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Determining the Effect of Trust on Supply Chain Network Performance with Linguistic Summarization Over Heterogeneous Information Network

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Abstract. Industries have increasingly adopted supply chain management practices to sustain competitive advantage, fostering collaboration among supply chain partners for effective coordination. While prior research has explored whether inter-partner relationships influence supply chain network performance, these studies have primarily focused on perceived effects rather than emprical observations. This study investigates the impact of trust on supply chain network performance through linguistic summarization. Its originality lies in integrating linguistic summarization with heterogeneous information network modelling, a novel method for evaluating trust-driven performance effects in supply chains. We modelled supply chain networks as heterogeneous information networks, representing companies and products as distinct node types, and their interactions as varied link types. A linguistic summarization framework was developed for these networks, and its application in the automotive industry enabled the validation of literature-derived hypotheses through the truth degree of linguistic summaries. The findings demonstrate that trust significantly enhances organizational performance, particularly in terms of profitability. Supply chain managers, analysts, and researchers especially gain from this study since it offers a data-driven, interpretable framework for assessing how trust affects network performance, which promotes cooperation, transparency, and decision-making.

Key words: heterogeneous information network, linguistic summarization, operational performance, organizational performance, supply chain management, trust.

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1. Introduction

Supply chains are inter-organizational networks among different companies, including suppliers, manufacturers, distributors, and customers, operating through a value chain in the industry (Capaldo and Giannoccaro, 2015; Surana *et al.*, 2005). Working together, both internally within an organization and externally with different companies – aka supply chain partners, – is essential for effective Supply Chain Management (SCM) (Emmett and Crocker, 2016). SCM integrates key business processes from end-users through original providers who supply customers with products, services, and information to add value at the lowest cost to the supply chain (Christopher, 2005; Cooper *et al.*, 1997).

The structure of efficient supply chain systems could be captured by complex network models (Surana *et al.*, 2005; Hearnshaw and Wilson, 2013; Pathak *et al.*, 2007), categorized into four main classes: social networks, information networks, technological networks, and biological networks (Newman, 2003). A Supply Chain Network (SCN) fits the definition of an information network, which is formed by interacting components. In most studies on network science, each node has the same type of objects (e.g. companies), and each link has the same type of connections (e.g. material flow). Such networks are called homogeneous information networks. On the other hand, most real-world networks follow the definition of Heterogeneous Information Networks (HIN), where nodes and links have different types (Sun and Han, 2012). Since the existing studies for the analysis of homogeneous information networks in the literature cannot be applied directly to HINs, the analysis of HINs has emerged as an area of research gaining importance (Shi *et al.*, 2017). For example, in a SCN, while nodes represent customers, suppliers, products, etc., links represent relations like supply/supplied-by, purchase/purchased-by. Examining all nodes by assuming they are similar could result in some critical information loss. It is thus desirable to model SCNs as HINs, with a structure where organizations and their relationships have different types, like most real-world networks. By defining components such as raw materials and finished products as other types of nodes, SCNs become capable of presenting the indirect interactions between an organization's suppliers and customers. Furthermore, the relevant feature vectors for both nodes and links will enrich the information content of the network.

Four tasks have been highlighted in HIN literature: (1) classification (Shehnepoor *et al.*, 2017; Zhang *et al.*, 2021), which predicts the label of all types of objects based on some objects with known labels, (2) clustering (Sun *et al.*, 2012; Zhou *et al.*, 2020), which groups objects so that similar ones are in the same cluster while dissimilar ones are in different clusters, (3) link prediction (Davis *et al.*, 2013; Wang *et al.*, 2021), which estimates the likelihood of the existence of a link between two nodes, and (4) similarity (Shi *et al.*, 2014; Wang *et al.*, 2016a), which evaluates the similarity of objects. Beyond these foundational tasks, advanced tasks include (1) recommendation (Shi *et al.*, 2019; Xing *et al.*, 2025), which utilize intricate network relationships, employing meta-path and meta-graph frameworks to enhance individualized recommendation, (2) representation learning (Dong *et al.*, 2017; Zhang *et al.*, 2025), which aims to encapsulate structural and semantic information into low-dimensional vectors to facilitate various downstream tasks, and (3) information diffusion (Zhang *et al.*, 2016), which examines the propagation of information, behaviours, or influence across diverse networks, yielding essential insights into network dynamics and forecasting. Foundational tasks create the essential analytical framework for comprehending HINs, whereas advanced tasks utilize deeper structural and semantic insights, enabling complex analytical skills and improved prediction performance.

As for SCM, statistical analysis, simulation, and optimization are the headings highlighted in the literature (Narayanan *et al.*, 2015; Tiwari *et al.*, 2018). There are two types of statistical analysis techniques: descriptive and predictive. The former employs data to extract information about the characteristics of the SCN. The latter makes future predictions based on historical data. The simulation enables developers to determine how the system is affected under various system configurations and levels of complexity. The optimization derives knowledge from a complex system with numerous factors and constraints. Although it is beneficial to solve SCM problems under the three categories, the studies on SCNs are rare and related to SCNs being considered complex adaptive networks, not as HINs (Surana *et al.*, 2005; Choi *et al.*, 2001; Li *et al.*, 2017).

Linguistic Summarization (LS), proposed by Yager (1982), can be described as a descriptive data summarization method. Understanding and interpreting the results of analytical methods is challenging for people who do not have sufficient knowledge about the subject. By LS, the obtained information is expressed with natural language that allows better understanding. By way of illustration, “Most of the trusted suppliers supply materials in low lead times. [0.78]” is a LS with an assigned truth degree which takes value in the unit interval. If the generated summary form is valid, the truth degree is closer to one. LS has become a popular approach since it may bring valuable information from data (Ramos-Soto *et al.*, 2016; Conde-Clemente *et al.*, 2017; Kaczmarek-Majer and Hryniewicz, 2019; Nguyen *et al.*, 2021; Özdoğan *et al.*, 2021). LS is a multidimensional framework that integrates fuzzy quantifiers, linguistic variables, and aggregation functions to generate understandable data summaries. Although many works have been done in the field of the supply chain, quite limited studies generate LSs from network data. Aydoğan *et al.* (2021) used LS to support strategic decisions in single objective and bi-objective supply network design, in which the stages of the supply chain show the nodes, and the material flows between them show the relations.

The performance of an SCN can be measured in terms of resource, output, and flexibility (Beamon, 1999). The resources may consider the costs of manufacturing, distribution, inventory, and return on investment for high-level efficiency. The output may consider sales, profit, fill rate, on-time delivery, stock out cases, response time to customer, lead time, shipping errors, and customer complaints about the degree of customer service. The flexibility may take the ability to respond to a changing environment. As partnership quality in SCNs indicates Supply Chain Network Performance (SCNP), it has received significant attention in the literature (Yang *et al.*, 2020; Zhou *et al.*, 2016; Li *et al.*, 2015). However, most previous studies on relationship dynamics are qualitative analyses based on querying hypotheses. Though it will be examined in detail in the literature review section, we would like to exemplify the subject here. For example, Rodriguez-Lopez *et al.*

(2017) point out the hypothesis that “The higher the trust, the better the economic performance”. While the hypothesis is compatible in some studies, like in Akhtar and Khan (2015), conflicting with others, like in Arora *et al.* (2021). Therefore, quantitative ways are needed to reveal the interaction between supply network relations and SCNP. Given this context, the study’s main hypothesis is that trust between supply chain network participants significantly and favourably affects the network’s performance, especially when it comes to organizational and operational results. By this means, the validity of qualitative studies can be tested with quantitative studies, like truth degree in LS.

Despite the increasing interest in trust dynamics within SCNs, previous research has primarily depended on qualitative assessments or uniform modelling methods that neglect the structural complexity of actual systems. This study’s originality is in the amalgamation of linguistic summarization and HIN modelling, a combination not previously utilized in supply chain trust research. This connection facilitates the extraction of interpretable, semantically rich summaries from intricate, multi-type relational data, so connecting data-driven analysis with managerial insight. Additionally, by substantiating literature-derived assumptions using the truth values of language summaries, the study offers a quantitative yet comprehensible alternative to conventional trust-performance modelling.

This paper aims to generate and evaluate LSs on how relationships affect SCNP. The supply network is modelled as an HIN to minimize information loss. Generated summaries are used to test the validity of the qualitative studies in the existing literature. There are several essential areas to which this study makes an original contribution:

- SCNs were modelled with HINs, unlike classical approaches. Thus, the information loss from assuming that each node/link is monotype is prevented.
- The effect of supply network relationships on SCNP has been analysed using heterogeneous modelling.
- LS generated the hypotheses in the literature. The validity of the hypotheses was checked by the truth degree of the summaries. Compatible/conflicting results were reported.
- For the first time, a real case study was also performed about the interpretability of LS, explained in Section 3.3.
- The approach helps enterprises gain actionable insights from complicated relational data without advanced data literacy. This promotes human-in-the-loop decision-making, supply chain transparency, and trust-based collaboration in digitally mature organizations.

The remainder of the study is organized as follows: Section 2 presents the extant studies that reveal the relationships affecting performance in SCNs. Our LS procedure of HINs is explained in detail in Section 3. The methodology overview is summarized in a diagram in Section 4. A realistic case study is conducted, and LS results are compared with existing literature in Section 5. The results are discussed in Section 6. The paper is concluded with Section 7.

2. Related Works

Research into SCM consists of statistical analysis, simulation, and optimization (Tiwari *et al.*, 2018; Wang *et al.*, 2016b). Many statistical analysis studies have been conducted to date to investigate how the trust relationship among SCN members affects SCNP. These studies established hypotheses about the effect of trust on SCNP, such as "Inter-firm trust positively affects a firm's operational performance (OPP)" (Shi and Liao, 2015). Similar hypotheses were tested using questionnaires applied to companies. The research question that started the systematic review was, "How does trust affect the performance of supply chain networks?" To do a systematic literature review, this study is advanced by creating a Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) list (Liberati *et al.*, 2009). Due to its constant coverage of high-quality, peer-reviewed journal articles in engineering and management sciences, the Web of Science Core Collection was chosen as the only database. The last thirteen year of the literature (January 2012–May 2025) is considered to focus on up-to-date studies, and the review process is summarized as follows:

- Literature Search
  Database: Web of Science Core Collection
  Limits: SCI-E articles (not in Social Science Citation Index), in the English language, in years between 2012-2025 returned from the search string ("supply chain" OR "supply network") AND "trust" AND "performance".
  Search Results ($n = 228$)
- Articles Screened on Basis of Title and Abstracts
  Excluded: ($n = 131$)
  Included: ($n = 97$)
- Manuscript Review
  Excluded: ($n = 65$)
  Included: ($n = 32$)

The evaluation only included papers that specifically looked at the connection between SCNP and trust; studies that didn't specifically address this relationship were not included. Two authors separately reviewed the titles and abstracts of the publications that were retrieved in order to minimize subjectivity in the selection process. Any discrepancies were then discussed and settled until an agreement was achieved. Based on the PRISMA list, the final 32 articles are summarized in Table 1 regarding a trust-SCNP relationship.

Table 1 provides a systematic summary of chosen studies examining the impact of trust on SCNP. The table classifies the studies according to the type of effect examined (direct, indirect, or moderating), the nature of the trust variable (e.g. inter-firm, supplier, or customer trust), the dimension of performance assessed (operational or organizational), and the specific performance metrics utilized (such as lead time, profitability, delivery reliability, or innovation). The concluding column encapsulates the study's findings regarding the impact of trust on performance, indicating whether the effect is favourable, negative, or mixed. This classification elucidates the operationalization and measurement of trust

Table 1
Summary of studies on the effect of trust on SCNP.

Study	Type of effect	Performance dimension	Performance measures	Result
Devaraj *et al.* (2012)	Moderating	Operational	Cost, quality, responsiveness	+
Youn *et al.* (2013)	Indirect (information sharing)	Organizational	Environmental performance, business performance	+
Nagati and Rebolledo (2013)	Indirect (knowledge exchange)	Operational	Quality, lead time, cost	+
Chen *et al.* (2013)	Indirect (knowledge exchange)	Operational	Quality, speed, cost	+
Jie *et al.* (2013)	Direct	Operational	Quality	+
Michalski *et al.* (2014)	Direct	Organizational	Innovation	±
Jones *et al.* (2014)	Direct	Operational	Cost, due date, productivity	+
Wu *et al.* (2014)	Indirect (information sharing and collaboration)	Both	Return on investment/asset, sales, market share, cost	+
Yang (2014)	Indirect (agility)	Operational	Cost	+
Yang (2014)	Indirect (agility)	Organizational	Market share, return on asset	−
Brinkhoff *et al.* (2015)	Direct	Operational	Project success	+
Li *et al.* (2015)	Moderating	Organizational	Return on investment, sales, profit, market share	+
Shi and Liao (2015)	Direct	Operational	Quality, cost, lead time, quick response, efficiency	+
Ryoo and Kim (2015)	Indirect (knowledge exchange)	Operational	Efficiency	+
Narayanan *et al.* (2015)	Direct	Both	Agility	+
Akhtar and Khan (2015)	Direct	Organizational	Profitability, sales, market share	+
Mutonyi *et al.* (2016)	Indirect (loyalty)	Organizational	Sales	+
Odongo *et al.* (2016)	Direct	Operataional	Quality, responsiveness, efficiency	+
Zhou *et al.* (2016)	Direct	Organizational	Market share, profitability, innovation, cmpetitive position	+
Rodriguez-Lopez *et al.* (2017)	Direct	Organizational	Economic performance	+
Susanty *et al.* (2017)	Indirect (loyalty)	Both	Cost, sales, profitability, return on investment	−
Amentae *et al.* (2018)	Direct	Operational	Efficiency, flexibility, quality, dairy losses	+
Zhong *et al.* (2020)	Direct	Operational	Response time	+
Narwane *et al.* (2020)	Indirect (cloud of things adaptation)	Operational	Quality, productivity	+
Yang *et al.* (2020)	Direct	Organizational	Innovation, market share, customer satisfaction	+
Arora *et al.* (2021)	Direct	Organizational	Return on investment, profit growth, market share, sales volume	−
Arora *et al.* (2021)	Direct	Operational	Cost, quality, lead time, customer service	+
Kim and Chai (2022)	Direct	Both	Return on investment/asset, income, market share, cost, lead time	+
Zhang *et al.* (2022)	Moderating	Operational	Quality	+
Akhtar *et al.* (2023)	Direct	Organizational	Sustainability	+
Narwane *et al.* (2023)	Indirect (cloud of things adaptation)	Both	Agility, productivity, quality, maintenance	+
Owot *et al.* (2023)	Indirect (information sharing)	Both	Cost, sales	+
Wang *et al.* (2023)	Indirect (c-commerce behavior)	Both	Innovation, agility, reputation, productivity	+
Fang *et al.* (2024)	Indirect (innovation)	Organizational	Circular economy	±

in the literature, emphasizing both consistent trends and contradictory results. The table facilitates the identification of theoretical and methodological shortcomings addressed in the present work.

Based on the examined literature, numerous significant research gaps may be discerned: (i) although most studies acknowledge the significance of trust in supply chain performance, the operationalization of trust exhibits considerable variability and is frequently constrained to unidirectional or static perspectives, (ii) the majority of analyses depend on perceived relationships obtained from surveys, rather than on actual or structural network data, (iii) there is little emphasis on capturing the heterogeneous and multi-relational characteristics of supply chain interactions; current models frequently depict the supply chain as a homogenous or linear system, and (iv) the interpretability of findings is seldom considered; few studies provide comprehensible or linguistically articulate insights to assist decision-makers. The deficiencies shown in the summary findings of Table 1 and the extensive literature discourse necessitate the strategy advocated in this study.

2.1. *Sources Evaluation*

The review's sources were methodically assessed using predetermined standards. Articles were accepted if they (I1) were authored in English between 2012 and 2025 and were peer-reviewed journal articles indexed in SCI-E; (I2) specifically looked at the connection between supply chain/network performance and trust; and (I3) included enough metadata for analysis. Articles that (E1) were duplicates, (E2) did not directly examine the trust–performance relationship, or (E3) were non-journal publications (conference papers, book chapters, or non-indexed) were not included. To guarantee traceability and transparency, each chosen article was thereafter compared to these standards.

2.2. *Threats to Validity*

Despite a methodical approach, there are always possible risks to validity. First, it's possible that pertinent research indexed in other databases was overlooked by relying solely on the Web of Science Core Collection as the data source. Second, limiting the study period to 2012–2025 can leave out older but equally important research. Two authors separately reviewed the articles to reduce subjectivity, and any differences were settled by consensus. The inherent constraints of systematic literature reviews are lessened but not completely eliminated by these measures.

3. Linguistic Summarization for Heterogeneous Information Networks

This section presents the fundamental elements of the suggested methodology. The text initially outlines the conventional LS methodology, subsequently introducing an enhanced LS framework tailored for HINs. Ultimately, it addresses the interpretability facet of LS, highlighting the semantic clarity and decision-making assistance that LSs can provide in intricate relational contexts like supply chains. The theoretical backdrop from the literature is compiled in Section 3.1, our suggested adaption to heterogeneous information networks is presented in Section 3.2, and a previously suggested but untested method is implemented in Section 3.3, which makes up this study's original contribution.

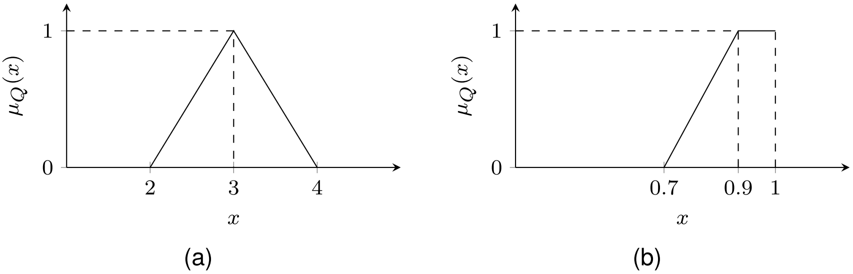

Fig. 1. (a) “between 2 and 4” absolute quantifier, (b) “most” relative quantifier.

3.1. *Basic Linguistic Summarization*

Yager (1982) introduced fuzzy LS as a descriptive data mining method that uses fuzzy sets for modelling natural language statements while producing easy-to-understand summaries from large data sets.

Before introducing LS, a brief background on fuzzy sets is given. The degree to which an element belongs to a set is characterized by a binary condition in a classical set; however, in a fuzzy set, the degree of belonging to a set takes a value in the unit interval [0, 1]. A fuzzy subset F on the universe X is defined as $F = \{\langle x, \mu_F(x)\rangle | x \in X\}$ where $\mu_F(x) : X \to [0, 1]$ is the membership degree of x. The α-cut of F is the crisp set $F_\alpha = \{x \in X | \mu_F(x) \geqslant \alpha\}$.

Let Y represent the set of objects $Y = \{y_1, y_2, \dots, y_M\}$, S represents the set of attributes $S = \{s_1, s_2, \dots, s_K\}$, and X_k represent the domain of s_k $(k = 1, 2, \dots, K)$. There are four components of a LS: (i) a linguistic quantifier Q (e.g. few, most) labelled with a fuzzy set, (ii) a linguistic summarizer A (e.g. low transportation cost) labelled with a fuzzy set, (iii) a linguistic pre-summarizer B (e.g. medium lead time) labelled with a fuzzy set, and (iv) truth degree of the summary *TD* which describes how far the data supports the summary generated. It is common to use two types of quantifiers, absolute and relative, in quantified sentence structures. Absolute quantifiers are defined as a possibility distribution over non-negative integer, i.e. “between 2 and 4”. Relative quantifiers are defined as a possibility distribution in the range [0,1], i.e. “most”. Absolute and relative quantifiers are shown in Fig. 1(a) and 1(b), respectively.

For LS, Zadeh (1983) proposed type-I and type-II sentence structures with quantity meaning as “Q Ys are/have A. [*TD*]”and “Q B Ys are/have A. [*TD*]”, respectively. After extracting potential summaries from a data set, an evaluation is performed to compute the *TD* of these sentences. When the *TD* value increases, more data satisfies the summarizer and pre-summarizer. *TD*s of type-I and type-II summary forms are proposed in (1) and (2). When using absolute quantifiers in summary form, r is equal to 1; when using relative quantifiers in summary form, r is equal to the total number of objects M. Absolute quantifiers can only be used in type-I summary form.

$$TD = \mu_Q\left(\frac{\sum_{i=1}^{M} \mu_A(y_i)}{r}\right), \tag{1}$$

$$TD = \mu_Q\left(\frac{\sum_{i=1}^{M}(\mu_A(y_i) \wedge \mu_B(y_i))}{\sum_{i=1}^{M}\mu_B(y_i)}\right). \tag{2}$$

Following the proposal of Zadeh's scalar cardinality-based method in (1) and (2), other methods were introduced alternatively based on fuzzy cardinality (Delgado *et al.*, 2000), mass-assignment (Martin and Yun, 2009), as well as representational level theory (Sánchez *et al.*, 2012). Refer to Boran *et al.* (2016) for a detailed analysis of the related literature.

This study presents a novel integration of LS with HIN modeling and trust-weighted relationships, building upon its prior applications in domains such as clinical analysis and behavioral assessment (e.g. Oztürk *et al.*, 2024). This combination facilitates the creation of interpretable summaries derived from intricate, multi-relational supply chain data—a modeling setting previously unexamined in earlier LS implementations.

The following subsection offers a comprehensive explanation of the technique, detailing the modeling and evaluation of LS over HINs.

3.2. *Linguistic Summarization Over Heterogeneous Information Networks*

An information network is formally defined as a directed graph $G = (V, E)$ with an object type mapping function $\tau : V \to N$ and a link type mapping function $\phi : E \to L$, where each object $v \in V$ belongs to one particular object type $\tau(v) \in N$, and each link $e \in E$ belongs to a particular relation type $\phi(e) \in L$. When the types of objects $|N| > 1$ or the types of links $|L| > 1$, the network is called HIN. A network schema is a meta template $T_G = (N, L)$, a directed graph defined over object types N, with relations from link types L. Since the paths between any two objects on T_G carry rich semantics, they constitute a vital characteristic of HINs. These paths, called metapaths, are defined on T_G, and denoted in the form of $N_1 \xrightarrow{L_1} N_2 \xrightarrow{L_2} \cdots \xrightarrow{L_l} N_{l+1}$, which defines a composite relation $L = L_1 \circ L_2 \circ \ldots \circ L_l$ between types $N_1, N_2, \ldots, N_{l+1}$, where $\circ$ denotes the composition operator on relations (Sun and Han, 2012).

The objects to be quantified belonged to a single group in a matrix data structure for the LS studies carried out to date. In contrast, the objects to be quantified belong to various groups in the network data structure. The fact that the number of objects to be quantified is more than one necessitates comprehensive procedures for assigning meaning to expressions to evaluate them. In this context, the sentences generated and evaluated can be examined in the following groups according to the number of nodes they contain. Single-node sentences are not included here as they can be evaluated with a basic LS approach.

- Two-node: It is a summary structure that can be created on the $(N \xrightarrow{L} N)$ metapath provided by a single link between two node types. A two-node summary is in the form "$Q_1\ A_1\ N_1\ B_1\ L_1\ Q_2\ A_2\ N_2\ [TD]$". There are three main components of the summary form: (i) two linguistic quantifiers Q_1 and Q_2 which quantify the nodes of N_1 and N_2, (ii) three linguistic summarizers A_1, A_2 and B_1, the first two summarizing the nodes of N_1 and N_2 and the last summarizing the link of L_1, (iii) truth degree of the summary TD. For example, "Most high trust customers purchase few special products at a high profit” can be a LS in two-node summary form. Here, Q_1 is “most”, Q_2 is “few”, A_1 is “high trust”, A_2 is “special”, B_1 is “high profit”, N_1 is the set of customers, N_2 is the set of products, and L_1 is the set of purchasing relations.

- Three-node: It is a summary structure that can be created on the ($N \xrightarrow{L} N \xrightarrow{L} N$) metapath provided by two links between three node types. A three-node summary is in the form “Q_1 A_1 N_1 B_1 L_1 N_2 B_2 L_2 Q_2 A_2 N_3 [*TD*]”. There are three main components of the summary form: (i) two linguistic quantifiers Q_1 and Q_2 which quantify the nodes of N_1 and N_3, (ii) four linguistic summarizers A_1, A_2, B_1 and B_2, the first two summarizing the nodes of N_1 and N_3 and the last two summarizing the links of L_1 and L_2, (iii) truth degree of the summary *TD*. For example, “About half high trust suppliers supply raw materials at high lead times, which are part of few bearing products at low costs” can be a LS in three-node summary form. Here, Q_1 is “about half”, Q_2 is “few”, A_1 is “high trust”, A_2 is “bearing”, B_1 is “high lead time”, B_2 is “low cost”, N_1 is the set of suppliers, N_2 is the set of raw materials, N_3 is the set of products, L_1 is the set of supplying relations, and L_2 is the set of being part of relations.

The meaning of such sentences, including multiple quantifiers and relations between objects, can be specified through polyadic quantifiers (Peters and Westerstahl, 2006; Szymanik, 2016). To work with polyadic quantification in natural language, it is necessary to describe it in monadic quantifiers that use Boolean combinations and operators like iteration. Formally, the iteration operator is defined as $It(Q, Q')[A, B, R] \Leftrightarrow Q[A, \{a \mid Q'[B, R_{(a)}]\}]$, where Q and Q' are generalized quantifiers, both of type $(1, 1)$, A and B are subsets of the universe, R is a binary relation over the universe, and $R_{(a)} = \{b \mid R(a, b)\}$. For example, “Most suppliers supply small quantities of raw materials” is a polyadic quantification, and iteration may be used to express the meaning in terms of its constituents. The “supply” is a relation between the sets of “suppliers” and “raw materials”. The sentence is true under one interpretation, if and only if a set contains most suppliers, each of whom supplies a little raw material. These studies also refer to nested quantifiers in Díaz-Hermida *et al.* (2003).

The key task in LS is to determine *TD*. Since the knowledge derived from HINs is not in the forms of type-I or type-II quantified sentences, absolute or relative quantifiers cannot be used to model it. Various research in natural language combines linguistic quantifiers with logical perspectives to investigate the structural forms of quantified sentences (Barwise and Cooper, 1981; Keenan, 1996; Keenan and Westerstahl, 1997). Glöckner (2000) has contributed to combining linguistics and logic by proposing a semi-fuzzy quantifier, the generalized form of a fuzzy linguistic quantifier. A semi-fuzzy quantifier has features from both the classical quantifier and the fuzzy quantifier and accepts crisp arguments like a classical quantifier and produces a *TD* in [0, 1] like a fuzzy quantifier (Díaz-Hermida and Bugarín, 2011).

Semi-fuzzy quantifiers are easy to define but hard to evaluate compared with fuzzy quantifiers. The transformation procedures eliminate the difficulty, whose domain is a semi-fuzzy quantifier, and the range is a fuzzy quantifier. These procedures are called Quantifier Fuzzification Mechanisms (QFMs) (Díaz-Hermida *et al.*, 2003; Glöckner, 2000).

A probabilistic QFM, F^I, is defined as in (3), where X_S is a fuzzy property for $s = 1, \dots, S$, $(X_s)_{\alpha_s}$ is α-cut of X_s, and Q is a semi-fuzzy quantifier of arity S.

$$F^I(Q)(X_1, \dots, X_s) = \int_0^1 \dots \int_0^1 Q\big((X_1)_{\alpha_1}, \dots, (X_s)_{\alpha_s}\big) d\alpha_1 \dots d\alpha_s. \tag{3}$$

If different α-cuts on $X_1, \dots, X_s$ are finite, F^I is defined as in (4), where $0 = \alpha_{s,m_s+1} < \alpha_{s,m_s} < \dots < \alpha_{s,1}$, $\alpha_{s,0} = 1$, $1 \leqslant s \leqslant S$, and $\mathfrak{m}(\alpha_{s,j}) = \alpha_{s,j} - \alpha_{s,j+1}$, $j = 0, 1, \dots, m_s$.

$$\begin{aligned} &F^I(Q)(X_1, \dots, X_S) \\ &\quad = \sum_{i_1=0}^{\mathfrak{m}_1} \dots \sum_{i_s=0}^{\mathfrak{m}_s} Q\big((X_1)_{\alpha_{1,i_1}}, \dots, (X_s)_{\alpha_{s,i_s}}\big)\mathfrak{m}(\alpha_{1,i_1}) \dots \mathfrak{m}(\alpha_{s,i_s}). \end{aligned} \tag{4}$$

Genç *et al.* (2020) proposed semi-fuzzy quantifiers to evaluate the summaries in the form of polyadic quantification. The semi-fuzzy iteration operator is defined as $It(Q, Q')[A, B, R] \Leftrightarrow Q[A, \{a \mid Q'[B, R_{(a)}]\}]$, where Q and Q' are semi-fuzzy quantifiers, A and B are the fuzzy subsets of the universe X for the attributes v_1 and v_2, R is a fuzzy relation, $R_{(x_i)} = \{x_j \mid R(x_i, x_j)\}$, and F is a QFM. When applied to QFM F^I for finite case, (5) provides the fuzzy value for *TD*.

$$\begin{aligned} &It\big(Q, Q'\big)[A, B, R] \\ &\quad \Leftrightarrow \sum_{i_3=0}^{\mathfrak{m}_3} \sum_{i_4=0}^{\mathfrak{m}_4} Q\Bigg(A_{\alpha_{3,i_3}} \sum_{i_1=0}^{\mathfrak{m}_1} \sum_{i_2=0}^{\mathfrak{m}_2} Q'(B_{\alpha_{1,i_1}}, R_{(x_i)_{\alpha_{2,i_2}}})\mathfrak{m}(\alpha_{1,i_1})\mathfrak{m}(\alpha_{2,i_2})\Bigg)_{\alpha_{4,i_4}} \mathfrak{m}(\alpha_{3,i_3})\mathfrak{m}(\alpha_{4,i_4}). \end{aligned} \tag{5}$$

3.3. *Interpretability of Linguistic Summaries*

In fuzzy quantification, there are three key research areas: (i) interpretation, (ii) reasoning, and (iii) summarization, the aim of which are to define clearly the meaning of fuzzy quantifiers, to extract more knowledge from rules employing fuzzy quantifiers, and to provide the best quantifying expressions in a particular circumstance, respectively (Glöckner, 2006). To increase the applicability of summarization to the real world, its linguistic quality needs to be increased. This is a matter of including interpretation in the summarization (Ramos-Soto and Pereira-Fariña, 2018).

Lesot *et al.* (2016) examined interpretability in two ways: on an individual sentence basis and a global basis for whole sentences. Each sentence should represent the data to be summarized. This level of representation is commonly measured by truth degree as well as Yager's informativeness measure (Yager, 1982), Kacprzyk's quality measures (Kacprzyk and Zadrozny, 2005), and Wu and Mendel's method (Wu and Mendel, 2011). Rank-based or score-based thresholding can identify high-quality sentences among a whole set of generated sentences (Pilarski, 2011). After generating all possible summaries, they are sorted in descending order of *TD*. The rank-based thresholding method extracts the top

k sentences, whereas the score-based method extracts sentences with a *TD* greater than a predetermined threshold.

On a global basis, interpretability can be evaluated in terms of consistency, non-redundancy and information (Lesot *et al.*, 2016). A summary set is consistent if the following two properties are satisfied: non-contradiction and double negation. The non-contradiction property asserts that two contradictory sentences have complementary truth degrees. For example, LS_1: "$Q\ B\ Y$s are/have A" is in contradiction with LS_2: "$Q\ B\ Y$s are/have $\neg A$" and LS_3: "$\neg Q\ B\ Y$s are/have A". Therefore, their truth degree should be complementary such that $1 - TD_{LS_1} = TD_{LS_2} = TD_{LS_3}$. The double negation property asserts that the *TD* should not be affected by applying two contradictions. For example, LS_4: "$\neg Q\ B\ Y$s are /have $\neg A$" is the double negation of LS_1. Therefore, their truth degrees should be equal such that $TD_{LS_1} = TD_{LS_4}$.

When different sentences with the same meaning are included in a sentence set, the unnecessary ones should be removed. Inclusion and similarity are examples of non-redundancy. Inclusion property asserts that if a sentence is included in another sentence in terms of quantifier or summarizer, the included one should be filtered out from the set. For example, LS_5: "$Q'\ B'\ Y$s are /have A'" is included in LS_1 if $Q' \subseteq Q$ or $A' \subseteq A$. Similarity property asserts that if two sentences' similarity values are greater than a predetermined value, one of the sentences should be removed. The similarity between LS_1 and LS_5 is calculated as in (6) (Wilbik and Keller, 2012).

$$\begin{aligned}&\operatorname{sim}(LS_1, LS_5)\\&\quad = \min\bigl(\operatorname{sim}\bigl(Q, Q'\bigr), \operatorname{sim}\bigl(B, B'\bigr), \operatorname{sim}\bigl(A, A'\bigr), \operatorname{sim}(TD_{LS_1}, TD_{LS_5})\bigr).\end{aligned} \tag{6}$$

Properties of sentence inference and underlying meaning convey the information to the user through the relations between sentences. Sentence inference is a matter of reasoning. For example, sentences of LS_6: "*All* $B\ Y$s are/have A" and LS_7: "*All* $A\ Y$s are/have C" form a new sentence LS_8: "*All* $B\ Y$s are/have C". The underlying meaning is achieved through the presummarizer B. For example, if all the sentences are in the form of LS_1 based on all possible Bs having a high *TD*, then all LS_1 sentences can be replaced by a single sentence LS_9: "$Q\ Y$s are/have A".

Ramos-Soto and Pereira-Fariña (2018) proposed a complementary approach to improve the interpretability of summary sets. It is emphasized how different components that make up LSs can improve interpretability. The first of these components is the summarizer. For example, while any system designer assigns fuzzy linguistic terms like "low-medium-high" to any attribute, a Natural Language Generation (NLG) expert assigns fuzzy linguistic terms like "cold-mild-hot" to an attribute of temperature or "short-average-tall" to an attribute of height. Assigning meaning to the summarizer by an NLG expert contributes to interpretability. The second LS component is the quantifier. For example, a sentence set containing LS_{10}: "*Most* Ys are/have A", LS_{11}: "*Few* Ys are/have B" and LS_{12}: "*Few* Ys are/have C" can form a new sentence LS_{13}: "Ys are/have A in general, B and C occasionally". Another example is a sentence set containing LS_{11}, LS_{12} and LS_{14}: "*Few* Ys are/have A" can form a new sentence LS_{15}: "Ys are/have very variable on attribute v_k".

The third LS component is *TD*. *TD* of LS can be used to measure how we are certain about the sentence. For example, let $TD_{LS_9} = 0.2$, then LS_9 can be replaced with LS_{16}: “There is little evidence of that Q Ys are/have A”. The last component is the sentence evaluation mechanism. As discussed earlier in the literature, scalar cardinality-based methods can be misleading as they do not distinguish between a large number of small membership degrees and a small number of large membership degrees (Boran *et al.*, 2016).

Both Lesot *et al.* (2016) and Ramos-Soto and Pereira-Fariña (2018) represent a starting idea about the interpretability of LS and encourage future researchers to perform an empirical study on interpretability. The real case study presented in the current study provides the first investigation into its applicability.

4. Methodology Overview

This section delineates the methodology framework employed to assess the impact of trust on SCNP, as illustrated in Fig. 2. The procedure involves a sequence of organized phases underpinned by a blend of diverse network modelling, fuzzy clustering, and LS. The suggested method facilitates the creation of interpretable, quantified assertions based on network-structured data.

Box 1 presents the input data as an HIN consisting of several node types (e.g. suppliers, products) and link types (e.g. supply, purchase). In addition to being a different type, every node and link may possess numerical or categorical properties.

In Box 2, numerical variables like profitability or cost are segmented into fuzzy clusters utilizing the Fuzzy C-Means (FCM) algorithm (Bezdek *et al.*, 1984). FCM was used to produce linguistic membership degrees through a data-driven approach. This enables fuzzy sets (e.g. “low”, “medium”, “high”) to accurately represent the data distribution, hence diminishing reliance on subjective, expert-defined thresholds. The resultant membership functions are therefore both comprehensible and empirically substantiated. Membership degrees to linguistic categories such as low, medium, and high are computed and recorded as fuzzy sets (e.g. $\mu_{\text{high}}(x_i)$), which then function as summarizers in the LS process.

In Box 3, metapaths that serve as the structural equivalent of LS statements are extracted. A metapath delineates a schema-level trajectory linking nodes via significant relationships, exemplified by Supplier–Supplies–Raw material. These pathways encapsulate semantically interpretable sequences inside the network. For instance, the metapath Supplier → Supplies → Raw material may substantiate a statement such as: “Most of the highly trusted suppliers supply sheet-metal raw materials”.

In Box 4, sentence structures involving two- and three-node metapaths are generated. Each sentence structure consists of a quantifier Q (e.g. most), a summarizer or qualifier A or B (e.g. high profitability), and a truth degree ($TD \in [0, 1]$).

In Box 5, these sentence structures are evaluated using iteration-based methods. The truth degree *TD* is calculated for each summary, based on fuzzy set operations and network semantics.

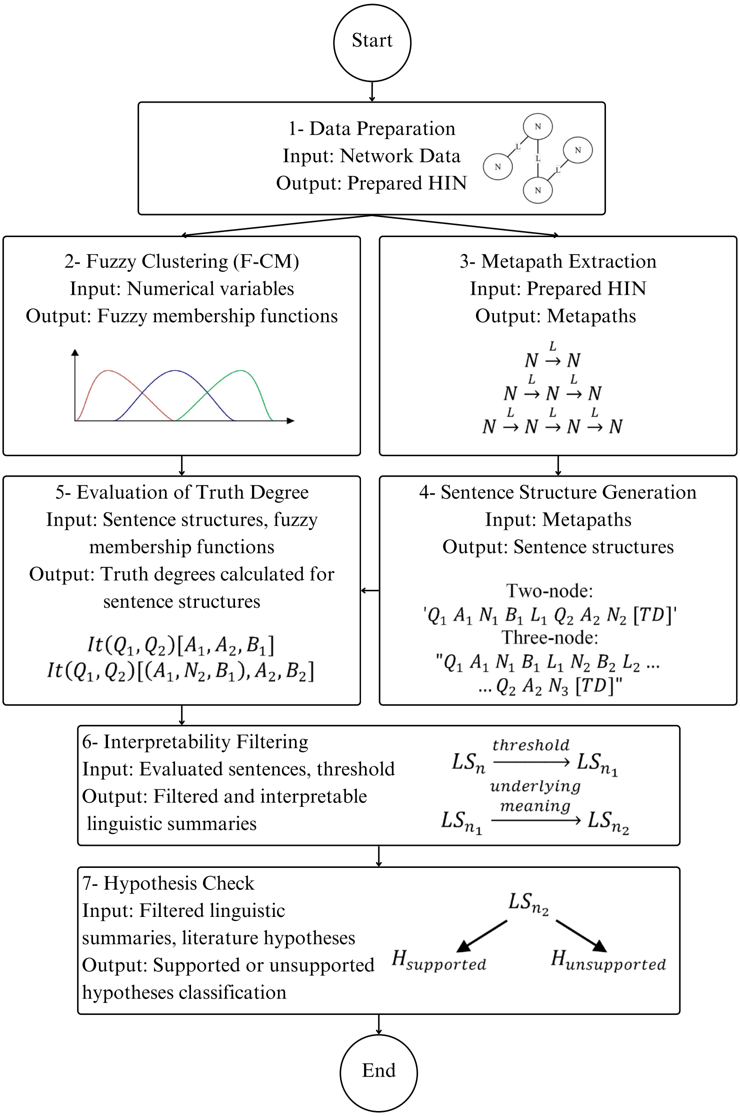

Fig. 2. Methodology overview diagram.

In Box 6, all possible combinations are generated and filtered using a predefined threshold τ (e.g. $TD < \tau$). Sentences with low truth degrees are discarded. The remaining summaries are processed for interpretability (e.g. consistency, similarity).

Finally, in Box 7, the validated LSs are compared with theoretical hypotheses from the literature. Each summary is then discussed as either supporting or contradicting existing claims, enabling a transparent and data-driven validation framework.

The chosen methodology was picked for its capacity to reconcile semantic interpretability with structural modelling efficacy. LS offers clear, comprehensible summaries for decision-makers, whereas FCM guarantees that linguistic concepts correspond to inherent groupings within the data. The HIN model facilitates multi-relational supply chain representations, allowing for phrase structures that incorporate trust-based pathways and performance-associated nodes. This combination was selected over alternative black-box or rule-based methodologies because it aligns with the data's complexity and the study's interpretability objectives.

The novelty of this methodology lies in the integration of fuzzy LS with HINs—an approach that enables interpretable reasoning over complex relational data, which is rarely achieved in existing supply chain analytics literature.

5. Case Study and Results on Supply Chain Network Data

SCNs are highly needed for analysis as they contain rich information from many stages between the raw material supplier and the customer who purchased the finished product. Most real-world problems are attempted to be solved in theory with several assumptions, detracting solutions from reality. Apart from assuming that nodes and relations are of the same kind, modelling SCNs as HINs is a technique that should be used since minimizing information losses. This section of the study offers modelling of rich and complicated supply network systems and the discovery of meaningful summaries suitable for human perception.

5.1. *Data Definition*

Relevant data of raw material suppliers and purchasers of finished products (customers) were collected from the Enterprise Resource Planning (ERP) system of a company by using the purchasing reports, sales reports, and bill of materials of significant items produced. The company is a global manufacturing firm producing steel parts not only for the automotive industry but also for various industries like home appliances and electric motors. The data set includes 214 nodes of four types and 466 links of three types. There are 31 customer nodes, 66 product nodes, 95 raw material nodes, and 22 supplier nodes among the 214 nodes. There are 72 links between customers and products, 95 links between suppliers and raw materials, and 299 links between products and raw materials. The supply network data and its network schema are presented in Fig. 3(a) and 3(b), respectively. Supplier node (SUP), raw material node (RAW), product node (PRD), and customer node (CUS) are different types of nodes in the data set. There is a purchase/purchased by link ($R1$) between the product and the customer, a supply/supplied by link ($R2$) between the supplier and the raw material, and a part of/consist of link ($R3$) between the raw material and the product. Network-level statistics of the supply network are presented in Table 2. For example, the largest distance between any two nodes in the SCN is 10. Since the relations are undirected, reciprocity is equal to 1. The average connection number of a node is equal to 4.355.

Table 3 and Table 4 present a comprehensive summary of the factors utilized in the HIN construction. Table 3 enumerates the definitions of attributes and categorical values

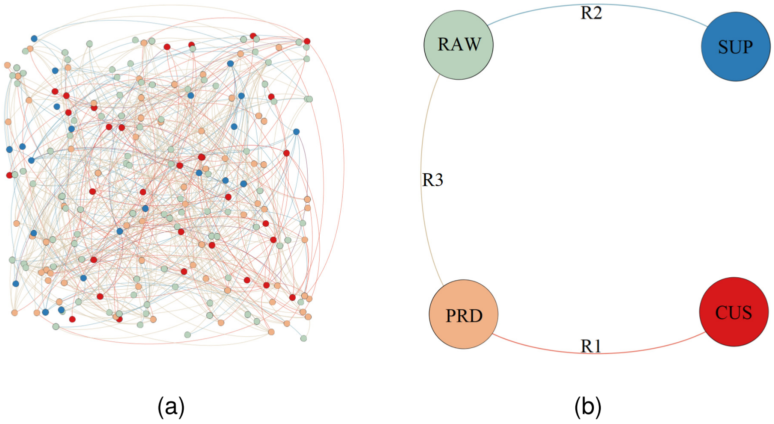

Fig. 3. (a) Supply network, (b) network schema of the supply network.

Table 2
Network level statistics of the supply network.

Feature	Value
Number of nodes	214
Number of links	466
Average degree	4.355
Diameter	10
Average path length	4.185
Reciprocity	1
Density	0.020
Clustering coefficient	0

for nodes (e.g. suppliers, products), whereas Table 4 delineates the qualities of linkages, including supplying, purchasing, etc. Trust and continuity variables of customer nodes, trust, quality, agility, and collaboration variables of supplier nodes are defined in fuzzy linguistic terms. Group, sector, application, and location variables of customer nodes, product group and status variables of product nodes, material type variable of raw material nodes, and competitive price and location variables of supplier nodes provide extra descriptive information about nodes and are defined categorically. Since the trust values obtained from the managers may contain personal judgment, the relationship between trust and other variables was verified with Bayesian networks. Bayesian networks obtained using Netica software (Netica, 2022) are given in Fig. 4 for customer node, and Fig. 5 for supplier node, respectively. Profitability, visibility, and volume variables of $R1$ links and lead time variable of $R2$ links are defined numerically in the data set. Quality, cost, and efficiency variables of $R3$ links are defined in fuzzy linguistic terms.

Since the impact of relationships in supply chains on SCNP has been a field of research that has gained attention in recent years, concepts such as trust and collaboration are gaining importance (Yang *et al.*, 2020; Zhou *et al.*, 2016; Li *et al.*, 2015; Demiray *et al.*, 2017). Beamon (1999) recommended that when measuring SCNP, it should examine

Table 3
Node variables and possible values used in the HIN.

Node type	Variable	Definition	Value
Customer	CustomerID	ID variable of customer nodes	⟨CUS001-CUS031⟩
	Trust	The level of willingness to take risks inherent in the relationship with the customer	⟨low, medium, high, very high⟩
	Continuity	The level of customer's regular orders	⟨low, medium, high⟩
	Group	Segment of the customer	⟨aftermarket, OEM⟩
	Sector	Industry of which the customer performs	⟨Automotive, Distribution, Manufacturing⟩
	Application	Final product of the customer to be sold to consumers	⟨Agriculture, Appliances, Auto, Other, Motor⟩
	Location	Domestic or international location of the customer	⟨domestic, export⟩
Product	ProductID	ID variable of product nodes	⟨PRD001-PRD066⟩
	Product Group	Type of the product	⟨Bearing, Ring, Roller⟩
	Status	Special or standard status of the product	⟨Special, Standard⟩
Raw material	RawmaterialID	ID variable of raw material nodes	⟨RAW001-RAW095⟩
	Material type	Type of the raw material	⟨Cage, Grease oil, Packaging, Rivet, Seal, Sheet metal, Steel bar, Tube⟩
Supplier	Supplier ID	ID variable of supplier nodes	⟨SUP001-SUP022⟩
	Trust	The level of willingness to take risks inherent in the relationship with the supplier	⟨low, medium, high⟩
	Quality	The level of superiority of the supplier	⟨standard, high, very high⟩
	Agility	The level of moving quick and easy action of the supplier against changes	⟨low, standard, high, very high⟩
	Collaboration	The level of supplier's willingness to co-operate	⟨low, medium, high⟩
	Competitive Price	Being competitive or not in terms of price level among alternative suppliers	⟨yes, no⟩
	Location	Domestic or international location of the supplier	⟨domestic, import⟩

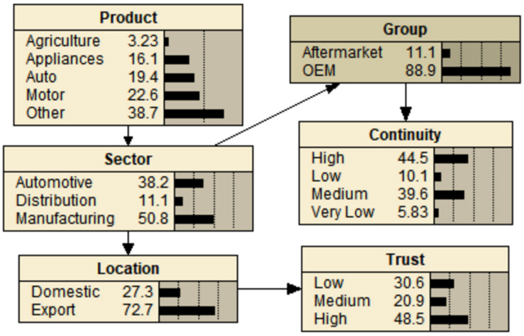

Fig. 4. Bayesian network for customer node variables.

Table 4
Link variables and possible values used in the HIN.

Link type	Variable	Definition	Value
R1 purchase/ purchased by	ID 1	ID variable of customer nodes	⟨CUS001-CUS031⟩
	ID 2	ID variable of product nodes	⟨PRD001-PRD066⟩
	Purchase	Variable indicating whether the specific product is purchased by the specific customer	⟨0,1⟩
	Profitability	Profitability level of trade for the Company	⟨low, medium, high⟩
	Visibility	How far the future requirements of the customer can be known by the Company	⟨low, medium, high⟩
	Volume	Sales quantity of the product to the customer	⟨low, medium, high⟩
R2 supply/ supplied by	ID 1	ID variable of supplier nodes	⟨SUP001-SUP022⟩
	ID 2	ID variable of raw material nodes	⟨RAW001-RAW095⟩
	Supply	Variable indicating whether the specific raw material is supplied by the specific supplier	⟨0,1⟩
	Lead time	Lead time of supplying	⟨low, medium, high⟩
R3 part of/ consist of	ID 1	ID variable of product nodes	⟨PRD001-PRD066⟩
	ID 2	ID variable of raw material nodes	⟨RAW001-RAW095⟩
	Part of	Variable indicating whether the raw material is a sub-part of the product	⟨0,1⟩
	Quality	Effect of the raw material on the quality of the product	⟨low, medium, high, very high⟩
	Cost	Effect of the raw material on the cost of the product	⟨low, medium, high, very high⟩
	Efficiency	Effect of the raw material on the efficiency of the production of the product	⟨low, medium, high⟩

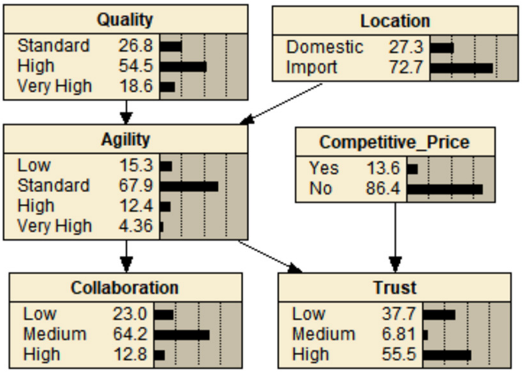

Fig. 5. Bayesian network for supplier node variables.

in terms of resources, outputs, and flexibility. Efficiency and cost variables of $R3$ links are performance indicators related to resources. Profitability and volume variables of $R1$ links, lead time variable of $R2$ links, and quality variable of $R3$ links are performance indicators related to outputs. The visibility variable of $R1$ links is a performance indicator related to flexibility. To sum up, we will focus on customer and supplier trust and their impact on SCNP.

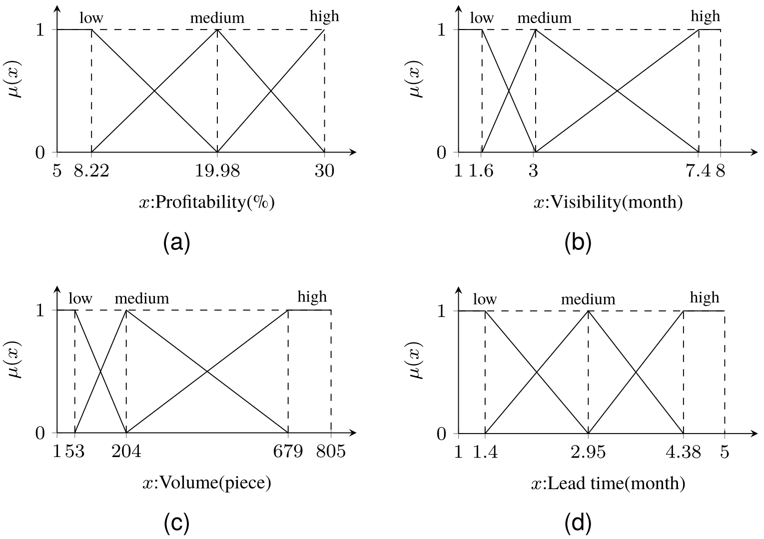

Fig. 6. Fuzzy sets of numerical variables (a) profitability, (b) visibility, (c) volume, and (d) lead time.

Table 5
The metapaths and summary forms.

Class	Metapaths	Summary forms
Two-node	$(CUS \xrightarrow{R_1} PRD)$	"Q_1 A_1 CUS A_2 R_1 Q_2 A_3 PRD".
	$(SUP \xrightarrow{R_2} RAW)$	"Q_1 A_1 SUP A_2 R_2 Q_2 A_3 RAW".
	$(RAW \xrightarrow{R_3} PRD)$	"Q_1 A_1 RAW A_2 R_3 Q_2 A_3 PRD".
Three-node	$(CUS \xrightarrow{R_1} PRD \xrightarrow{R_3} RAW)$	"Q_1 A_1 CUS A_2 R_1 PRD A_3 R_3 Q_2 A_4 RAW".
	$(SUP \xrightarrow{R_2} RAW \xrightarrow{R_3} PRD)$	"Q_1 A_1 SUP A_2 R_2 RAW A_3 R_3 Q_2 A_4 PRD".

The profitability, visibility, and volume variables of $R1$ links and the lead time variable of $R2$ links are clustered into three fuzzy sets by FCM algorithm (Bezdek *et al.*, 1984). Fuzzy sets extracted by the FCM algorithm are depicted in Fig. 6. Due to the fact that triangular membership functions are both simple and easy to comprehend, it was decided that they would be used. In addition, the terms "low", "medium", and "high" were selected in order to offer a balanced granularity that is both dependable and understandable (Pedrycz, 1994).

5.2. *Metapaths and Summary Forms*

There may be following metapaths classified based on the number of nodes in the dataset: two-node ($N \xrightarrow{L} N$) and three-node ($N \xrightarrow{L} N \xrightarrow{L} N$). The metapaths and corresponding summary forms of the dataset are shown in Table 5.

Table 6
LSs On $(CUS \overset{R_1}{\to} PRD)$ in which $A_2 =$ *highProfitability* and $Q_1 = most$.

#	Linguistic summary	*TD*
1	Most motor-producing customers purchase few bearing type products at a high profit.	1.00
2	Most motor-producing customers purchase few ring type products at a high profit.	1.00
3	Most motor-producing customers purchase few roller type products at a high profit.	1.00
4	Most motor-producing customers purchase few standard products at a high profit.	1.00
5	Most motor-producing customers purchase few special products at a high profit.	1.00
6	Most customers in automotive sector purchase few bearing type products at a high profit.	0.75
7	Most customers in automotive sector purchase few ring type products at a high profit.	0.75
8	Most customers in automotive sector purchase few roller type products at a high profit.	0.75
9	Most customers in automotive sector purchase few standard products at a high profit.	0.75
10	Most customers in automotive sector purchase few special products at a high profit.	0.75
11	Most high trust customers purchase few bearing type products at a high profit.	0.71
12	Most high trust customers purchase few ring type products at a high profit.	0.71
13	Most high trust customers purchase few roller type products at a high profit.	0.71
14	Most high trust customers purchase few standard products at a high profit.	0.71
15	Most high trust customers purchase few special products at a high profit.	0.71

5.3. *Generation, Evaluation and Discussion of Summaries*

LSs for all possible combinations of quantifiers and variables were generated and evaluated with a MATLAB code (MATLAB, 2017). A total of 218646 LSs were generated, 8550 of which pertained to $(CUS \overset{R_1}{\to} PRD)$, 4896 to $(CUS \overset{R_1}{\to} PRD)$, 4320 to $(RAW \overset{R_3}{\to} PRD)$, 164160 to $(CUS \overset{R_1}{\to} PRD \overset{R_3}{\to} RAW)$, and 36720 to $(SUP \overset{R_2}{\to} RAW \overset{R_3}{\to} PRD)$ metapaths. 4415 of the 218646 summaries have a *TD* greater than or equal to the threshold value of 0.7, a value considered reasonable. In the remaining summaries, important features for each metapath in Table 5 were examined. For example, an important feature in terms of ORganizational Performance (ORP) on $(CUS \overset{R_1}{\to} PRD)$ is high profitability. In the summary form "$Q_1\ A_1\ CUS\ A_2\ R_1\ Q_2\ A_3\ PRD$", let $A_2 =$ *highProfitability* and $Q_1 =$ *most*. The reduced 15 LSs and their *TD*s are shown in Table 6. Note that LSs #1-5 are generated for every A_3 of product from Table 3. Therefore, it is possible to interpret LSs #1-5 in a single LS as "Most motor-producing customers purchase few products at a high profit [1.00]" according to the underlying meaning of Lesot *et al.* (2016). *TD* of the interpreted LS is minimum of initial LSs. Similarly, LSs #6–10 and #11–15 can be interpreted as "Most customers in automotive sector purchase few products at a high profit [0.75]" and "Most high trust customers purchase few products at a high profit [0.71]", respectively.

Similarly, the initial LSs generated about important features on other metapaths from Table 5 are interpreted, and final LSs are presented in Table 7. High profitability, high visibility, and high volume are examined on $(CUS \overset{R_1}{\to} PRD)$. It has been found that customer features of application, sector, and trust are important for profitability, while product features are not. For high visibility, the customer features of the application and sector are important. For high volume, neither customer features nor product features are important. The low lead time was examined on $(SUP \overset{R_2}{\to} RAW)$. It has been found

Table 7
Final LSs About Important Features on Metapaths from Table 5.

Metapath	#	Linguistic summary	*TD*
$(CUS \overset{R_1}{\rightarrow} PRD)$	1	Most motor-producing customers purchase few products at a high profit.	1.00
	2	Most customers in automotive sector purchase few products at a high profit.	0.75
	3	Most high trust customers purchase few products at a high profit.	0.71
	4	About half auto-producing customers purchase few products at a high visibility.	0.86
	5	About half of the customers in automotive sector purchase few products at a high visibility except roller type.	0.78
	6	Very variable customers purchase very variable products at a high volume.	0.90
$(SUP \overset{R_2}{\rightarrow} RAW)$	7	Most very highly agile suppliers supply few raw materials at low lead times.	1.00
	8	Most very highly agile suppliers supply most seal type raw materials at low lead times.	0.80
$(RAW \overset{R_3}{\rightarrow} PRD)$	9	Most standard products consist of few raw materials at a high quality.	0.94
	10	Most bearing type products consist of few raw materials at a high quality.	0.91
	11	Most bearing type products consist of few raw materials at low costs.	1.00
	12	Most roller type products consist of few raw materials at low costs.	1.00
	13	Most standard products consist of few raw materials at low costs.	0.96
	14	Most product consist of few raw materials at a high efficiency.	1.00
$(CUS \overset{R_1}{\rightarrow} PRD \overset{R_3}{\rightarrow} RAW)$	15	Very variable customers purchase products which consist of very variable raw materials at a medium quality.	0.81
$(SUP \overset{R_2}{\rightarrow} RAW \overset{R_3}{\rightarrow} PRD)$	16	Very variable suppliers supply raw materials at high lead times which consist of very variable products at very high costs.	0.74

that the supplier's agility level is important for lead time, while raw material features are not. High quality, low cost, and high efficiency were examined on $(RAW \overset{R_3}{\rightarrow} PRD)$. It has been found that status and group features are important, while raw material features are not. For low cost, the product features of status and group are important. For high efficiency, neither product features nor raw material features are important. As there are fewer LSs that pass the threshold on metapaths $(CUS \overset{R_1}{\rightarrow} PRD \overset{R_3}{\rightarrow} RAW)$ and $(SUP \overset{R_2}{\rightarrow} RAW \overset{R_3}{\rightarrow} PRD)$, interpreted summaries are also limited. According to them, any features of object types are not meaningful in terms of quality, lead time, and cost.

In addition to these, the results on trust relationships are also examined in detail to com-

Table 8
Customer Trust and ORP.

#	Linguistic summary	*TD*
ORP_1	Most high trust customers purchase few products at a high profit.	0.71
ORP_2	About half high trust customers purchase few products at a high visibility.	0.69
ORP_3	Few high trust customers purchase few products at a high volume.	0.96

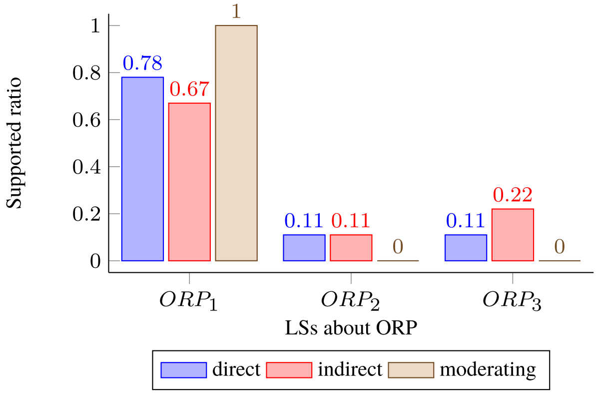

Fig. 7. The ratio of hypotheses supported by ORP_{1-3}.

pare with the related works in Section 2. As mentioned earlier, profitability, visibility, and sales are measures of ORP. The relation between trust and these measures is investigated on $(CUS \overset{R_1}{\to} PRD)$. The results $(ORP_1 - ORP_3)$ in terms of customer trust and ORP are presented in Table 8. When the direct effect of trust on ORP is examined, ORP_1 supports seven of the nine hypotheses (Akhtar and Khan, 2015; Yang *et al.*, 2020; Rodriguez-Lopez *et al.*, 2017; Zhou *et al.*, 2016; Kim and Chai, 2022; Akhtar *et al.*, 2023; Narayanan *et al.*, 2015), ORP_2 supports one of the nine hypotheses (Michalski *et al.*, 2014), and ORP_3 supports one of the nine hypotheses (Arora *et al.*, 2021). Although some studies do not examine whether the trust affects SCNP or not, these are the kinds of studies from which we can make this inference indirectly. When the indirect effect of trust on ORP is examined, ORP_1 supports six of the nine hypotheses (Wu *et al.*, 2014; Youn *et al.*, 2013; Narwane *et al.*, 2023; Owot *et al.*, 2023; Wang *et al.*, 2023; Mutonyi *et al.*, 2016), ORP_2 supports one of the nine hypotheses (Fang *et al.* (2024)), and ORP_3 supports two of the nine hypotheses (Yang, 2014; Susanty *et al.*, 2017). In another study, it was argued that trust plays a moderating role in SCNP (Li *et al.*, 2015). While ORP_1 supports this hypothesis, ORP_2 and ORP_3 do not. The support ratio for hypotheses regarding the trust's direct, indirect, and moderating effect with ORP_{1-3} are shown in Fig. 7 with histograms. It is seen that trust is the most effective on profitability among ORP measures.

Lead time, efficiency, cost, and quality are measures of OPP. The relation between trust and these measures is studied on the metapaths of $(SUP \overset{R_2}{\to} RAW)$, $(CUS \overset{R_1}{\to} PRD \overset{R_3}{\to} RAW)$ and $(SUP \overset{R_2}{\to} RAW \overset{R_3}{\to} PRD)$. The results $(OPP_1 - OPP_7)$ in terms of supplier

Table 9
Customer Trust and OPP.

#	Linguistic summary	*TD*
OPP_1	Few high trust suppliers supply few raw materials at low lead times.	0.99
OPP_2	Most high trust customers purchase products which consist of few raw materials at a high efficiency.	0.02
OPP_3	Most high trust customers purchase products which consist of few raw materials at low costs.	0.02
OPP_4	Most high trust customers purchase products which consist of few raw materials at a high quality.	0.02
OPP_5	About half high trust suppliers supply raw materials which are part of few products at a high efficiency.	0.39
OPP_6	About half of the high trust suppliers supply raw materials which are part of few products at low costs.	0.52
OPP_7	Most high trust suppliers supply raw materials which are part of few products at a high quality.	0.04

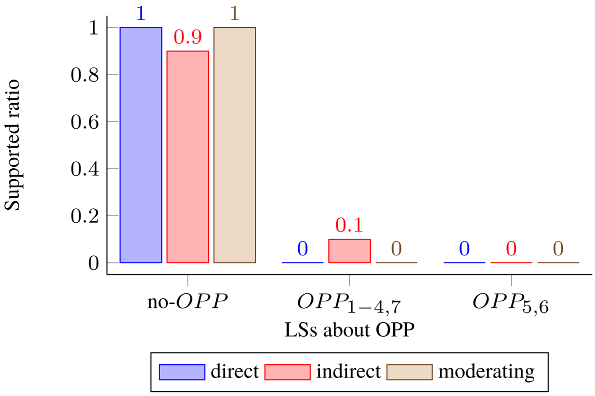

Fig. 8. The ratio of hypotheses supported by OPP_{1-7}.

and customer trust and OPP are presented in Table 9. When the direct effect of trust on OPP is examined, no study was found to support OPP_{1-7}. When the indirect effect of trust on OPP is examined, $OPP_{1-4,7}$ support one of the ten hypotheses (Susanty *et al.*, 2017). No study was found to support or oppose $OPP_{5,6}$. When the moderating effect of trust on OPP is examined, no study was found to support OPP_{1-7}. The support ratio for hypotheses regarding trust's direct, indirect, and moderating effect with OPP_{1-7} are shown in Fig. 8 with histograms. It is seen that the trust is almost not effective on OPP.

LSs in Table 9 can be reinterpreted in terms of *TD*. LSs with a *TD* close to zero were combined with the expression "There is almost no evidence" and made independent of the *TD*. Similarly, LSs with a *TD* close to 0.50 were combined with the expression "There is some evidence" and the ones close to 1 were combined with the expression "There is strong evidence". The reinterpreted LSs are presented in Table 10.

In summary, for the interpretability in LS, we first applied a score-based threshold on an individual basis. Then, we examined interpretability in terms of information conveyed

Table 10
Reinterpreted LSs of Table 9.

#	Linguistic summary
OPP_1	There is strong evidence that few high trust suppliers supply few raw materials at low lead times.
OPP_2	There is almost no evidence that most high trust customers purchase products which consist of few raw materials at a high efficiency.
OPP_3	There is almost no evidence that most high trust customers purchase products which consist of few raw materials at low costs.
OPP_4	There is almost no evidence that most high trust customers purchase products which consist of few raw materials at a high quality.
OPP_5	There is some evidence that about half high trust suppliers supply raw materials which are part of few products at a high efficiency.
OPP_6	There is some evidence that about half high trust suppliers supply raw materials which are part of few products at low costs.
OPP_7	There is almost no evidence that most high trust suppliers supply raw materials which are part of few products at a high quality.

on a global basis. A group of sentences was expressed in a single sentence due to the underlying meaning feature. Meanwhile, non-redundancy was also ensured as the first sentences in the just mentioned group were removed. We also reinterpreted the LSs in terms of quantifier and *TD*. Thus, we have applied most of the interpretability measures mentioned in Section 3.3 on our real case study.

6. Discussion

This study presents an innovative amalgamation of LS and HIN modelling to examine the impact of trust on SCNP. The findings indicate that consumer trust significantly influences ORP metrics, including profitability and volume, although its impact on OPP is little. These findings largely validate prior literature indicating a favourable association between trust and performance, while also revealing discrepancies that may stem from contextual variables or data-driven analysis.

This study provides an objective and measurable approach to hypothesis verification by calculating the truth degrees of language summaries, in contrast to typical studies reliant on surveys and perceived associations. This data-driven yet comprehensible method connects intricate analytics with management insight, fostering transparency and trust in decision-making.

Furthermore, the suggested method facilitates digital transformation objectives by enabling firms to uncover concealed patterns in supply chain data through a comprehensible manner. This is especially crucial for non-technical users, allowing them to participate in network-level assessments and strategic development.

A principal advantage of the technique is its capacity to manage heterogeneous, multi-type relational data without reducing information to simplified models. Nevertheless, the results must be understood in light of the study's limitations, which include its dependence on a singular real-world dataset from the automotive industry and the subjective nature of trust evaluations. Future research may extend this framework to various industries, implement dynamic trust modelling, or integrate real-time data.

The method improves the interpretability, traceability, and utility of supply chain analytics within the framework of digital transformation.

Several significant discoveries resulted from the analysis:

- Trust relationships, when structurally represented within an HIN, can be statistically associated with supply chain performance via LSs.
- Customer-side trust exhibits a more pronounced correlation with ORP indicators, such as profitability and sales volume, than with operational metrics like delivery time or responsiveness.
- Not all predicted impacts of trust identified in the literature were substantiated; specifically, certain operational advantages were tenuous or inconsistent.
- The methodology effectively validated literature-derived hypotheses in a clear and interpretable manner, hence improving decision support in trust-sensitive supply networks.
- The application of LSs within a trust-enhanced HIN facilitated comprehensible insights from intricate relational data, connecting data analytics with management reasoning.

The insights of this study apply to both academic and industrial sectors. Industrial supply chain managers and analysts can use the proposed methodology to assess how network trust affects organizational and operational performance using enterprise-level data (e.g. ERP systems). In complicated supply chains including automotive, home appliances, and electrical equipment, reliable coordination is crucial. A reproducible, data-driven strategy that can be applied to multiple businesses and circumstances helps academics investigate trust and performance. Thus, the findings inform management decision-making and promote supply chain trust concept.

Notwithstanding the merits of the suggested methodology, many limitations must be recognized. The study relies on a singular real-world dataset from the automobile sector, thereby constraining the generalizability of the results. Secondly, trust levels were deduced rather than actually measured, which may impact their accuracy. The linguistic labels and fuzzy clusters employed in the summarization process depend on parameter configurations that may involve a degree of subjectivity. The model is presently static and fails to account for the temporal dynamics of trust relationships across time. These constraints highlight significant prospects for future endeavours, encompassing the incorporation of dynamic trust modelling, real-time data streams, and adaptive fuzzy systems across diverse fields.

7. Conclusion

This paper set out to determine the effects of trust on SCNP with LS over HIN. In this study, SCN was modelled as an HIN for the first time. The lack of information caused by excluding object types such as products and raw materials in SCN has been eliminated. With the advantage of HIN, the relationships were revealed from the interactions between node attributes (i.e. trust level) and link attributes (i.e. lead time). A systematic literature review was done, and hypotheses for the direct, indirect, and moderating effect of trust on OPP and ORP were extracted. An application was performed with a quantitative dataset in the automotive industry to eliminate the shortcomings of existing studies based on personal perceptions. While the summary forms containing nested quantified nodes were expressed by iteration-based polyadic quantification in line with linguistic logic, they were evaluated by semi-fuzzy quantifier-based method. The study concluded that consumer trust had a greater influence on ORP than OPP. Furthermore, the proposed methodology effectively tested or challenged existing ideas in a data-driven and interpretable fashion. The findings indicate that trust modelling in supply chains is enhanced by both structural representation and linguistic interpretation, presenting a promising avenue for future research and managerial applications. Given the growing focus on digital transformation within supply chains, the suggested method enhances this framework by providing a clear and interpretable approach for examining trust-related dynamics. This facilitates more intelligent, data-driven decisions while maintaining clarity, which is essential in multi-stakeholder contexts.

The results show that customer trust effectively affects ORP for profitability and volume measure. The research has also shown that neither customer nor supplier trust is effective on OPP. The results indicate that trust throughout the supply chain is consistently correlated with enhanced SCNP, especially regarding profitability indicators at organizational level. This validates literature-derived hypotheses and illustrates the utility of LS for evaluating performance-related trends in diverse networks. Although findings are the results obtained by evaluating with a quantitative method, they are limited because they belong only to one company operating in the automotive sector. Furthermore, the results are encouraging, it is crucial to acknowledge that the present solution is constrained in scope and presumes static, inferred trust connections. Subsequent research may improve this approach by integrating real-time trust data, examining further industries, and optimizing the linguistic parameterization process. It should be noted that different outcomes could be obtained when the research is repeated with additional variables for other sectors. Further research might be carried out in another sector.

7.1. *Lessons Learned*

This study produced numerous significant insights for both research and practice:

- Structural modelling of trust yields more profound insights than mere subjective evaluations.
- LS connects intricate material with comprehensibility.
- Empirical assessment can contest assumptions commonly accepted in the literature.
- Hybrid methodologies that integrate fuzzy logic with network models can improve explainable analytics inside supply chain environments.

Nomenclature

SCM	Supply Chain Management
SCN	Supply Chain Network
HIN	Heterogeneous Information Network
LS	Linguistic Summarization/Summary
SCNP	Supply Chain Network Performance
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
OPP	OPerational Performance
ORP	ORganizational Performance
QFM	Quantifier Fuzzification Mechanism
NLG	Natural Language Generation
FCM	Fuzzy C-Means
ERP	Enterprise Resource Planning

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