactions among members of SC networks, enhance innovation capabilities and improve the overall performance of organisations and SCs.

However, despite the scholarly confidence that SCL can improve organisational and SC performance, empirical studies have yielded mixed results. For instance, based on the findings of a questionnaire survey, Suh *et al.* (2019) revealed the positive effect of supplier knowledge sharing on overall organisational performance. However, they also found that the transfer of institutionalised knowledge can lead to conflicts among SC partners, in turn damaging relationships. Dobrzykowski *et al.* (2015) surveyed 711 manufacturers and found that while absorbing knowledge from SC partners can improve an organisation's financial performance, this relationship was relatively weak. Nguyen and Harrison (2019) obtained similar results, with SCL having a limited effect on financial performance. They rationalise that firms in mature markets tend to seek to improve existing processes rather than focusing on financial growth and market share. Emden *et al.* (2005) investigated a sample of mixed industries and found that the positive effect of SCL on SC performance was significantly greater than that on financial performance. In addition, although scholars generally believe that SCL can improve relationships, a supplier's over-reliance on one or more customers means could compromise their innovation capacity, endangering their overall success in the long term (Yli-Renko *et al.*, 2001).

Finally, different forms of learning and knowledge affect organisational and SC performance differently. For example, Nagati and Rebolledo (2013) found that tacit knowledge learned from customers has a more significant effect on organisational performance than does explicit knowledge; they further explained that it is challenging to replicate and convey tacit knowledge, increasing its inherent value. However, other scholars believe that the acquisition of tacit knowledge depends on informal learning behaviours and direct contact at the individual level; thus, it is more difficult for firms to benefit from tacit knowledge than from explicit knowledge (Yang, Y. *et al.*, 2019). In summary, the way in which SCL can improve firm-level and SC-level performance remains unclear.

2.4. Sampling

To determine the normalised correlations between constructs, we used the generic meta-analysis methodology and techniques suggested by Hunter and Schmidt (2004). First, we undertook a systematic review of research published in peer-reviewed journals in English up to December 2021 to locate empirical studies on the SCL–performance relationship. To obtain the largest number of studies possible, we used a broad range of search terms in three well-known databases: the ABI/INFORM Collection, Scopus and Web of Science. We derived search terms from SCL-related reviews (Gosling *et al.*, 2016; Yang, Y. *et al.*, 2019) (see Table II). The asterisk symbol (*) was added to select terms to increase the number of potential studies found (Gimenez and Tachizawa, 2012). The entire selection process, including the search strategy, is shown in Figure 1.

[Insert Table II about here]

[Insert Figure 1 about here]

After undertaking the keyword search and extracting articles, we manually excluded any duplicate articles, resulting in 697 papers from an initial 1,269 papers. Next, we carefully read the abstracts (or the full text if we were uncertain) of the 697 papers to screen for relevance. After excluding studies that did not focus on the effects of SCL on the organisation, 168 papers remained for the following round of selection. We then scrutinised the papers to identify valid samples according to three selection criteria based on expert discussion: (i) quantitative analysis of the effect of SCL on one or more performance dimensions; (ii) reported effect size of the relationship between the independent (SCL) and dependent variables (performance); and (iii) the use of a unique dataset. If multiple studies used the same dataset, only one was included in the meta-analysis. Following these criteria, each researcher individually conducted content analysis and evaluation. After applying the three selection criteria, we ultimately identified 54 papers. The 54 empirical articles are summarised in Table III.

[Insert Table III about here]

2.5. Descriptive analysis

As shown in Figure 2, the time frame of the sampled articles was 2001 to 2020. We did not limit studies to a particular period. Prior to 2009, there were relatively few studies in this field. No more than one paper was published annually between 2001 and 2008. In 2018, the number of published papers reached a peak. Although the volume of published articles on SCL is not significantly greater than other prominent study topics, empirical studies on the SCL–performance relationship is a growing trend.

[Insert Figure 2 about here]

Table IV summarises the theoretical lenses adopted in the sampled articles. Various theories were employed, with the most common being the knowledge-based view (KBV) (24%) and the resource-based view (RBV) (22%). Because articles used more than one theory, the total percentage exceeds 100% in Table IV.

[Insert Table IV about here]

Table V summarises the analytical methods used in the selected studies. Most (57%) adopted covariance-based structural equation modelling as their primary data analysis technique, followed by partial least squares structural equation modelling (19%).

[Insert Table V about here]

2.6. Data coding and measurements

We followed a standard meta-analytical procedure to conduct coding (Chen, Moretto, *et al.*, 2021; Zheng *et al.*, 2021). Coding was undertaking by two co-authors with academic backgrounds in SC management research and meta-analysis. Initially, the two researchers worked individually, then compared their coding outcomes. Any discrepancies in coding outcomes were addressed by reviewing and recoding articles until consensus was reached (Bullock and Svyantek, 1985). If the two researchers could not reach an agreement on coding, a third researcher was included. In this way, the research team achieved consensus on all coding results.

Specifically, each study was coded based on learning source, learning type, knowledge type, learning content, performance type, industry and region. SCL was categorised into learning from customers and learning from suppliers (Zhang, H.-Y. and Lv, 2015). Learning type was categorised into absorptive learning and joint learning (Choi *et al.*, 2019). Performance was categorised into firm performance (i.e. financial and innovation performance) and SC performance (Geng *et al.*, 2017; Jean *et al.*, 2016; Ryoo and Kim, 2015). Knowledge type was divided into explicit and tacit knowledge (Lei *et al.*, 2019). Learning content was divided into business, process and technical knowledge (Ryoo and Kim, 2015). Finally, industry comprised manufacturing, mixed and other industries (Wang, W. *et al.*, 2018), while region comprised developed and less-developed regions (United Nations, 2022). The following sections present the measures used for each subgroup in the meta-analysis.

2.6.1. Independent variable: SCL source

After reviewing the sample articles, we found that the independent variables were mostly based on learning activities across the SC. Most sampled articles specified the source of learning—either suppliers or customers. Therefore, we adopted the method proposed by H.-Y. Zhang and Lv (2015) and divided SCL into two groups based on learning source: suppliers or customers. Combining this classification with definitions of SCL, we revised the definition of SCL to firms creating and using new collective knowledge and improving their interorganisational learning capability to jointly obtain a competitive advantage with their customers or suppliers. Thus, we divided learning source into (i) customers, (ii) suppliers and (iii) not specified.

2.6.2. Dependent variable: performance

Given that performance is a multidimensional construct, we reviewed our sample studies to identify a range of performance dimensions as dependent variables for comparing the specific effects of SCL on performance. After several rounds of discussion within the research team and with external experts, we coded performance according to three dimensions: financial performance, innovation performance and SC performance.

Financial performance refers to a firm's overall profitability (Dobrzykowski *et al.*, 2015; Geng *et al.*, 2017; Shang, 2009). Specifically, we considered a growth in sales, profits or return on investments the main measures of financial performance in our sample articles (Geng *et al.*, 2017; Shang, 2009; Wang, W. *et al.*, 2018).

Innovation performance refers to the use of creativity to improve products, renew product development processes and develop new products with better performance through innovation (Jean *et al.*, 2016; Jean and Sinkovics, 2010; Liao and Barnes, 2015). Measures of innovation performance included technological competitiveness, new product development cycle time, the novelty of proposed products and capacity utilisation (Jean *et al.*, 2016; Liao and Barnes, 2015; Prajogo and Sohal, 2003).

SC performance refers to the benefits derived from SC cooperation (Ryoo and Kim, 2015). In our meta-analysis, we used various indicators related to SC operations efficiency (i.e. supply chain cycle time, the adaptability of services to satisfy consumer demands, total inventory costs and frequency of delivery) and SC partner relationships (i.e. partnerships with suppliers or customers, customer satisfaction and investment of resources into relationships) as measures of SC performance (Cai *et al.*, 2013; Chen, Li, *et al.*, 2022; Li, 2006; Zhao and Wang, 2011).

For articles that did not clearly indicate the type of performance or focused on more than one of the above types of performance, we considered overall firm performance.

2.6.3. Moderators

Apart from the independent and dependent variables, we also explored the role of moderators in the SCL–performance relationship. Implementing SCL under different conditions may give rise to different performance effects. In meta-analyses, control variables from previous empirical studies frequently serve as possible moderating variables (Wang, W. *et al.*, 2018). Therefore, common control variables from previous studies, including industry and economic region, were selected as potential moderators. In addition, the use of different dimensions of the same concept or structure may limit the universality and comparability of research conclusions. Therefore, operationalisation of the constructs was taken as another set of regulators, as suggested in previous meta-analyses (Delbufalo, 2012; Golicic and Smith, 2013). Knowledge type and SCL content were typically used as moderators in existing SCL studies. In this study, we considered learning type, knowledge type, learning content, operationalisation of performance, industry and region as potential moderators. To examine moderation effects, a subgroup analysis was applied to each moderation group.

2.6.3.1. Learning type

Scholars have discovered different dimensions to learning behaviours. Based on previous studies, Huo *et al.* (2020) summarise the different dimensions of SCL as relationship learning, joint learning, mutual learning and alliance learning. Gosling *et al.* (2016) suggest three forms of SCL: single-loop learning, single-loop learning plus and double-loop learning. To avoid an overlap of learning types, we followed Choi *et al.* (2019) to classify SCL into two groups: absorptive learning and joint learning. Absorptive learning is defined as a firm utilising the expertise and capabilities of a partner company (Lane and Lubatkin, 1998). Choi *et al.* (2019) argue that absorptive learning tends to be a unidirectional and single-loop type of learning between organisations. By acquiring knowledge from partners, absorptive learning can help firms broaden their knowledge base. In contrast, joint learning has been defined as multiple firms collaborating and using resources and information from partners with similar expertise to jointly create new knowledge (Fang and Zou, 2010). For papers that did not specify the exact learning type, we defined learning as general.

2.6.3.2. Knowledge type

We divided the knowledge type involved in SCL into explicit and tacit knowledge (Lei *et al.*, 2019). Explicit knowledge is formal and structured and easier to identify, store and retrieve. In contrast, tacit knowledge is intuitive, poorly defined and largely derived from experience (Kogut and Zander, 1992). Therefore, tacit knowledge is mostly anchored in action, commitment and engagement and is difficult to clearly convey (Polanyi, 1962). For papers that did not specify the exact knowledge type, we defined knowledge type as general.

2.6.3.3. SCL content

In their case study, Gong *et al.* (2018) used learning content complexity as a research construct. Ryoo and Kim (2015) divided the knowledge exchanged with SC partners into knowledge about sales and marketing, knowledge about technology and knowledge about strategy. Inspired by this classification method, we divided the knowledge involved in SCL into business knowledge, process knowledge and technical knowledge. For papers that did not specify the exact content of the SCL, we defined knowledge content as general. Business knowledge refers to a firm's broad understanding of customer needs and preferences, the business environment, employee development and the future direction of business strategies (e.g. Xu *et al.*, 2018; Zhang, M. *et al.*, 2018). Process knowledge mainly focuses on improving operational efficiency. This was extracted from articles that defined SCL content as experience that can be applied to improve management efficiency, specific knowledge to improve manufacturing efficiency and market information to improve firms' ability to adapt to market changes (e.g. Jean *et al.*, 2016; Nagati and Rebolledo, 2013; Yang, J. *et al.*, 2009). Technical knowledge was defined as the knowledge comprising technology and methods for improving product performance in SCs (e.g. Cousins *et al.*, 2011; Nguyen and Harrison, 2019; Shang, 2009).

2.6.3.4. Economic region and industry type

We identified other moderators from previous meta-analyses on the topic of operations management (Geng *et al.*, 2017; Wang, W. *et al.*, 2018), which indicated that economic region and industry type may affect the SCL–performance relationship. After reviewing the sample articles, we classified industry type into manufacturing, mixed and other industries. 'Other' industries mainly comprised third-party logistics companies, retailers and service companies (e.g. Cai *et al.*, 2013; Flint *et al.*, 2008; Shang, 2009). In addition, in line with the United Nations (2022) classification of development in *World Population Prospects 2022*, economic region was divided into developed and less-developed regions.

3. Research framework and hypotheses

The RBV suggests that a firm's capabilities form the foundation of its future development and can strengthen its competencies through continuous and collaborative learning (Powell *et al.*, 1996). Extending from the RBV, the KBV suggests that knowledge is a firm's most important resource to achieve innovative results (Grant, 1996; Kogut and Zander, 1992; Roy and Sivakumar, 2010). Rather than being limited to organisational borders, knowledge may arise from connections between businesses in the SC (Bessant *et al.*, 2003; Capó-Vicedo *et al.*, 2011; Håkansson *et al.*, 1999; He *et al.*, 2011). According to Grant (1996, p. 120), the KBV centres on 'the task of production through the transformation of inputs into outputs where the issues of creating, acquiring, storing and deploying knowledge are the fundamental organizational activities'. Regarding SCL, knowledge is transferred between SC partners through learning behaviours. Firms obtain knowledge by learning from the experiences of other organisations as well as from customers, suppliers and other stakeholders. Therefore, the KBV has been widely adopted in the SC management literature on the relationships between knowledge, learning behaviours and business outcomes (e.g. Choi *et al.*, 2019; Haq, 2020; Nguyen and Harrison, 2019; Yang, J. *et al.*, 2009). Therefore, we adopted KBV as our main theoretical lens through which to develop our research hypotheses.

3.1. The SCL–performance relationship

With the advancement of knowledge and awareness of its potential benefits at the organisational level along the SC, SCL is considered a vital research stream of organisational learning (Mohr and Sengupta, 2002; Nonaka, 1994; Spekman *et al.*, 2002). Learning from SC partners may facilitate the transfer of knowledge among organisations to help address SC issues or improve existing processes. According to the KBV, knowledge can help firms gain sustainable advantages over their competitors (Kogut and Zander, 1992). For example, through learning, a firm can develop its own learning resources to understand newly discovered industry trends and gain tactical insights (Mohr and Sengupta, 2002). Although interorganisational learning may lead to unintended and undesirable knowledge transfer and enhance frictions between businesses (Fang and Zou, 2010; Van Wijk *et al.*, 2008), prior research has highlighted the positive effect of interorganisational learning for firms to create advanced products and share their expertise, thereby maintaining a competitive advantage (e.g. Holmqvist, 2003; Luo and Tung, 2007).

Moreover, learning from SC partners may contribute to process optimisation and market responses, as seen in empirical tests (Ghobakhloo and Hong, 2015; Nagati and Rebolledo, 2013). According to Haq (2020), learning from suppliers can reduce the cost of operations and boost production volume and efficiency, while learning from customers can help firms understand customer expectations to improve their production and marketing strategies. These competitive advantages are inseparable from a firm's overall performance. Therefore, performance consequences can be considered a vital outcome of SCL. By applying KBV as a theoretical lens, we propose the following hypothesis:

H1: SCL has an overall positive effect on firm performance.

In this meta-analysis, SCL was categorised into two groups based on learning source: learning from suppliers and learning from customers. Given that the knowledge of suppliers and customers differs, the effect on the firm may also differ. Suppliers are an important source of knowledge because they have in-depth information about components and materials, which is crucial for purchasers to design new commodities (Revilla and Villena, 2012). Thomas (2013) supports this view, stating that suppliers can serve as a source of fresh insight for product design and cost management. Therefore, learning from suppliers is important for a company to reduce their research and development cycles, create quality products and further improve their innovation performance (Robertson, 1992; Sukoco *et al.*, 2018). In contrast, knowledge gained from customers can provide companies with innovative ideas to improve their competitive advantage, help them meet customer demands, discover new opportunities, open new markets, reduce potential risks and avoid developing products that do not meet customer needs (García-Murillo and Annabi, 2002). In particular, previous studies have shown that compared with learning from suppliers, learning from customers has a stronger effect on firms' innovation performance (Zhang, H.-Y. and Lv, 2015). Therefore, we propose the following hypotheses:

H2a: Learning from suppliers is positively associated with firm performance.

H2b: Learning from customers is positively associated with firm performance.

H2c: The performance effect of learning from customers is stronger than that of learning from suppliers.

3.2. Moderation effects

The first moderator in this study is learning type. We divided SCL into absorptive and joint learning to explore how different types of SCL affect firm and SC performance. Indeed, the literature pays much more attention to absorptive learning than to joint learning (Choi *et al.*, 2019). As a new global SC network phenomenon, joint learning has received limited research attention (Fang and Zou, 2010). Absorptive learning is unilateral and unbalanced and refers to the absorption of knowledge and information by a firm from a partner company. In contrast, joint learning may be accomplished by enhancing each partner's unique knowledge base in a bidirectional and interactive manner. According to Choi *et al.* (2019), joint learning can encourage partners to work collaboratively. A cooperative enterprise may view the relationship as an appropriate partnership and exchange.

On the contrary, absorptive learning, being unilateral, helps firms enhance their own capabilities, leading to asymmetric knowledge exchange and rendering partners hesitant to work more actively in their relationships (Fang and Zou, 2010). Therefore, in the SC network, compared with absorptive learning, joint learning may create better relationships between partners, thereby enhancing SC performance. Thus, we propose the following hypothesis:

> **H3**: The effect of joint learning on firm performance is stronger than that of absorptive learning.

The knowledge gained from SCL is considered a resource that can help firms gain a competitive advantage through SC capabilities (Craighead *et al.*, 2009). Knowledge enables the SC to respond more effectively to dynamic business environments. While the existing literature highlights the benefits of knowledge for firm performance, it does not differentiate between different types of knowledge in SCL (Wowak *et al.*, 2013). We classify knowledge into explicit and tacit knowledge (Lei *et al.*, 2019; Polanyi, 1962). In SCL, to strengthen profitability and the ability to deal with risks, firms tend to integrate explicit and tacit knowledge (Jap, 2013; Yang, Y. *et al.*, 2019), which have different effects on their SCL capabilities because tacit knowledge is more difficult to disseminate. Tacit knowledge requires informal learning behaviours and exchanges at the individual level (Yang, Y. *et al.*, 2019). Therefore, we believe that the effect of tacit knowledge in SCL on performance will be weaker than that of explicit or general knowledge. Therefore, based on the above discussion, we pose the following hypothesis:

> **H4**: The effect of explicit knowledge derived from SCL on firm performance is stronger than that of tacit knowledge.

With respect to learning content, inspired by Gong *et al.* (2018) and Ryoo and Kim (2015), we categorised SCL content into business, process and technical knowledge. In the sample articles, technical knowledge includes innovative ideas, engineering information and knowledge of product development (Cousins *et al.*, 2011; Nguyen and Harrison, 2019; Shang, 2009). Because technical knowledge focuses more on product development, while other types of knowledge focus more on organisational structure, process optimisation and market strategy, we believe that it is less likely to be disseminated; that is, firms will be less willing to share their core technical knowledge. Technical knowledge is key to maintaining firm competitiveness; thus, enterprises will be more cautious about revealing it when engaging in SCL. This barrier mainly arises from a distrust of one's partners (Lindsey, 2008; Riege, 2005). In contrast, business knowledge helps companies understand customer needs and preferences as well as market information (Zhang, M. *et al.*, 2018). Firms have a greater chance of gaining a competitive advantage by learning business knowledge. Hence, we propose the following hypotheses:

> **H5a**: The effect of SCL on firm performance is weaker when SCL comprises technical knowledge.

> **H5b.** The effect of SCL on firm performance is stronger when SCL comprises business knowledge.

In this meta-analysis, we divided firm performance into financial, innovation, SC and general performance. Considering that different performance measures focus on different aspects of firm performance, the effect of SCL may differ for each performance measure. For instance, Tseng (2014) showed that SCL has a greater impact on a firm's SC performance than on its financial outcomes, while Nguyen and Harrison (2019) and Dobrzykowski *et al.* (2015) found a relatively weak effect of SCL on financial performance. Therefore, we propose the following hypothesis:

> **H6**: The effect of SCL on firm performance varies according to the performance measure used.

Most of the studies in our sample were based on data collected from manufacturing industries, while the remaining few focused on mixed or other industries, such as third-party logistics companies. There were major variations across industries, including their structure, the goods and services provided, their capabilities and functions and consumer demands (Wang, W. *et al.*, 2018). Therefore, firms in different industries can perform differently with the same degree of learning behaviour. Hence, we propose the following:

H7: The SCL–performance relationship varies according to industry type.

Finally, regarding economic region, developed and less-developed regions may differ in terms of culture, education, strategic priorities, social and economic environments, and laws and regulations (Wang, W. *et al.*, 2018). Therefore, given the significant differences in the business environments of different regions, we propose the following:

H8: The SCL–performance relationship varies according to economic region.

4. Methodology

4.1. Meta-analytical approach

According to Hunter and Schmidt (2004), a meta-analysis is a means of statistically summarising the effect size between variables found in prior research. The overall population effect size, which may vary from the effect size found in each study, relates to how the independent variable affects the dependent variable (Damanpour, 1991). As mentioned above, we extracted the reported correlations from the sample articles. For articles that used other forms of coefficients such as Student's *t*, Cohen's *d*, F-statistics or β coefficients, we used the formulae shown in Table VI to convert them to the corrected correlations (Geng *et al.*, 2017; Peterson and Brown, 2005; Wang, W. *et al.*, 2018). Next, the Fisher z-transformation, which has the advantage of optimal weighting (Geyskens *et al.*, 2009), was applied to generate the effect size.

[Insert Table VI about here]

If a study reported multiple correlations in one measure, we averaged and combined them into one correlation (Geng *et al.*, 2017; Hunter and Schmidt, 2004). For example, there were several correlations for some SC performance measures, such as delivery cycle performance and manufacturing flexibility performance. In this case, both delivery cycle performance and manufacturing flexibility performance met the coding criteria for SC performance; thus, we combined the two effect sizes (SCL–delivery cycle performance and SCL–manufacturing flexibility performance) into one effect size (SCL–SC performance). Subsequently, as a standard practice in the meta-analysis, we used a single estimate derived from the averaged correlations (Hunter and Schmidt, 2004).

Various meta-analysis software is available, including Comprehensive Meta-Analysis, Stata, Python and R (Geng *et al.*, 2017). We adopted R to transform effect size and conduct the sample tests for publication bias and heterogeneity because all researchers had prior experience with it.

4.2. Publication bias

Publication bias is a type of bias that can occur in meta-analyses because it is difficult for researchers to locate all the relevant literature related to a topic (Rosenthal, 1979), and articles that confirm research hypotheses are published more readily than those that disconfirm research hypotheses (Rosenthal and DiMatteo, 2001). Given that it may affect the validity of results, publication bias was tested using a funnel plot and a fail-safe *N* (Rothstein *et al.*, 2005).

The funnel plot shown in Figure 3 was nearly symmetrical, quantitatively indicating that the publication bias of the sample was within an acceptable range. Fail-safe *N* was also employed to identify publication bias. According to Orwin (1983) and Rosenthal (1991), fail-safe *N* can be used to determine the required number of studies with zero effect size to yield a non-significant p-value. Using Orwin's (1983) approach, fail-safe *N* was 417 ($p < 0.0001$). Using Rosenthal's (1991) approach, fail-safe *N* was 30,766 ($p < 0.0001$). Therefore, the results of both the funnel plot and fail-safe *N* suggest that there was no significant publication bias in the sample articles.

[Insert Figure 3 about here]

The radial plot shown in Figure 4 compares the inverse of the standard errors on the horizontal axis to the observed effect sizes, which were then normalised by the relevant standard errors on the vertical axis (Galbraith, 1994).

[Insert Figure 4 about here]

Figure 5 shows the forest plot, which presents effect sizes with appropriate confidence intervals.

[Insert Figure 5 about here]

Figure 6 presents the outlier influence diagnostics using multiple indicators to show independent research that may have more impact.

[Insert Figure 6 about here]

5. Results

In this meta-analysis, assuming exchangeability of the sample data (Schwarzer *et al.*, 2015), we applied a random effects model to analyse the main effects. To conduct the subgroup analyses, we applied a mixed effects model under the assumption of homoscedasticity (Schwarzer *et al.*, 2015).

Table VII shows the meta-analysis results for the main effects of SCL on performance and the differential effects of learning source. Following the meta-analysis of Geng *et al.* (2017) and the guidelines of Chen, Jia, *et al.* (2021) and Cohen *et al.* (2003), we categorised our correlations, or the strength of our estimated effect sizes, into weak (0.10–0.30), moderate (0.30–0.50) and strong (> 0.50).

As shown in Table VII, the overall effect of SCL on performance was positive and significant (ES = 0.424, $p = 0.000$, 95% CI [0.360, 0.499]). The confidence interval excluded zero, confirming the positive SCL–performance relationship. Hence, H1 was supported.

In terms of learning source, SCL from customers (ES = 0.478, p = 0.000), suppliers (ES = 0.370, p = 0.001) and unspecified SC participants (ES = 0.443, p = 0.000) had positive effects on performance. The 95% confidence intervals of all three relationships excluded zero, confirming the significant positive relationship between learning from different sources and firm performance. Further, the effect size from learning from customers was stronger than that of learning from suppliers; therefore, H2a, H2b and H2c were supported.

[Insert Table VII about here]

We considered three subgroups of learning type: absorptive learning, joint learning and general learning. As shown in Table VIII, the effect size of absorptive learning was 0.372 (p = 0.000, 95% CI [0.292, 0.452]). The effect size for joint learning was higher than that for absorptive learning (ES = 0.491, p = 0.000). Thus, H3 was supported. General learning had the highest effect size (ES = 0.561, p = 0.000).

Further, SCL was divided into three subgroups according to the nature of the knowledge—general, explicit or tacit knowledge. As shown in Table VIII, all were positively related to performance, but they varied according to the type of knowledge. As we hypothesised, explicit knowledge (ES = 0.501, p = 0.000) had a stronger effect than did tacit knowledge (ES = 0.372, p = 0.000). Thus, H4 was supported.

Table VIII shows the subgroup analysis results for SCL content. All types of SCL content had significantly positive effects on performance. In particular, business knowledge showed a strong positive effect (ES = 0.686, p = 0.000), while general knowledge (ES = 0.461, p = 0.000) and process knowledge (ES = 0.467, p = 0.000) showed moderate positive effects. As we predicted, compared with other types of knowledge, technical knowledge showed the weakest positive effect (ES = 0.344, p = 0.000). Thus, H5a and H5b were supported.

With regard to the moderators, SCL was positively associated with all types of performance: financial performance (ES = 0.388, p = 0.000), general performance (ES = 0.525, p = 0.000), innovation performance (ES = 0.377, p = 0.000) and SC performance (ES = 0.521, p = 0.000).

Therefore, the SCL–performance relationship varied depending on the performance measure, supporting H6.

In terms of industry type, manufacturing industries (ES = 0.451, p = 0.000), mixed industries (ES = 0.451, p = 0.000) and other industries (ES = 0.569, p = 0.000) were all significantly positive. The effect size for the manufacturing industry was lower than that of other industries, supporting H7.

In terms of economic region, the subsample results indicate that both developed (ES = 0.463, p = 0.000) and less-developed (ES = 0.463, p = 0.000) regions were positively and moderately associated with the SCL–performance relationship. Therefore, H8 was not supported.

6. Discussion

6.1. Theoretical contributions

The conclusions of previous research on the role of SCL in company performance are inconsistent. In this meta-analysis, we systematically summarised the extant empirical findings on the SCL–performance relationship to provide a comprehensive conclusion and explored the effects of potential moderating factors on the SCL–performance relationship.

First, our results revealed a significant and positive correlation between SCL and performance, supporting the conclusions of some previous empirical studies (e.g. Ghobakhloo and Hong, 2015; Nagati and Rebolledo, 2013; Shang, 2009) and disconfirming others (e.g., Nguyen and Harrison, 2019). Learning from both suppliers and customers had a significantly positive effect on performance. In addition, our results support those of H.-Y. Zhang and Lv (2015) that learning from customers has a stronger effect on performance than does learning from suppliers. However, we expanded the performance measures of H.-Y. Zhang and Lv (2015) from innovation performance only to various aspects of firm performance. Customers can provide rich and important market knowledge for new product development to firms, directly improving product development and benefiting firm performance (Lemon *et al.*, 2002; Zhang, H.-Y. and

Lv, 2015). Meanwhile, knowledge provided by suppliers can help with new product development and enhance end products and manufacturing processes, thereby helping firms improve their product development capabilities and performance (Cousins *et al.*, 2011).

Second, this analysis revealed the differentiated effects of various knowledge categories of SCL on performance. We found that all three types of knowledge in SCL are positively associated with performance. Specifically, we found that explicit knowledge has a stronger effect than does tacit knowledge, which was expected given that tacit knowledge is more difficult to convey and assimilate, thus may be an obstacle to SCL for firms (Yang, Y. *et al.*, 2019). By quantitatively analysing the impact of different types of knowledge in SCL, we filled the gap in this research (Wowak *et al.*, 2013).

Third, this study revealed the differentiated effects of learning type on the SCL–performance relationship. Specifically, the results indicate that both absorptive learning and joint learning positively affect a firm's performance. Moreover, our results supported those of Choi *et al.* (2019) that joint learning has a stronger effect on performance than does learning from suppliers. However, we expanded the performance measures of Choi *et al.* (2019) from innovation performance only to include financial and SC performance. While both absorptive and joint learning can bring knowledge and information to a firm to improve its performance, joint learning may benefit not only the focal company but also its partners in the SC. In contrast, in absorptive learning, the focal company unilaterally absorbs the knowledge, information and capabilities of its partners, which may lead to unequal information exchange in the partnership. In other words, the partner company may view the focal company as exploitative and be reluctant to share its knowledge. Our study highlighted the significance of joint learning in SCL.

Fourth, we analysed the effects of four types of knowledge content in SCL on performance: general knowledge, business knowledge, process knowledge and technical knowledge. Among these, business-related knowledge had the strongest effect on performance. General and process knowledge had similar performance effects. While technical knowledge also had a positive effect on performance, its effect was weaker than that of other types of knowledge. Our regression indicates that companies are more willing to share non-technical knowledge in SCL. This finding is consistent with the existing literature that companies choose to maintain the competitiveness associated with their own technology (Lindsey, 2008). Non-technical knowledge involves a wider scope, including market information and process optimisation, which has a significant effect on overall performance. Possible explanations for this finding include the challenges with communicability and the narrow scope of technical knowledge; thus, there are fewer integration issues (Cai *et al.*, 2013). While performance improvements associated with technical communication are easier to observe, non-technical knowledge plays a greater role in helping companies cope with market changes and optimise their production or management processes, thus having a stronger effect on performance.

Fifth, the meta-analysis confirmed the effect of performance operationalisation on the SCL–performance relationship. The empirical research on SC-level performance is lacking. We constructed not only firm-level (i.e. financial and innovation) performance but also SC-level performance. Our results confirm the significant positive effects of SCL on all four performance measures (general, financial, innovation and SC performance); however, the effect on financial performance was weakest. From the KBV perspective, SCL is an effective method for firms to gain a competitive advantage by, for example, strengthening relationships with their SC partners and increasing flexibility in response to market changes (Blome *et al.*, 2014; Jean and Sinkovics, 2010; Rojo *et al.*, 2018). However, SCL requires resources and investments such as information technologies and making time for meetings; thus, it may not attain a corresponding return in the short term. In addition, firms in mature markets tend to seek to improve existing processes and focus on efficiency issues rather than on financial expansion (Bonanno and Haworth, 1998; Nguyen and Harrison, 2019), which may also explain why financial performance was significantly lower than the other performance dimensions. Meanwhile, SCL had the strongest positive effect on SC performance, confirming that it could significantly optimise a firm's operations management processes, production processes and SC flexibility at the SC level.

Sixth, the meta-analysis revealed that compared with manufacturing industries, other types of industries were associated with stronger effects on the SCL–performance relationship. Previous research has shown that industries display varying characteristics such as average market profitability, inventory levels, industry concentration and competition intensity (Geng *et al.*, 2017), which may affect the implementation of SCL. The results of this analysis further support the moderation effect of industry type.

Seventh, the effect of SCL on firm performance was strong and significant for both developed and less-developed regions. Although there are major differences in the cultural, educational and business environments between different regions and countries (Wang, W. *et al.*, 2018), the results showed that the level of economic development may not matter, and SCL could be applied in countries and regions with a range of economic development levels.

6.2. Managerial implications

The findings of this research have practical implications for managers involved in SCL. First, we provide solid evidence that SCL can improve performance and is independent of industry type and degree of economic development in the region. Although learning from both customers and suppliers has positive effects on performance, the former is more important. Therefore, to maintain a firm's competitiveness, we recommend that managers allocate more resources to learning from customers in the SCL process. In addition, SCL content is an important factor affecting firm performance. The results show that compared with technical knowledge focused on product development, non-technical knowledge focused on process optimisation and market information is superior in improving firm performance. Therefore, managers should develop a learning plan that focuses more on market information and process optimisation to attain a stronger competitive position.

Moreover, the results show that the effect of SCL on financial performance is weaker than its effect on SC, innovation and general performance. Given that SCL depends on corporate resources, it may not have a significant effect on financial performance in the short term.

However, SCL can help firms gain many non-financial competitive advantages and improve their overall performance in the long term. Therefore, managers should note that SCL may not improve the firm's financial performance in the short term. Overall, SCL has tremendous value at the strategic level. SC managers, especially those of small and medium-sized enterprises, should balance resource allocation between learning objectives and learning content according to their firm's value proposition and product characteristics when considering and implementing SCL.

6.3. Limitations

Although this research makes theoretical contributions to the SCL–performance relationship literature and practical contributions to business practice, it has some limitations. First, there are certain inherent limitations in meta-analyses. In particular, data are gathered from various sources from different time frames, and we may have a biased understanding of questionnaire content, which could result in inaccurate assessments (Wang, W. *et al.*, 2018). Second, given that we were unable to collect a large number of sample studies for all variables, we could only test the effects of different dimensions of SCL on overall performance rather than on individual measures of performance. Thus, it remains unclear how different dimensions of SCL affect different measures of performance (i.e. SC performance, innovation performance and general performance). Third, we only analysed the moderating effect of a few variables (i.e. learning source, knowledge type, SCL content, firm performance type, industry type and economic region). Therefore, it is not clear how other moderators such as company age, investment size and product type affect the relationship between SCL and firm performance. Finally, because of data availability issues, SCL antecedents, mediators of the SCL–performance relationship and potential 'white space' in this field could not be effectively analysed.

6.4. Future research directions

Based on the critical contributions and limitations of this study, we provide several suggestions for future research. First, we included three different measures of performance in this analysis:

financial, innovation and SC performance. However, in our sample articles, scholars tended to ignore how SCL affects sustainable performance. Sustainability is a hot topic in SC management research; therefore, we call on future researchers to explore how SCL affects sustainability such as environmental or social performance. Future researchers could also explore how SCL affects a firm’s circular economy adoption and environmental and social governance practices to obtain competitive advantage (e.g. Chen, Jia, *et al.*, 2022; Gong *et al.*, 2018). Second, based on our fine-grained measures of SCL and performance, new relations between the two may be tested in the future. For example, future research could focus on how different knowledge content and types affect firm performance to improve the understanding of the mechanisms of SCL and provide suggestions for managers. Specifically, future researchers can design questionnaires that clearly distinguish between learning type (i.e. absorptive or joint learning) or content (i.e. business, process or technical knowledge) to gather richer information from respondents. Moreover, it is worthwhile exploring how other learning types (e.g. single-loop or double-loop learning) and sources (e.g. other SC partners) affect the SCL–performance relationship to deepen our understanding of SCL. Third, our results show that compared with the manufacturing industry, other industries have a stronger effect on the SCL–performance relationship. However, these other industries in the sample articles mainly included third-party logistics, leasing and service companies, which do not represent all industries. Therefore, the effect of SCL on industries other than manufacturing requires further study. Finally, given that we found that the SCL–performance relationship was positive overall, future research should explore the antecedents of and barriers to SCL to improve our understanding of how to promote firms’ SCL behaviours across SCs.

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Table I. Definitions of supply chain learning

Study	Supply chain learning definition
Bessant *et al.* (2003)	Learning behaviours in an interorganisational context
Sweeney *et al.* (2005)	Organisational integration and the search for new solutions to improve performance and process efficiency
Theodorakopoulos *et al.* (2005)	Interorganisational learning that takes place between supplying and purchasing organisations
Flint *et al.* (2008)	Multiple organisations collaborating on supply chain and product issues to find joint solutions
Ngai *et al.* (2011)	Developing new knowledge or insights that can enhance supply chain capability and competitive advantage
Biotto *et al.* (2012)	An intangible strategic resource, a competence and a bonding element deeply embedded in the supply relationships that drive supply management success and can create a competitive advantage
Lambrechts *et al.* (2012)	Building the capacity to create new knowledge and possibilities through a joint process where actors can learn collectively how to rethink and renew their supply chain frame
Golgeci and Arslan (2014)	A type of interorganisational learning along the supply chain
Silvestre (2015)	Learning of new capabilities in which supply chains jointly develop technological, organisational and business model innovations, enhancing integration, collaboration and sustainability performance
H. Y. Zhang and Lv (2015)	Rooted in organisational learning in which staff continually acquire knowledge, perfect their behaviours and optimise the organisational system to maintain the sustainable survival of the organisation and healthy and harmonious developments in internal and external environments
Gosling *et al.* (2016)	Derives from interorganisational learning in which organisational members act jointly to create collective knowledge
Ojha *et al.* (2016)	A resource characterised by the degree to which all supply chain partners stress four key learning routines across the supply chain: team orientation, system orientation, learning orientation and memory orientation
Huo *et al.* (2020)	The process of a firm acquiring, assimilating and exploiting knowledge across its internal functions as well as from its major suppliers and customers

Note: Adapted from Y. Yang *et al.* (2019).

Table II. Keywords used in the systematic literature review

A. Supply chain related	B. Learning related	C. Performance related
Supply chain*	Supply chain learning	Performance
Procurement	Organizational learning	Benefit
Purchas*	Inter-organizational learning	Outcome
Sourcing	Inter-firm learning	Advantage
Logistic*	Inter-partner learning	Consequence
Supply network	Cross-cultural learning	Effect
Value chain*	Mutual learning	Return
Demand chain*	Dyadic learning	Firm value
	Joint learning	Profit*
	Cross-border learning	Innovation
	Relationship learning	Financial
	Knowledge management	Operational
	Knowledge sharing	
	Knowledge exchange	
	Knowledge transfer	

Note: * denotes any string of characters.

Table III. Reviewed papers

Paper		Analysis method	Sample size	Theoretical approach	Region
1	Yli-Renko *et al.* (2001)	CB-SEM	180	Social capital theory	UK
2	Spekman *et al.* (2002)	Regression analysis	160	NS	North/South America, Europe
3	Selnes and Sallis (2003)	CB-SEM	315	OLT	Scandinavia
4	Emden *et al.* (2005)	CB-SEM	184	Social exchange theory	US
5	L.-Y. Li (2006)	Regression analysis	414	Social capital theory	Mainland China
6	Flint *et al.* (2008)	CB-SEM	322	OLT	US, Sweden, Denmark
7	Lai *et al.* (2009)	Regression analysis	71	Dyadic learning perspective	Taiwan
8	Sambasivan *et al.* (2009)	CB-SEM	164	KBV	Malaysia
9	Shang (2009)	CB-SEM	136	RBV	Taiwan
10	J. Yang *et al.* (2009)	CB-SEM	137	KBV	Mainland China
11	Hernández-Espallardo *et al.* (2010)	CB-SEM	219	TCE, RBV	Colombia
12	Jean and Sinkovics (2010)	CB-SEM	246	RBV	Taiwan
13	Cousins *et al.* (2011)	CB-SEM	111	IPT	UK
14	Zhao and Wang (2011)	Regression analysis	306	NS	Mainland China
15	Jean *et al.* (2012)	CB-SEM	246	RBV, TCE	Taiwan
16	Liu (2012)	CB-SEM	160	RDT, network theory	Taiwan
17	Bucic and Ngo (2013)	Regression analysis	389	Contingency theory	Australia
18	Cai *et al.* (2013)	CB-SEM	198	Commitment–trust theory, RDT	Singapore
19	Feng *et al.* (2013)	CB-SEM	176	OLT, IPT	Mainland China
20	Nagati and Rebolledo (2013)	CB-SEM	218	KBV	Canada
21	Noruzy *et al.* (2013)	CB-SEM	106	Transformational leadership	Iran
22	Blome *et al.* (2014)	Hierarchical regression	141	KBV, contingency perspective	Germany
23	Schoenherr *et al.* (2014)	PLS-SEM	195	KBV	US

Paper		Analysis method	Sample size	Theoretical approach	Region
24	Asgari *et al.* (2015)	PLS-SEM	185	KBV	Malaysia
25	Dobrzykowsk *et al.* (2015)	CB-SEM	711	IPT	Global
26	Liao and Barnes (2015)	CB-SEM	92	RBV	NS
27	Ryoo and Kim (2015)	PLS-SEM	70	RBV	NS
28	H.-Y. Zhang and Lv (2015)	Path analysis	167	Intellectual capital perspective	Mainland China
29	Ghobakhloo and Hong (2015)	PLS-SEM	408	RBV	Iran, Malaysia
30	Jean *et al.* (2016)	CB-SEM	204	KBV, RDT, ILT	Taiwan
31	Leal-Millán *et al.* (2016)	PLS-SEM	140	KBV	Spain
32	J. J. Wang *et al.* (2016)	Regression analysis	323	Institutional theory, OLT	Mainland China
33	Taher *et al.* (2017)	Pearson correlation analysis	120	KMT	Iran
34	Basheer *et al.* (2018)	CB-SEM	248	OLT	Pakistan
35	M. Li *et al.* (2018)	PLS-SEM	300	Absorptive capacity theory, boundary spanning theory	Mainland China
36	Phengchan and Thangpreecharparnich (2018)	CB-SEM	150	KBV	Thailand
37	Rojo *et al.* (2018)	CB-SEM	302	Dynamic capabilities perspective	Spain
38	Sáenz *et al.* (2018)	CB-SEM	155	Contingency theory	Spain
39	Sukoco *et al.* (2018)	CB-SEM	211	RBV	Indonesia
40	Xu *et al.* (2018)	PLS-SEM	205	Institutional theory, RBV	Mainland China
41	M. Zhang *et al.* (2018)	Hierarchical regression	276	Absorptive capacity theory	Mainland China
42	Zhu *et al.* (2018)	PLS-SEM	366	Relational view, KBV	Mainland China
43	de Zubielqui *et al.* (2019)	CB-SEM	291	NS	Australia
44	K. Choi *et al.* (2019)	CB-SEM	190	KBV, ILT, RDT	Taiwan
45	Duangjan and Wang (2019)	PLS-SEM	85	RBV	Thailand
46	Iyer *et al.* (2019)	CB-SEM	152	RBV	US

Paper		Analysis method	Sample size	Theoretical approach	Region
47	Jimenez-Ngai *et al.* (2019)	PLS-SEM analysis	200	RBV	Spain
48	Nguyen and Harrison (2019)	CB-SEM	650	KBV	Global
49	Im *et al.* (2019)	Regression analysis	238	Alignment–misalignment perspective	US
50	Jen *et al.* (2019)	Regression analysis	120	NS	China
51	Suh *et al.* (2019)	SEM	352	NS	US
52	Haq (2020)	CB-SEM	213	KBV	China
53	G. Li (2020)	SEM	287	RBV	China
54	C. Wang and Hu (2020)	Regression analysis	236	KMT, innovation capability theory	China

Note: CB-SEM: covariance-based structural equation modelling; ILT: interpartner learning theory; IPT: information processing theory; KBV: knowledge-based view; KMT: knowledge management theory; NS: not specified; OLT: organisational learning theory; PLS-SEM: partial least squares structural equation modelling; RBV: resource-based view; RDT: resource dependence theory; SEM: structural equation modelling: TCE: transaction cost economics; UK: United Kingdom; US: United States.

Table IV. Theoretical lenses used in sample papers

Theory	Number	%
Knowledge-based view	13	24
Resource-based view	12	22
Organisational learning theory	5	9
Contingency theory	3	6
Information processing theory	3	6
Resource dependence theory	3	6
Transaction cost economics	3	6
Absorptive capacity theory	3	6
Interpartner learning theory	2	4
Institutional theory	2	4
Social exchange theory	2	4
Social capital theory	2	4
Not specified	4	9
Other theories	10	19

Table V. Methodologies used in sample papers

Method	**Number**	**%**
Covariance-based structural equation modelling	31	57
Partial least squares structural equation modelling	10	19
Regression analysis	9	17
Hierarchical regression	2	4
Path analysis	1	2
Pearson correlation analysis	1	2

Table VI. Formulae used to calculate correlations

Statistic to be transformed	Formula used to calculate correlation	Note
Student's t	$r = \sqrt{(t^2)/(t^2 + df)}$	Can be used for either paired or unpaired t-test
F-ratios	$r = \sqrt{(F)/\big(F + df(error)\big)}$	Can be used only for one-way ANOVA
χ^2	$r = \sqrt{\chi^2/n}$	χ^2 = chi-square value, n = sample size; can be used when $df = 1$
d	$r = (d)\sqrt{d^2 + 4}$	d = Cohen's d
β	$r = 0.98 \times \beta + 0.05$, if $\beta \geq 0$; $r = 0.98 \times \beta$, if $\beta < 0$	β = beta coefficient of the regression result, $\beta \in (-0.5, 0.5)$

Note: r denotes the correlation between an independent variable and a dependent variable.

Source: Adapted from Peterson and Brown (2005), Geng *et al.* (2017) and W. Wang *et al.* (2018).

Table VII. Meta-analysis results of the main effect and differential effects of learning sources

Main effect (random-effects model)								
Heterogeneity analysis	τ^2	I^2	H^2	Q				
	0.036	88.48	9.51	522.147				
Model results	*n*	*K*	ES	SE	*z*	*p*	LL	UL
Supply chain learning	12,441	54	0.424	0.028	15.993	0.000	0.360	0.499
Differential effects (mixed-effects model)								
Heterogeneity analysis	τ^2	I^2	H^2	QE	QM			
	0.037	89.51	9.53	510.579^{***}	255.585^{***}			
Model results	*n*	*K*	ES	SE	*z*	*p*	LL	UL
Customer	4,849	20	0.478	0.046	10.475	0.000	0.388	0.567
Supplier	1,555	9	0.370	0.070	5.294	0.000	0.233	0.506
Not specified	6,037	25	0.443	0.041	10.855	0.000	0.363	0.523

Note: τ^2 = estimated residual heterogeneity; I^2 = total heterogeneity divided by total variability; H^2 = total heterogeneity divided by sampling variability; Q = heterogeneity; QE = test of residual heterogeneity; QM = test of moderators; *n* = total number of samples; *K* = number of sampled studies; ES = effect size (estimated model coefficient); SE = sampling standard error; *z* and *p* = tests of significance; LL = lower limit; UL = upper limit.

Table VIII. Subgroup analysis of moderators

Learning type		τ^2	I^2	H^2	QE	QM			
	Heterogeneity analysis	0.033	89.59	8.76	423.355***	281.717***			
	Model results	*n*	*K*	ES	SE	*z*	*p*	LL	UL
	Absorptive learning	5,849	23	0.372	0.041	9.118	0.000	0.292	0.452
	General learning	565	3	0.561	0.114	4.936	0.000	0.338	0.784
	Joint learning	6,027	28	0.491	0.037	13.199	0.000	0.418	0.564
Knowledge type		τ^2	I^2	H^2	QE	QM			
	Heterogeneity analysis	0.035	89.04	9.13	465.834***	265.897***			
	Model results	*n*	*K*	ES	SE	*z*	*p*	LL	UL
	Explicit knowledge	5,094	22	0.501	0.043	11.666	0.000	0.417	0.585
	General knowledge	5,195	24	0.417	0.041	10.065	0.000	0.336	0.498
	Tacit knowledge	2,601	8	0.372	0.070	5.337	0.000	0.235	0508
Supply chain learning content		τ^2	I^2	H^2	QE	QM			
	Heterogeneity analysis	0.034	88.80	8.93	490.983***	275.774***			
	Model results	*n*	*K*	ES	SE	*z*	*p*	LL	UL
	Business knowledge	342	2	0.686	0.142	4.830	0.001	0.408	0.965
	General knowledge	7,068	31	0.461	0.036	12.889	0.000	0.391	0.531
	Process knowledge	2,255	9	0.467	0.066	7.092	0.000	0.232	0.456

	Technical knowledge	2,776	12	0.344	0.057	6.003	0.000	0.232	0.456
Performance type		τ^2	I^2	H^2	QE	QM			
	Heterogeneity analysis	0.029	86.88	7.62	372.029***	326.758***			
	Model results	*n*	*K*	ES	SE	*z*	*p*	LL	UL
	Financial performance	2,196	6	0.246	0.074	3.305	0.000	0.100	0.391
	General performance	164	1	0.525	0.187	2.804	0.005	0.158	0.891
	Innovation performance	4,135	17	0.377	0.044	8.476	0.000	0.289	0.464
	SC performance	5,946	30	0.521	0.034	15.366	0.000	0.455	0.588
Industry type		τ^2	I^2	H^2	QE	QM			
	Heterogeneity analysis	0.036	89.26	9.31	494.304***	259.347***			
	Model results	*n*	*K*	ES	SE	*z*	*p*	LL	UL
	Manufacturing	7,956	33	0.451	0.035	12.722	0.000	0.381	0.520
	Other	654	4	0.569	0.102	5.592	0.000	0.370	0.769
	Mixed	3,831	17	0.402	0.049	8.138	0.000	0.305	0.499
Region		τ^2	I^2	H^2	QE	QM			
	Heterogeneity analysis	0.036	89.28	9.22	434.392***	261.931***			
	Model results	*n*	*K*	ES	SE	*z*	*p*	LL	UL
	Developed	3,837	17	0.463	0.049	9.437	0.000	0.367	0.559
	Less developed	6,491	30	0.463	0.037	12.505	0.000	0.391	0.536

Note: τ^2 = estimated residual heterogeneity; I^2 = total heterogeneity divided by total variability; H^2 = total heterogeneity divided by sampling variability; Q = heterogeneity; QE = test of residual heterogeneity; QM = test of moderators; *n* = total number of samples; *K* = number of sampled studies; ES = effect size (estimated model coefficient); SE = sampling standard error; *z* and *p* = tests of significance; LL = lower limit; UL = upper limit.

Figure 1. Literature review process

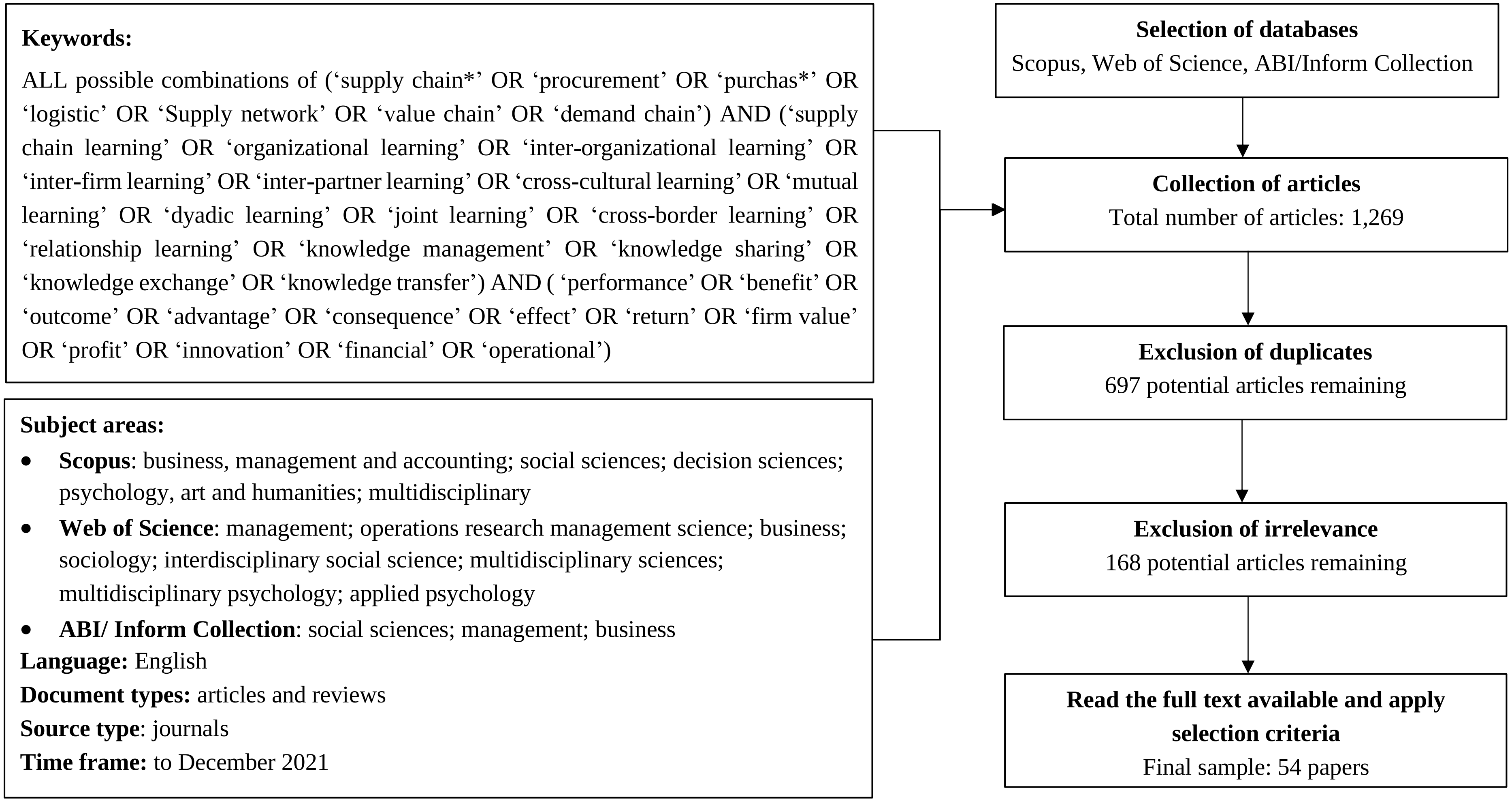

Figure 2. Distribution of reviewed papers, 2001–2020

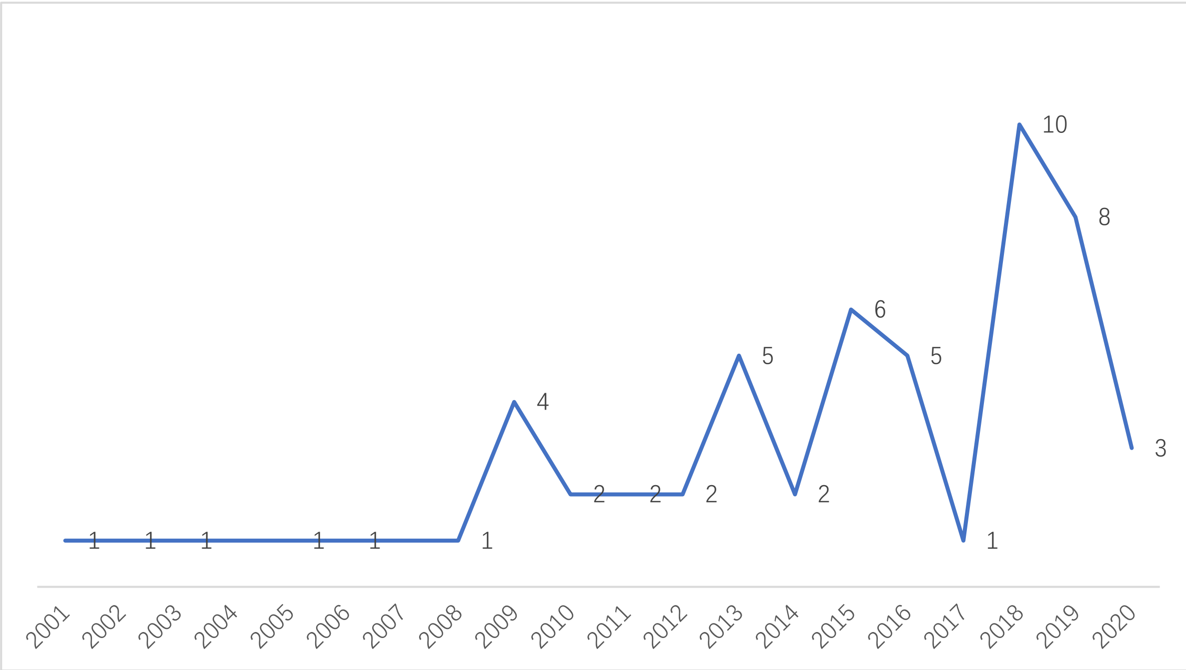

Figure 3. Funnel plot of the sampled articles

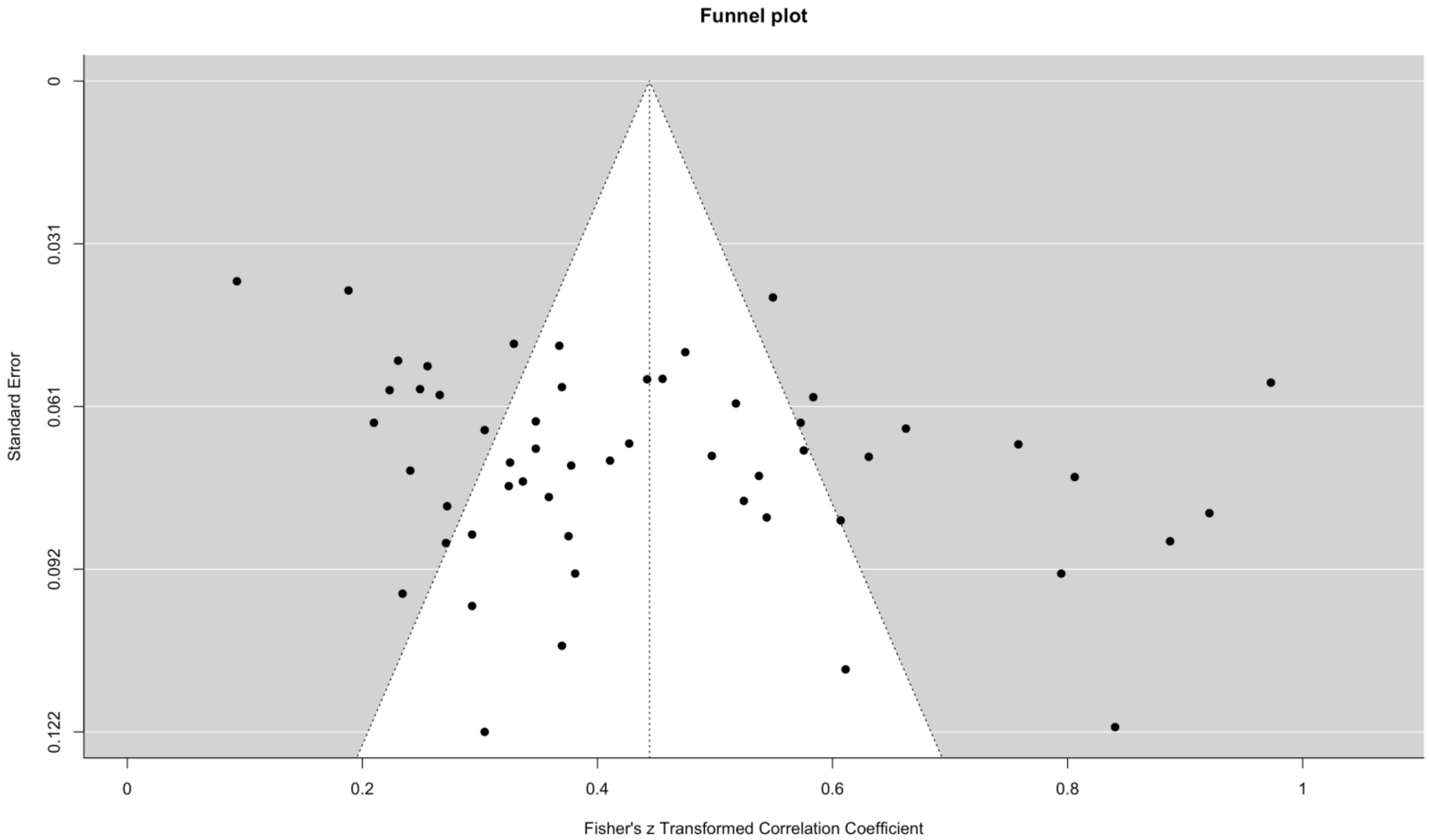

Figure 4. Radial plot

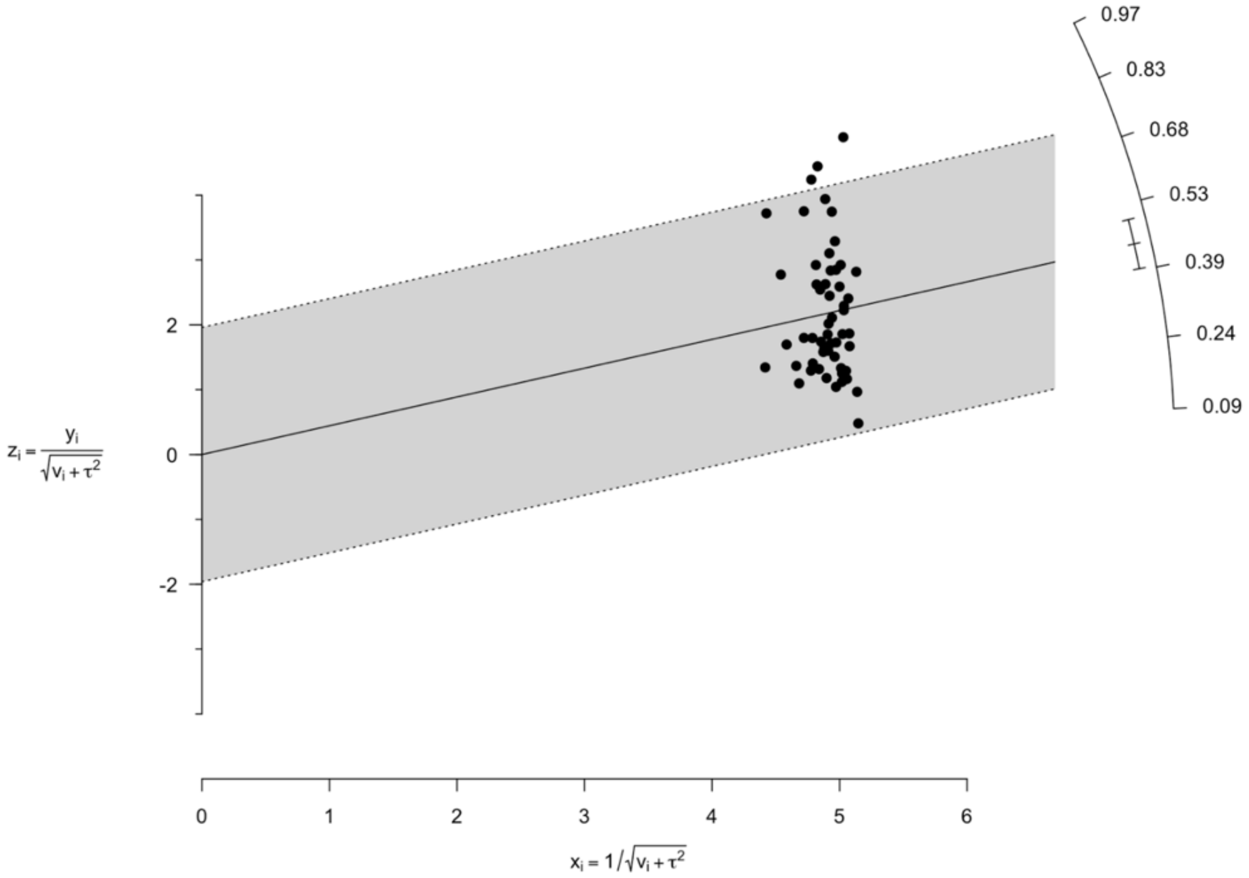

Figure 5. Forest plot

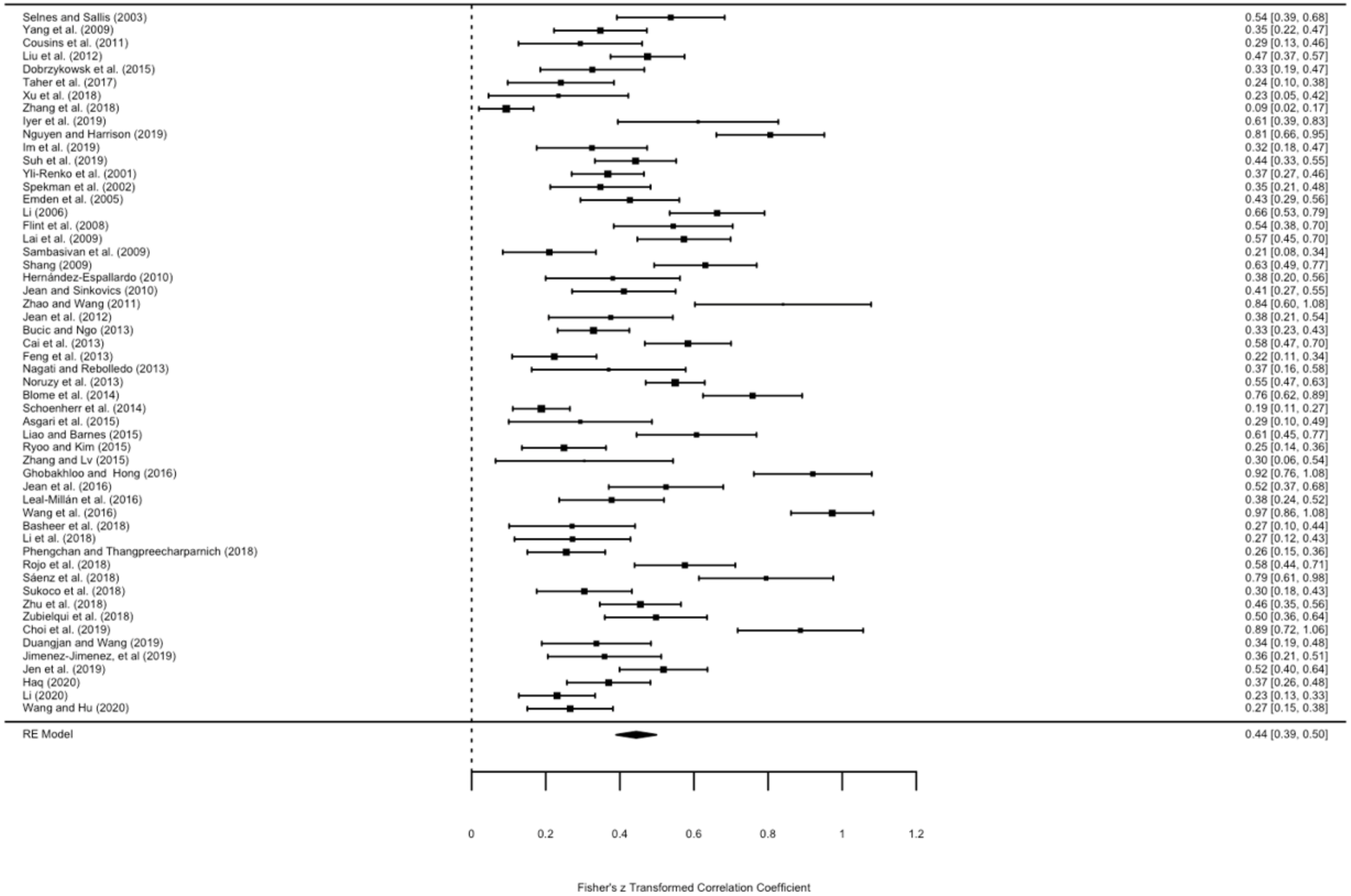

Figure 6. Outlier/influence diagnostics