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Impact of Enterprise Supply Chain Digitalization on Cost of Debt: A Four-Flows Perspective Analysis Using Explainable Machine Learning Methodology

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Abstract: Rising costs, complex supply chain management, and stringent regulations have created significant financial burdens on business sustainability, calling for new and rapid strategies to help enterprises transform. Supply chain digitalization (SCD) has emerged as a promising approach in the context of digitalization and globalization, with the potential to reduce an enterprise's debt costs. Developing a strategic framework for SCD that effectively reduces the cost of debt (CoD) has become a key academic challenge, critical for ensuring business sustainability. To this end, under the perspective of four flows, SCD is deconstructed into four distinct features: logistics flow digitalization (*LFD*), product flow digitalization (*PFD*), information flow digitalization (*IFD*), and capital flow digitalization (*CFD*). To precisely measure the four SCD features and the dependent variable, *COD*, publicly available data from Chinese listed manufacturing enterprises such as annual report texts and financial statement data are collected, and various data mining technologies are also used to conduct data measurement and data processing. To comprehensively investigate the impact pattern of SCD on CoD, we employed the explainable machine learning methodology for data analysis. This methodology involved in-depth data discussions, cross-validation utilizing a series of machine learning models, and the utilization of Shapley additive explanations (SHAP) to explain the results generated by the models. To conduct sensitivity analysis, permutation feature importance (PFI) and partial dependence plots (PDPs) were also incorporated as supplementary explanatory methods, providing additional insights into the model's explainability. Through the aforementioned research processes, the following findings are obtained: SCD can play a role in reducing CoD, but the effects of different SCD features are not exactly the same. Among the four SCD features, *LFD*, *PFD*, and *IFD* have the potential to significantly reduce CoD, with *PFD* having the most substantial impact, followed by *LFD* and *IFD*. In contrast, *CFD* has a relatively weak impact, and its role is challenging to discern. These findings provide significant guidance for enterprises in furthering their digitalization and supply chain development, helping them optimize SCD strategies more accurately to reduce CoD.

Keywords: supply chain digitalization; cost of debt; machine learning; Shapley additive explanations; business sustainability

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1. Introduction

Sustainability, defined as development that "meets the needs of the present without compromising the ability of future generations to meet their own needs" [1], aims to ensure intergenerational equity. Similarly, business sustainability refers to a firm's ability to meet short-term financial needs without compromising future ones [2]. If the possibility of jeopardizing a company's future operations exists, business sustainability becomes untenable. Today, debt financing is an essential part of corporate capital structure, and minimizing the cost of debt (CoD) is critical for maintaining cost-effective and sustainable operations [3–5]. KPMG [6] highlighted that improving resource efficiency and cutting costs are viable paths to business sustainability, making it crucial to examine sustainability through the lens of debt costs. Meanwhile, manufacturing enterprises, as vital drivers of economic growth, job creation, and technological innovation, play a critical role in the global economy's sustainable development. However, with the acceleration of globalization and intensifying market competition, manufacturing enterprises face increasing financial pressures [7]. High fixed asset investments, rising raw material costs, complex supply chain management, and increasingly stringent environmental regulations all contribute to the financial burden on companies and affect their business sustainability. In this context, finding innovative solutions to alleviate financial pressures, which can help ensure the sustainable economic development of enterprises, has become a key focus for both academia and industry. Furthermore, with globalization becoming an irreversible trend, companies are compelled to prioritize the development and management of their supply chains, which has sparked discussions among researchers on various factors affecting supply chains [8]. Despite the close links between supply chains and corporate financing behavior—particularly in terms of funding and debt sources from upstream and downstream partners—debt financing remains a critical focus, as debt continues to be the primary source of funding for enterprises. With the rapid advancement of digital technologies, the processes, structures, and management of supply chains have undergone reevaluation and transformation [9], giving rise to a new supply chain paradigm—supply chain digitalization (SCD) [10]. SCD represents a shift towards digital supply chains, where companies leverage digital technologies to establish an integrated, self-optimizing supply chain system that proactively responds to dynamic market changes and improves the likelihood of achieving organizational goals [11–13]. In view of the advantages from SCD, especially after experiencing shocks such as city closures and logistics interruptions under the background of COVID-19, enterprises have increasingly emphasized it, leading to a surge of interest in transforming traditional supply chains into digitalization formats, becoming a prominent topic in operational management and sustainable development [8,14–18]. As enterprises increasingly integrate digitalization elements into their supply chain management, committing to supply chain development and investing in SCD have become essential, inevitably impacting the enterprise's financing capability.

As the result of the deep integration of digital technologies with supply chain management, SCD offers a new solution for manufacturing enterprises [19]. SCD optimizes resource allocation and process management across all stages of the supply chain by incorporating technologies such as big data, the Internet of Things (IoT), and artificial intelligence (AI). This allows companies to manage inventory more efficiently, improve cash flow, reduce procurement costs, enhance their ability to respond to risks, and support sustainable development. Particularly in an era marked by frequent uncertainties, SCD enhances the resilience and transparency of supply chains, enabling enterprises to quickly respond to market fluctuations and reduce the financial pressures arising from unexpected events, thus helping enterprises move forward steadily [20]. SCD not only alleviates the financial challenges faced by manufacturing enterprises but also helps establish a long-term mechanism for sustainable development. By accurately managing energy and resource consumption, SCD promotes the development of green supply chains, aiding companies in achieving energy conservation, emission reduction, and compliance with environmental standards [21]. Meanwhile, digitalized supply chains provide data-driven support for business model innovation, enabling enterprises to explore emerging models such as smart manufacturing and enhance their long-term competitiveness. Therefore, exploring how SCD can effectively mitigate financial pressures in manufacturing enterprises and contribute to their sustainable development holds significant theoretical and practical value.

In academia, CoD has evolved into a relatively mature research topic and has been extensively scrutinized from various perspectives. Prior research have elucidated the impact of internal factors such as ESG actions and performance [22], and external elements like environment regulatory penalties on CoD [23]. Collectively, these findings highlight the significant connection between corporate environmental responsibility and CoD. However, even in the era of robust growth in digital economy, only a few studies have investigated the implications of relevant aspects of manufacturing enterprise digitalization for CoD [24,25], let alone delving into SCD, which is the cross-concept of digitalization and supply chain. The concept of SCD interweaves digitalization with supply chain dynamics and remains an academic space for exploration. Intriguingly, SCD has demonstrated its potential to significantly enhance enterprise agility and competitive advantage [26]. This advancement bolsters solvency, inevitably piquing the interest of internal managers and external debt investors, potentially further affecting the company's CoD, while also influencing the company's sustainable development [27]. Therefore, it is essential for the academic community to explore how enterprises can strategically embrace SCD to reduce CoD, as analyzing its impact from the perspective of digital transformation and cost-efficient operations is key to understanding sustainable development.

From the technical background of the research methodology, business managers in the digital economy are confronted with an overwhelming amount of data from various sources, yet their cognitive resources remain limited. When making decisions based on vast amounts of data, information overload can easily lead to errors in judgment [28]. Therefore, it is crucial to analyze relationships between factors based on limited cognitive resources. For the sustainable economic development of enterprises, in addition to structured operational management data, a series of textual data also plays a vital role. Based on this, it is possible to extract a set of variables or features from textual data using existing knowledge and analyze how they influence the outcome variables. Moreover, multidimensional data-based research ideas have become more and more important [29,30], which means that a certain research object can be analyzed and discussed using multidimensional data. According to this context, it is crucial to guide practitioners on which SCD features to prioritize or delay to effectively reduce CoD. However, the traditional model-driven econometric methodology commonly employed in management research struggles to establish reliable causal inferences, particularly for events with one effect and multiple causes [31]. This limitation makes it challenging to explore the specific developmental model. In this regard, machine learning offers a compelling data mining and analysis approach due to its speed, accuracy, and adaptability to multidimensional data and can effectively uncover relationships between variables [32–34]. This enables tasks to be completed with fewer resources, helping decision-makers conserve various types of resources while achieving precise analysis, thus supporting sustainable development of organization. This approach is better suited for discussing SCD development patterns and is helpful in analyzing which types of SCD can effectively reduce CoD. Nevertheless, machine learning has its limitations about its explainability, so it becomes necessary to introduce methods from other fields to explain the output results of machine learning models [35–37]. This can assist researchers in more effectively observing and understanding the impact of development strategies like SCD on other variables such as CoD.

To sum up, the primary objective of this research is to explore the relationship between SCD and CoD, with a specific focus is on finding what pattern of SCD can help reduce CoD. To achieve this, two key research questions need to be addressed:

- How can enterprises comprehensively and conveniently understand their SCD? This research focuses on the topic of "How to develop SCD", which requires the investigation and deconstruction of SCD. Existing research indicates that the investigation of SCD is predominantly conducted using questionnaire methods. While this approach enables a more comprehensive analysis of SCD, it also comes with certain drawbacks, including high investigation costs, challenges in obtaining the required data, and difficulties in reproducing the experiment [38]. In this regard, drawing on previous research related to supply chain management [39–41] and considering the insights from the "2022 China Supply Chain Digitalization Upgrade Industry Research Report" [42], it has been suggested that the investigation and analysis of enterprise supply chains should encompass four aspects: logistics flow, product flow, information flow, and capital flow (referred to as a perspective named "four flows"). Furthermore, we also use text mining algorithms to quantify these four features [41]. The unique advantage of this perspective lies in its applicability to horizontal studies, as opposed to traditional vertical research that primarily focuses on suppliers and customers. Moreover, this perspective facilitates the decomposition of SCD into four distinct features, making it more convenient for researchers to perform quantitative analysis and aiding managers in making well-informed decisions.

- How can an enterprise strategically develop its SCD to effectively reduce CoD? Based on the decomposition of SCD into four features from the four flows perspective, the analysis will focus on identifying which specific features deserve more attention for reduce CoD. In other words, the objective is to help enterprises identify a viable strategy for developing SCD to reduce CoD. To achieve this, the research employs the explainable machine learning methodology to investigate the influence of SCD and its features on the reduction in CoD. This involves the use of advanced and reliable machine learning models, accompanied by explanations for the results using specific explanatory methods [35–37]. Additionally, alternative explanatory methods are employed for sensitivity analysis to further ensure the robustness of the results. Ultimately, the findings from this analysis will provide valuable insights for enterprises aiming to optimize their SCD strategies to reduce CoD, thereby ensuring both financial health and sustainable development.

The remaining sections of this paper are organized as follows: Section 2 presents the current research status of SCD and CoD. Section 3 outlines the research preparation, which including the research framework, and variables or features. Section 4 describes the dataset, and the analysis results based on an explainable machine learning methodology, followed by a theoretical discussion of these results. Finally, Section 5 provides a comprehensive summary of this research, offers theoretical guidance for decision-makers, and illustrates the limitations of our work.

2. Related Literature

This research focuses on how enterprises should strategically develop SCD to effectively reduce CoD. Hence, it becomes imperative to provide a succinct review of the pertinent literature related to SCD and CoD, so as to have a rough understanding of the current research status of the research objects. Subsequently, an exploration of the influence logic of SCD on CoD is conducted based on the existing literature. Meanwhile, it is essential to present and describe the background and overarching content of the research paradigm employed in this research.

2.1. The Existing Literature on the Focus of CoD

As enterprises expand their production scale and maintain daily operations, they often rely on debt financing. Therefore, how to obtain debt funds at the lowest possible cost has been a concern in both theoretical and practical fields, gradually making CoD a relative mature research object. Typically, CoD serves as the dependent variable in research. As Table 1 shows, the existing research discusses how to influence CoD from both internal and external influencing factors.

From the perspective of internal influencing factors, researchers have predominantly directed their attention towards the influence of corporate governance and corporate strategy on CoD. Examining corporate ownership strategies, Borisova and Borisova [4] investigated the potential impact of government ownership on debt costs using samples from both fully and partially privatized enterprises. They discovered a negative correlation between government ownership and credit spreads, a proxy for debt costs. Lugo [43], adopting a lending perspective of banks, explored how control exercised by insiders with ownership affects CoD, revealing a U-shaped relationship. Analyzing the impact of single strategic transformation decisions in response to external environments, Sun et al. [24]

conducted research on data from Chinese listed enterprises, revealing that digitalization transformation significantly reduces CoD. Considering a multi-dimensional strategic perspective, Ye et al. [3] delved into the domain of diversified strategies, finding that a greater disparity (strategic deviation) between a company's strategy and its industry norm results in elevated debt financing costs. Additionally, when considering personnel arrangements within enterprises, Liu et al. [44] identified socially responsible CEOs based on their charitable donations. They explored how this CEO type affects CoD and uncovered a negative correlation. Collectively, this area of discussion offers practical insights for enterprises to emulate and implement, thereby enriching the overall discourse.

Table 1. The existing literature on the focus of CoD.

Category	Authors & Studies	Key Findings
Internal Factors	Borisova [4]	Government ownership negatively impacts CoD (credit spreads).
	Lugo [43]	U-shaped relationship between insider ownership control and CoD.
	Sun et al. [24]	Digital transformation significantly reduces CoD for Chinese enterprises.
	Ye et al. [3]	Strategic deviation from industry norms increases debt financing costs.
	Liu et al. [44]	CEOs identified through charitable donations are negatively correlated with CoD.
	Apergis [22]	Positive ESG performance can reduce CoD by improving corporate reputation and reducing financial risks.
External Factors	Ding et al. [23]	Environmental administrative penalties increase CoD.
	Houston et al. [45]	Strong government ties reduce bank loan costs for corporations.
	Gong et al. [46]	Regulatory penalties increase CoD due to higher default and information risks.
	Gao et al. [47]	Increased media coverage inversely affects CoD by reducing bond yield spreads and enhancing investor awareness.
	Almaghrabi [48]	COVID-19 has created industry-specific impacts on CoD, with greater uncertainty in financial markets leading to increased CoD.
	Lan [49], Wu [50]	The rapid advancement of digital technologies challenges traditional financial practices, influencing CoD through process automation and transparency.
Future Directions	The impact of SCD on CoD has yet to be fully explored, even though SCD has become a major focus in academic research.	

Factors influencing CoD are not confined solely to the internal dynamics of the enterprise, external factors also hold an equally critical position, capable of inducing variations. On the one hand, the relationship between government and enterprises can lead to CoD fluctuations. Ding et al. [23] found that environmental administrative penalties imposed on companies significantly increase their CoD in the following year. Houston et al. [45] found that corporations with directors holding favorable government–enterprise ties often foster harmonious bank–enterprise relations, resulting in significantly reduced costs of bank loans. On the other hand, punitive actions by external regulatory bodies can elevate CoD. Gong et al. [46] utilized Chinese listed enterprises as their sample, collecting financial data and relevant information from announcements by the China Securities Regulatory Commission. Their research revealed that regulatory punishment announcements lead to an increase in the cost of debt. Moreover, sanctions resulting from adverse events can increase default and information risks, leading creditors to demand higher debt costs [23].

In addition, with the incessant evolution of digitalization technologies, the rapid and widespread dissemination of information via media has escalated. Should a company attract media coverage, it can trigger certain reactions that may reverberate in CoD. For instance, Gao et al. [47] postulate an inverse correlation between media coverage and CoD. To be specific, media reports mitigate information friction, enhance investor awareness, narrow bond yield spreads, and alleviate the complexities of corporate debt financing. While external factors are undoubtedly important, they are less susceptible to direct control by enterprises. Research in this aspect can provide direct policy recommendations for external stakeholders like governments, yet for enterprises, it will likely shift their focus and resources towards internal development strategies. In this study, external factors are more likely to be presented as a contextual background, whereas internal factors, by comparison, will be the focal point of our attention.

In summary, as a relatively mature academic research topic, scholars' current focus on the factors influencing CoD is not limited to those listed above. Additional factors include ESG performance [22] and the impact of COVID-19 [48]. Notably, the present time is marked by a flourishing digital economy, where digitalization technology is progressively permeating enterprises, presenting certain challenges to their financial practices [49,50]. Hence, when analyzing the influencing factors of CoD, discussions on digitalization are indispensable. Particularly, amid the ever-clear globalization trends, enterprises are also presented with analogous digitalization demands for supply chain management [10]. In this context, enterprises need to engage in a series of internal transformation activities in response to external environments, aligning their supply chain development with digitalization. Therefore, the discussion on the patterns of SCD's impact on CoD becomes exceptionally valuable.

2.2. The Current Research Status of SCD

As digitalization transformation becomes a core strategic focus for organizations [51], integrating digitalization-related elements into enterprise supply chain management is becoming increasingly essential, leading to the emergence of SCD. However, SCD remains a relatively novel research subject, contributing to a lack of empirical measurement within both academic and practical domains. As shown in Table 2, only a limited number of studies have been able to furnish empirical evidence for the impact of SCD, with many primarily focusing on the establishment of theoretical frameworks.

From limited quantitative research, it is evident that the prevailing emphasis on SCD predominantly revolves around strategic transformation steps that enterprises can potentially adopt. As a result, much of the discussion revolves around its impact on other variables. For instance, Nasiri et al. [26] conducted research using cross-sectional random sampling data from small and medium-sized enterprises in Finland, revealing the positive role of SCD in enhancing a company's competitive advantage. Zouari et al. [52] interviewed 300 managers in the field of supply chain management, employing factor analysis and Structural Equation Modeling (SEM) to discover that SCD promotes supply chain resilience. Zhao et al. [18] formulated a theoretical framework "supply chain digitalization $\rightarrow$ supply chain resilience $\rightarrow$ supply chain performance" and conducted research based on data from 210 Chinese manufacturing enterprises, suggesting that the application of SCD can ultimately enhance supply chain resilience. However, these studies predominantly relied on survey questionnaires, offering insights into the developmental patterns of only a limited number of enterprises. Furthermore, such data are not readily available to other researchers, making result replication a challenge. Shen et al. [21] recognized that by accurately managing energy and resource consumption, SCD promotes the development of green supply chains, helping companies achieve energy savings, emission reductions, and compliance with environmental standards. Chen et al. [41] investigates the impact of digital supply chain on sustainable trade credit provision, using data from Chinese listed firms between 2008 and 2020. By employing the TF-IDF algorithm to measure digital supply chain activities, the study finds a positive association between the digital supply chain and trade credit provision, particularly highlighting the roles of logistics, product, and information dimensions. Therefore, it becomes imperative to explore the use of publicly accessible enterprise data for conducting SCD-related research.

Table 2. The current research status of SCD.

Category	Authors & Studies	Key Findings
Empirical Research on SCD	Nasiri et al. [26]	Positive role of SCD in enhancing a company's competitive advantage.
	Zouari et al. [52]	SCD promotes supply chain resilience.
	Zhao et al. [18]	Developed a framework: "supply chain digitalization → supply chain resilience → supply chain performance", showing how SCD improves resilience and performance.
	Shen et al. [21]	SCD helps companies promote the development of green supply chains and achieve efficient energy management.
	Chen et al. [41]	SCD positively influences sustainable trade credit provision for Chinese listed firms, with logistics, product, and information flows showing significant impacts.
Conceptual models on SCD	Saberi et al. [53]	Proposed a conceptual framework distinguishing between inter-organizational and intra-organizational supply chain transformations under SCD.
	Du et al. [40]	Presented a multi-dimensional framework focusing on managing digitalized flows (information, logistics, and capital flow) within SCD to improve practical applications.
	Garay-Rondero et al. [54]	Developed a conceptual model of SCD for Industry 4.0, integrating artificial intelligence, cloud computing, machine learning, and digital platforms into supply chain management.
	Khan et al. [55]	Identified key factors promoting organizational performance via SCD, including supplier configuration, supply chain responsiveness, and information sharing, creating a comprehensive SCD framework for enhancing logistics, production, and information management.
Future Directions	1. Solely focusing on theoretical models lacks practical application. 2. Current studies often address single aspects of SCD, limiting comprehensive understanding. 3. Increasing empirical research is necessary.	

From a theoretical perspective, current research has strived to construct conceptual models related to SCD. For instance, Saberi et al. [53], while constructing a conceptual model, noted that SCD should be recognized and categorized into two evolutionary forms: inter-organizational and intra-organizational. This implies that SCD encompasses not only the implementation of digitalization technologies but also the integration of the supply chain and organizational structural changes according to market dynamics [13]. Moreover, Du et al. [40] argued that enterprises should pay attention to managing various aspects of supply chain digitalization such as information flow, logistics, and capital flow to enhance the practical applicability of the SCD conceptual model. Building upon authoritative prior research, Garay-Rondero et al. [54] developed an SCD conceptual model for the Industry 4.0 era, encompassing the application of digitalization-related elements such as artificial intelligence, cloud technologies, machine learning, and digitalization social media within supply chains. Khan et al. [55], using enterprises in Pakistan as a case study, identified key factors for enhancing organizational performance through SCD and analyzed their interplay. Notably, their focus included aspects of the supply chain such as supplier configuration, supply chain responsiveness, and information sharing, which impact logistics, production, and information within the supply chain. These studies have constructed a more comprehensive and multidimensional SCD conceptual model, encompassing various levels from within organizations to inter-organizational contexts. These models not only include the application of digitalization technologies but also emphasize integrated supply chains and transformative organizational structures. Through these studies, we have gained a better understanding of the potential impact of SCD on both organizational performance and supply chain operations, providing more accurate guidance for further research.

Taking a comprehensive view of these research, several noteworthy points emerge. Firstly, while the theoretical models developed manage to encompass multiple dimensions, these conceptual frameworks often tend to be complex and lack practical operability, making them less suitable for practical applications or empirical studies. Furthermore, focusing solely on theoretical discussions may not fully meet the demands of practical implementation, warranting the inclusion of more empirical evidence to further advance SCD research. Secondly, the majority of quantitative studies measure SCD from a single aspect, with few adopting a comprehensive approach that considers various facets of SCD. This limitation might hinder addressing the question of "how to develop SCD". Additionally, existing SCD measurement methods heavily rely on survey questionnaire data, which can be challenging for other researchers to obtain, and the results obtained from such studies might be difficult to reproduce.

2.3. Can SCD Affect CoD?

In fact, a theoretical deduction based on the existing literature can also reveal valuable insights into the impact pattern of SCD on CoD. For instance, the development of SCD can enhance various aspects of corporate performance, demonstrating the excellent growth potential [23]. When viewed through the lens of signaling theory [56], this growth potential could enhance the perception of foreign debt investors, resulting in a reduction in CoD. Additionally, the development of SCD in enterprises is inherently linked to the extensive adoption of digitalization technology. This application situation has the potential to enhance corporate transparency by enabling greater information disclosure to external parties [57]. It renders the company's development more comprehensible to external debt stakeholders and enhances their investment efficiency [58], thus further highlighting the significance of SCD in reducing CoD.

All in all, there is a possibility that SCD may have an impact on CoD, but the pattern of such an impact is currently unclear, and it may be difficult to provide suggestions for enterprises to prioritize which aspects of SCD can reduce CoD. In other words, while some theoretical support has been obtained, existing research on the impact relationship between SCD and CoD is still in its infancy, primarily due to the lack of empirical evidence to strengthen the logical connection. Therefore, further research in this area is necessary to offer more comprehensive decision support and guidance for enterprises.

2.4. Summary: How to Explore the Impact of SCD on CoD

In addition to the theoretical derivation of the relationship between SCD and CoD, existing empirical research on this relationship is still in its infancy. However, traditional empirical research often follows the research paradigm of "hypothesize-then-verify". This paradigm may not fully meet our research goals and address the research questions. Therefore, a relatively novel research paradigm, namely a data-driven paradigm with the explainable machine learning methodology, may be suited to explore the impact pattern of SCD on CoD.

In the digital economy, the business environment has become more dynamic and complex, leading to a shift towards multidimensional investigation of research subjects [29,30]. Consequently, it might be necessary to transition from the traditional 'hypothesize–verify' validation mindset to a 'data-driven' research paradigm [38]. This adaptation reflects the interaction between theoretical development and business practices, employing nonlinear thinking to address complex internal and external contexts. The conventional approach of attributing one variable's influence to another might fall short of this requirement [31]. Given these considerations, existing research has already started incorporating robust machine learning models into management studies. This move aims to derive more precise data analysis results from multidimensional and complex enterprise datasets [36]. Although machine learning models possess powerful data analysis capabilities, they may introduce a "black box effect" due to their inherent nature [32–34]. To address this, it is advisable to employ an explanatory method to assist researchers in understanding model outputs, thus developing an explainable machine learning methodology [35–38].

According to Cognitive Load Theory, the human working memory capacity is inherently limited. When the amount of information exceeds our cognitive resources, cognitive overload may occur, leading to reduced decision-making efficiency [28]. Some scholars have recognized that if a series of problems can be effectively solved using fewer information sources while keeping the decision-making process within cognitive limits, it would be significant. For instance, Dzyabura et al. [37] developed a model to predict return rates using only clothing image data and analyzed the effects of different image attributes (or features) on the model's output, providing valuable insights for the marketing field. However, when it comes to corporate operations, much of the relevant information is reflected in textual and language-based content. For the analysis of SCD and CoD, focusing on text data may be more appropriate. In the realm of text analysis, Pekar et al. [59] only used text data to extract topics and analyze key themes influencing crowdfunding performance, along with their direction of impact. These themes were generated using unsupervised algorithms, which can provide relatively objective results. However, such unsupervised methods may not be optimal for fields like corporate finance and supply chain management, where practical experience and domain knowledge are critical. In these domains, selecting key themes based on existing research and industry insights is often a more effective strategy.

When addressing the question of "how to develop SCD to reduce CoD", incorporating supervised text mining methods and explainable machine learning methodologies for multidimensional, data-driven analysis could be highly beneficial. By relying solely on text data, this approach helps prevent information overload, ensuring the decision-making process stays within cognitive limits. This integration not only aligns with the rapidly evolving technological landscape but also allows for more significant contributions to both theory and practice.

3. Research Preparation

This section presents the research framework, the specific concept and calculation methods for various features of SCD under the perspective of the four flows, and the approach to calculate CoD in this research. These components aim to provide an understanding of how the explainable machine learning methodology is employed to analyze the impact of SCD and its four flows features on CoD, preparing for subsequent research.

3.1. Research Framework

A research framework has been devised to thoroughly analyze and comprehend the influence of enterprise SCD on CoD from the perspective of the four flows. As shown in Figure 1, the research is divided into two interconnected sections, with each section comprising its own specific steps. CoD stands for the cost of debt, while *COD* refers to the variable format of CoD in this research.

In Section 1, the primary focus is on data acquisition and data preprocessing.

Data acquisition. The measurement of the key variables, CoD and SCD features, requires different approaches due to their distinct nature. For CoD, as a well-established concept in corporate finance, it is typically measured using financial data. The measurement approach for CoD is derived from existing research and practices to ensure its reliability and consistency. On the other hand, SCD is a relatively novel concept with a unique measurement method. To comprehensively capture its essence, SCD is decomposed into four features based on the perspective of the four flows [39–42]. These features are then quantified using text mining algorithms that analyze the SCD content present in annual reports. In order to meet the criteria for reliable feature measurement and ensure data availability and experimental repeatability, the data sources encompass the annual reports of Chinese listed manufacturing enterprises, along with financial data that encompass interest expenses. These original data provide the necessary foundation for exploring and analyzing the four SCD features and CoD in the research.

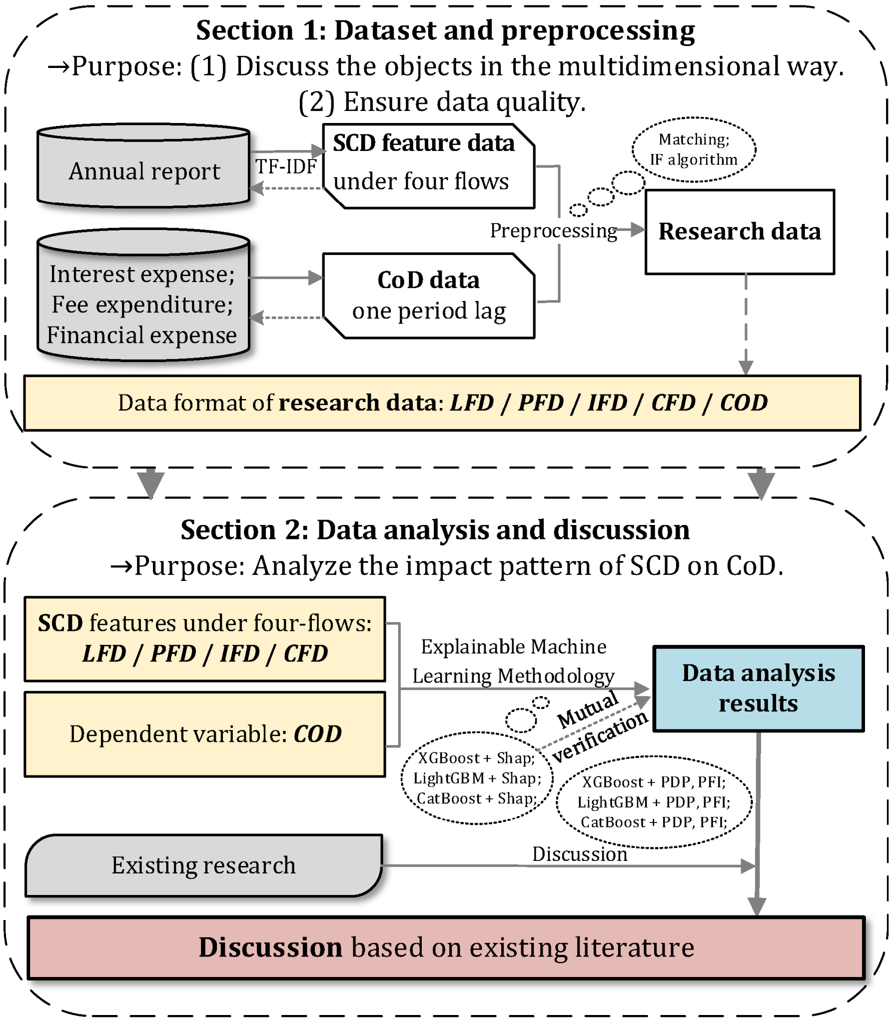

Figure 1. Research framework.

Data preprocessing. This part mainly includes data matching and data cleaning. In data matching, a time lag of one period is applied to the CoD data relative to the SCD features data to ensure the validity and value of the results. This time lag helps capture potential causal relationships between SCD and CoD. Additionally, to address the potential presence of inaccurate or unreliable data in the collected dataset, data cleaning involves preprocessing using the Isolation Forest (IF) algorithm. This algorithm is a swift outlier detection method based on ensemble idea, featuring linear time complexity and high precision. Its implementation effectively enhances the quality and integrity of the overall data [60]. Based on the aforementioned processes, a dataset with quality assurance, referred to as research data, can be obtained. The research data are divided into two parts: SCD feature data and CoD data. SCD feature data serve as explanatory variables, representing different aspects of supply chain digitalization. CoD data serves as the explained variable (or object feature), representing the cost of debt incurred by the enterprises. Moreover, the research data maintain the same format as the original data, enabling descriptive statistics to understand the distribution of the features.

Section 2 focuses on examining the impact of SCD on CoD in enterprises. To accomplish this objective, the research adopts the explainable machine learning methodology employed by Ha [35], Weng et al. [36], and Dzyabura et al. [37]. Moreover, the data analysis results will be discussed in conjunction with existing research to enhance the theoretical validity of them.

Data Analysis. To accomplish the research objectives, the research data are integrated into the explainable machine learning methodology. The core machine learning algorithm of these methodology consists of eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Categorical Boosting (CatBoost). Simultaneously using these algorithms can foster cross-validation and ensure the credibility of data analysis results, while also facilitating sensitivity analysis. This establishes a robust foundation for elucidating the influence relationship between SCD and CoD. However, these models may exhibit a "black box effect". To address this, we refer to the methodology used in existing studies [35–37,61–63] and employ Shapley additive explanations (SHAPs) to illuminate the models' output results, thereby enhancing our comprehension of how SCD influences CoD. SHAP values are derived from nonlinear machine learning models, which are capable of fully capturing complex multidimensional relationships from this type of model. This method can also reveal the direction and magnitude of a feature's impact on CoD, thereby reflecting the linear influence pattern between the feature and the outcome variable. In addition, to conduct an extra sensitivity analysis, we also incorporated permutation feature importance (PFI) and partial dependence plots (PDPs) as supplementary explanatory methods to reanalyze the model's explainability. Finally, a comparison of SHAPs across various models is conducted to further validate consistency and bolster confidence in the analysis of the impact of SCD on CoD.

Result discussion. Previous research on explainable machine learning methods has predominantly focused on the results of data analysis, a practice that frequently results in an inadequate grasp of the underlying reasons. To address this, we plan to further discuss the data analysis outcomes in conjunction with existing research on SCD and CoD, aiming to overcome the theoretical inadequacies inherent in this research paradigm. This part of the work provides a solid basis for drawing conclusions and deriving management implications in subsequent analyses, particularly in terms of promoting business sustainability by aligning cost reduction strategies with sustainable practices.

3.2. Variable Description

Sweller [28] points out that the human working memory is limited, and it is important to avoid a reduction in decision-making efficiency caused by overly complex tasks or overwhelming information. In this regard, achieving decision support and providing recommendations using only a single data source would be of great significance. This approach not only enhances the decision-making efficiency but also contributes to business sustainability by optimizing resource usage and minimizing waste in the decision-making process. Additionally, although unsupervised algorithms can objectively generate themes from text data, they may not be optimal for fields such as corporate finance and supply chain management. In these areas, practical experience and domain knowledge are essential for selecting key themes. Based on this understanding, this study builds upon the work of Chen et al. [41], focusing on the supervised extraction of SCD features from the text of listed companies' annual reports, particularly through the four flows framework (logistics flow, product flow, information flow, and capital flow). Furthermore, explainable machine learning methods are employed to analyze the potential impact of these text-based features on the CoD, providing a deeper understanding of their relationship and aiding managers in making effective decisions under limited cognitive resources. The following section will introduce the variables and their corresponding measurement methods in detail.

3.2.1. The Features of Supply Chain Digitalization

As mentioned in the literature review, the development trajectory of SCD encompasses two evolutionary forms: inter-organizational and intra-organizational [53]. This entails not only the implementation of digitalization technology but also the process of integrating supply chains and transforming organizational structures according to market dynamics [11–13]. Based on the above understanding, the discussion of SCD should focus on two main aspects: the internal organization (technical dimension) and the external market (market dimension). On one hand, today's enterprises are in the stage of Industry 4.0, which must rely on digitalization technologies such as cloud computing, the Internet of Things (IoT), and blockchain to drive the advancement of their supply chains towards intelligence and digitalization [64]. On the other hand, SCD encompasses four market objectives: logistics flow monitoring, product flow development, information flow sharing, and capital flow tracing [39,40]. These objectives correspond to the four directions of supply chain development that enterprises can prioritize in the future. These four goals are simply referred to as the "four flows" in this research. Therefore, when discussing SCD, it is crucial to consider both the technological dimension of digitalization and the market dimension under the perspective of the four flows of supply chain. Accordingly, SCD can be decomposed into four distinct features: logistical flow digitalization (*LFD*), product flow digitalization (*PFD*), information flow digitalization (*IFD*), and capital flow digitalization (*CFD*). Each SCD feature strictly reflects a specific aspect of the digital transformation in a company's supply chain. These features encompass various digitalization development directions, such as IoT, intelligent production, logistics monitoring, and electronic payments. Furthermore, this decomposition offers a multidimensional framework for analyzing the research subject, making it well suited for machine learning-based data analysis in subsequent stages. It also aids decision-makers in making well-informed choices, especially when operating under the constraints of limited cognitive resources. According to Chen et al. [41], the following mainly explains the connotations of these four features:

- *LFD* refers to utilizing technologies like IoT, smart logistics, and digitalization warehousing to optimize logistics resource allocation, offer personalized services, enable visual management, and reduce risks. This improves logistics efficiency, quality, and reliability in the supply chain.
- *PFD* refers to utilizing technologies such as automatic production, cloud manufacturing and 3D printing for smart product design, automated production, and quality control. It enables differentiated production and enhances product traceability and quality for the entities in the supply chain.
- *IFD* refers to utilizing digitalization tools like information centers, cloud services, and platforms for efficient information collection, processing, and sharing. This reduces redundancy, enhances accuracy, and improves communication within the supply chain.
- *CFD* refers to utilizing digitalization financial methods like mobile payments and digitalization currencies and online transaction for convenient, real-time fund management. This boosts fund utilization and profitability and improves the credit rating of the enterprise in the supply chain.

Since SCD belongs to the digitization within the academic scope, the idea of measuring it or its features can draw upon pertinent research on enterprise digitization. Currently, there are some measurement ideas available for assessing enterprise digitalization [65–67]. Among these, an approach involves leveraging text mining techniques to extract digitalization information from the annual reports of enterprises using specific digitalization keywords [66]. The annual report serves not only as a legal requirement for listed enterprises but also as an opportunity to convey their financial health, promote their culture and brand, and engage with a full spectrum of stakeholders. It provides a comprehensive overview of an enterprise's development trajectory over a year [68], so the analysis method based on the annual report is suitable for horizontally analyzing the enterprise's digitalization progress and related aspects, which is consistent with the four flows perspective of SCD in the research idea. Therefore, it is feasible to develop a measurement idea for SCD based on text mining techniques with annual reports and relevant keywords (annual report–keywords).

The approach of "annual report–keywords" is actually a supervised text mining method, so the TF-IDF algorithm can be used as the methodological component for this approach. TF-IDF is a weighted algorithm that calculates the supervised weights of keywords in a given text corpus, which can mitigate the overestimation of common word weights and the underestimation of keyword weights inherent in the term frequency word frequency calculation method. Therefore, one of the main tasks in this research is to identify the relevant keywords associated with SCD and the annual reports of enterprises. Specifically, due to the varying information captured by each feature, the selected keywords differ accordingly. For this, we refer to the research of Chen et al. [41] and use the keywords of SCD under the perspective of four flows and the keywords of digitalization technology provided by them. Moreover, it is crucial to include keywords related to digitalization-related technologies like intelligent systems to ensure a balanced emphasis on both technological and market dimensions of the enterprise. When calculating *LFD*, *PFD*, *IFD*, and *CFD*, it is essential to input the keywords for the four marketing orientations (four flows) as well as the keywords related to digitalization technology orientation into the TF-IDF algorithm to calculate the corresponding weights. In order to reflect the equal emphasis on the market and technology, it is necessary to further multiply the obtained weight of every flow by the weight of the digitalization technology. The calculation method for every feature is shown in Formula (1):

$$SCD\_feature_i = flow\_weight_i \times tech\_weight \tag{1}$$

where $SCD\_feature_i$ ($feature_i$ refers to *LFD*, *PFD*, *IFD*, and *CFD* in turn) means the final result calculated by each feature, $flow\_weight_i$ is the weight of the keywords of each feature calculated by TF-IDF and summed up, and $tech\_weight$ is the weight of the digitalization keywords calculated by TF-IDF and summed up.

3.2.2. Cost of Debt

COD is the variable expression form for CoD, which is also a relatively mature research object at present and the core dependent variable in this research. It primarily focuses on the price that enterprises need to pay to acquire funds, which directly affects their financing capability and is crucial to their business sustainability. In view of debt financing entailing more than just interest expenses, such as additional financial costs like bank fees [69], the measurement approach for *COD* is based on existing research with appropriate enhancements [3,70,71]. First, financial expense items such as interest expense, fee expenditure, and other financial expenses are picked up from a company's financial details for a certain period (usually a year). Subsequently, these items are aggregated to obtain the total debt financial cost. Finally, the total debt financial cost is divided by the sum of short-term and long-term debt of the business to obtain the *COD*. This calculation method can address the issue of incomparability in CoD calculation results arising from variations in the total debt levels among enterprises. Presented as formula (2), the calculation idea for *COD* is as follows:

$$COD = \frac{Int\_Exp + Fee\_Exp + Other\_Exp}{Short\_Debt + Long\_Debt} \tag{2}$$

where *COD* refers to the debt financing cost of a company in a certain year. *Int_Exp*, *Fee_Exp*, and *Other_Exp* are the interest expense, fee expenditure, and other financial expense, respectively. These items together reflect the specific cost that the company needs to pay for financing and borrowing in this year. *Short_Debt* and *Long_Debt* are the short-term debt and long-term debt of the company in this year, respectively. The summation of these item reflecting how much financing they can actually obtain.

4. Dataset, Analysis, and Discussion

This section provides details about the acquisition and preprocessing of the research data. Additionally, it also presents the analytical results obtained through the application of explainable machine learning methodology. Finally, these results are discussed in conjunction with the existing literature to ensure their theoretical significance.

4.1. Dataset

To acquire a comprehensive dataset (research data), we employed a series of processes encompassing data acquisition and data preprocessing. Elaborating on these processes can provide researchers with a holistic comprehension of the data landscape, thereby aiding the analysis in subsequent research phases. It is important to highlight that the research data intentionally exclude variables unrelated to SCD and CoD. This choice stems from the recognition that the introduction of irrelevant variables may introduce bias into the modeling and prediction processes, ultimately hindering the comprehensive exploration of data relationships. Moreover, using only a few sources of information to draw conclusions can reduce the cognitive load of decision-making and help avoid decision errors caused by information overload.

4.1.1. Data Acquisition

Considering the measurement requirements for SCD features and CoD and acknowledging that supply chain management is particularly critical for manufacturing enterprises, the data for this study are derived from publicly available information about Chinese manufacturing listed companies, including annual reports, interest expenses, financial expenses, and other relevant data. According to Zhao et al. [18] and Lu et al. [72], SCD is particularly prominent in manufacturing industries, where companies increasingly adopt digital management practices to enhance supply chain resilience and performance. As major players in the industry, listed companies not only have greater access to resources for implementing digital supply chain strategies but also are required by regulatory authorities to disclose comprehensive financial and operational data. This ensures that the data used in this study are representative of broader trends in supply chain digitalization within China's manufacturing sector.

The direct correlation between financial data and the extent of supply chain digitalization is established through advanced text mining techniques, which extract key digitalization indicators from annual reports, such as *LFD*, *PFD*, and *IFD*. These indicators reflect the companies' efforts in digitizing various aspects of their supply chains, and they are directly linked to the many financial behaviors and outcomes, let alone to CoD [41]. In addition, the use of these data aligns with the principles of data availability and experimental repeatability. Annual report data are obtained through automated web crawling from CNINFO (http://www.cninfo.com.cn/ (accessed on 20 July 2022)), while financial data are sourced from the reputable CSMAR financial database (https://data.csmar.com/ (accessed on 20 July 2022)), both of which are widely recognized and utilized by researchers studying Chinese listed enterprises. Furthermore, the dataset spans from 2008 to 2021, a period that captures the rapid growth in digitalization and informatization efforts, while also covering a relatively complete economic cycle.

4.1.2. Data Preprocessing and Descriptive Statistics

In this part, the primary tasks involve data matching and outlier removing. Firstly, After data acquisition, the dataset undergoes a matching process. Specifically, we perform double-index matching based on stock code and accounting periods and also introduce a lag for *COD* with respect to the first stage of SCD features. This lag treatment ensures that the research results obtained have sufficient logical coherence. At this stage, a total of 20,637 sample data points have been obtained. Secondly, after considering the potential impact of outliers on data analysis and the need to ensure data quality, the IF algorithm was applied to identify and remove any abnormal data points. This process resulted in a final dataset containing 19,277 sample data points, which is referred to as the research data. This elimination of outliers aims to improve the reliability and accuracy of the analysis results, enabling a clearer representation of the underlying patterns in the data. Finally, considering that the SCD features and CoD values obtained from the above calculation steps are relatively small, they are simultaneously multiplied by 10,000 times. This amplification operation of the data enables researchers to gain a comprehensive understanding of the dataset without affecting the modeling process and the interpretation of machine learning model results.

After the above work, descriptive statistical results about research data were obtained, as shown in Table 3. Referring to this table, it becomes apparent that many enterprises have achieved modest progress in SCD development. In terms of specific characteristics, *LFD* aligns more closely with traditional supply chain concepts and may be highly valued by enterprises. *PFD* and *IFD* follow, but they exhibit a wider variance, implying untapped potential within the data. *CFD*, on the other hand, displays the smallest variance, with most values being close to zero. This is likely because *CFD* represents a relatively novel SCD feature that may receive less attention from enterprises. Based on the SCD features and *COD*, there seems to be a certain impact pattern between the data distribution of various SCD features on *COD*, so there may be data relationships between them that are worth further exploration.

Table 3. Descriptive statistics for the research data.

	LFD	***PFD***	***IFD***	***CFD***	***COD***
mean	0.0621	0.1287	0.1317	0.0002	191.6762
std	0.2406	0.4096	0.3096	0.0067	152.0809
min	0.0000	0.0000	0.0000	0.0000	0.0000
50%	0.0000	0.0000	0.0162	0.0000	169.7250
75%	0.0200	0.0625	0.1060	0.0000	294.0340
max	4.1329	5.5103	3.4030	0.5250	662.4810

4.2. Data Analysis

To acquire insights into the impact of SCD and its features from the four flows perspective on CoD, the research data were loaded in a series of machine learning algorithms (XGBoost, LightGBM, and CatBoost) to build a model, and the model output results are explained by SHAPs. Additionally, for the sensitivity analysis, other interpretative methods, including PDPs and PFI, were also employed as replacements. Specifically, this process consists of two main components: model setting and explainable analysis.

4.2.1. Model Setting

The work of model setting includes data setting and model setting. Firstly, this research primarily focuses on understanding the impact pattern of SCD on CoD, so all available data were included in all machine learning models without partitioning the dataset. In addition, to ensure a fair and consistent comparison of the three models and considering that the *COD* is numerical rather than discrete, the learning rate of all three models was uniformly set to 0.1 and the loss function was selected as the squared loss function. Other parameters were kept using their default values. In short, both data setting and model setting should adhere to a unified standard for the models used. This standardization is essential because, in subsequent research, it is necessary to compare the output results of different models to validate their credibility.

4.2.2. Explainable Analysis

Based on the specified settings, the research data were input into the XGBoost, LightGBM, and CatBoost, and their model outputs were explained using the SHAPs. Correspondingly, the visualized explanations are presented in Figures 2–4 and Table 4. Upon closer examination, it becomes evident that these figures are categorized into left and right segments: (1) The left graph represents the global explanation and is composed of the entire sample data and their corresponding SHAP values. It visually displays the distribution of the SHAP value contributions of all SCD features to *COD*, indicating the linear influence direction of explanatory variables on the dependent variable, despite the underlying machine learning models being nonlinear. In the left figure, the blue sample points represent low feature values, while the red points indicate high feature values. The abscissa corresponds to the SHAP values associated with each feature. If the blue data points of a feature appear in the positive value area of the *x*-axis, it indicates that the feature has a negative impact on CoD. (2) The figure on the right is the feature contribution graph, which complements the information presented in Table 4. It shows the mean absolute SHAP value (mean ∣SHAP value∣) of each SCD feature on *COD* across different models, using the average values to represent the overall level of influence, thereby illustrating the total contribution of the explanatory variables to the dependent variable.

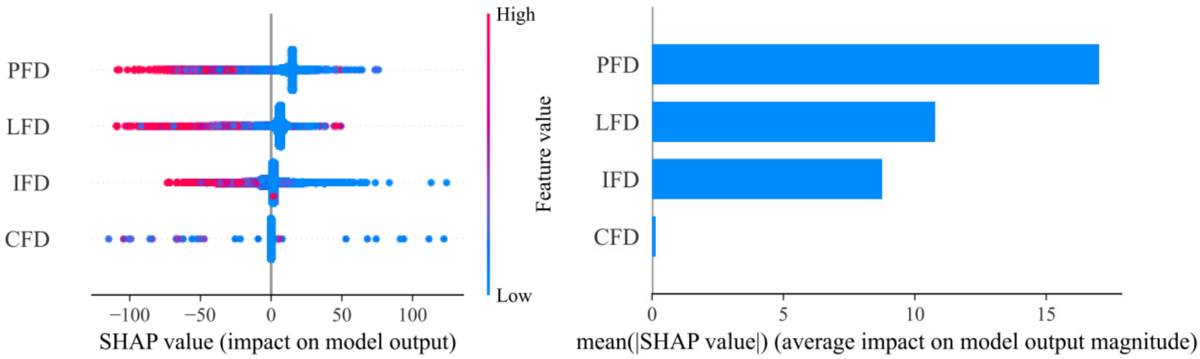

Figure 2. Contributions of SCD features to CoD under XGBoost.

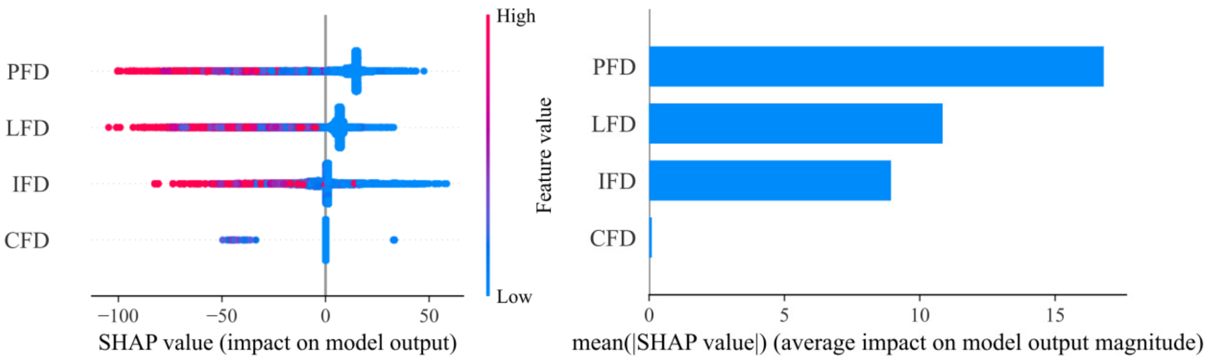

Figure 3. Contributions of SCD features to CoD under LightGBM.

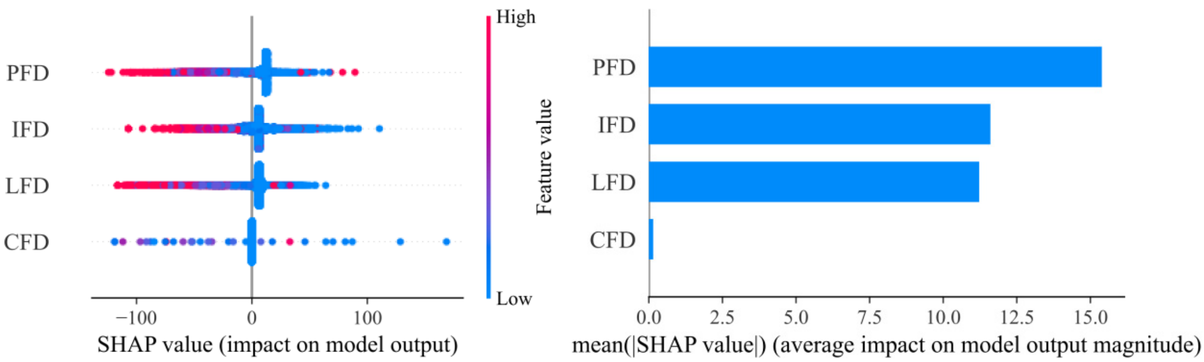

Figure 4. Contributions of SCD features to CoD under CatBoost.

Table 4. Contribution ordering of SCD features to *COD* under different models.

Feature	XGBoost		LightGBM		CatBoost	
	Mean |SHAP| Value	Order	Mean |SHAP| Value	Order	Mean |SHAP| Value	Order
LFD	10.7676	2	10.8443	2	11.2132	3
PFD	17.0149	1	16.7914	1	15.3879	1
IFD	8.7471	3	8.9285	3	11.6024	2
CFD	0.1265	4	0.0897	4	0.1408	4

Through observation and comparison of the three charts, the following findings about output analysis can be obtained: Firstly, from a global perspective, the overall development of SCD has a positive impact on reducing *COD*. This implies that as supply chain digitalization continues to develop, the cost of debt financing for enterprises will decrease. In addition, when analyzing the impact of individual SCD features on *COD*, the following observations can be made: *LFD* has a significant effect in reducing *COD*. Enterprises that focus on digitizing their logistics flow tend to experience lower debt financing costs. Similarly, *PFD* is also associated with lower *COD*. When enterprises invest in the digitalization of product flow, it leads to reduced debt financing costs. *IFD* also shows an impact on reducing *COD*. Enterprises that focus on digitizing the information flow are likely to experience lower debt financing costs. In contrast, the pattern of *CFD* impacts on *COD* is difficult to determine. This may be because the introduction of *CFD* has made the financing environment more complex and variable, making its impact on *COD* difficult to determine. The processes of explainable machine learning methodology analysis for the findings above are shown below.

Based on the output results presented in Figure 2 and Table 4, the following information can be obtained after training the XGBoost model on the research data:

- From a global perspective, the overall development of SCD has a reducing effect on CoD. It is evident from the visualization that the majority of the red data points are clustered on the left side of the abscissa, whereas the blue data points are concentrated on the right side. This observation suggests that, at a global level, SCD is more likely to have a reducing effect on CoD.
- *PFD* is the most important feature affecting CoD from the four flows perspective, with an average |SHAP| value of 17.0149. Moreover, it has a negative impact on CoD, as indicated by the majority of red data points located in the negative value range of the abscissa axis.
- *LFD* is the second most influential feature, with an average |SHAP| value of 10.7676. Furthermore, it also has a negative impact on CoD, with the majority of red data points situated in the negative value range of the abscissa axis.
- *IFD* ranks third among the features, with an average |SHAP| value of 8.7471. Similar to *PFD* and *LFD*, *IFD* has a negative impact on CoD, as indicated by the distribution of data points.
- *CFD* has the smallest average |SHAP| value of 0.1265, significantly lower than the other features. This suggests that *CFD* has a very limited influence power on CoD. The distribution of data points for *CFD* appears relatively sparse and scattered, creating a few challenges for discerning its specific impact on CoD.

According to Figure 3 and Table 4, we can also interpret the results of the research data following the LightGBM model analysis. From a global perspective, most of the red SHAP values are also in the negative range of *COD*, which can still illustrate the negative effect of SCD on CoD. Furthermore, apart from the numerical value of the average |SHAP| value, the contribution sequence and influence effect of each feature are consistent with the XGBoost model. Among these, the average |SHAP| value of *PFD* is 16.7914, the average |SHAP| value of *LFD* is 10.8443, and the average |SHAP| value of *IFD* is 8.9285. Furthermore, the red data points of these features are predominantly located on the left side of the abscissa axis. However, the average |SHAP| value of *CFD* is 0.0897, which also shows that the influence power of this feature on CoD is limited, and the influence effect is not easy to distinguish.

Based on Figure 4 and Table 4, we obtain the analysis results of the research data using the CatBoost model. Upon comparison, it is observed that there are both similarities and differences between the output results of CatBoost and the previous two models. Regarding similarities, it is also evident that the red data points are primarily situated on the left side of the negative abscissa in the global perspective, further confirming the reduction effect of SCD on CoD. The distribution patterns of all features are similar to the previous models, with *LFD*, *PFD*, and *IFD* showing negative impacts on CoD. The SHAP distribution of *CFD* are so scattered without clear patterns, making it difficult to explain its effects. Numerically, the average |SHAP| value of *PFD* is 15.3879, signifying its highest contribution to *COD* among all features. *CFD* has the lowest average |SHAP| value of 0.1408, consistently ranking last among all the features. From the view of differences, *IFD* ranks second, while *LFD* ranks third, with average |SHAP| values of 11.6124 and 11.2132, respectively.

When comparing the output results of the three models, although there are minor differences in how each model handles the contributions of SCD features to CoD, the overall trends and conclusions remain consistent. (1) *PFD* has the most significant negative impact on CoD, while *LFD* and *IFD* exhibit relatively strong negative effects, and *CFD* has the weakest influence. (2) From a global perspective, the development of SCD shows the potential to reduce CoD, as all features, with the exception of *CFD*, demonstrate negative impacts on CoD. Specifically, across all models, *PFD* consistently has the highest average SHAP value. For instance, in the XGBoost model, the average SHAP value for *PFD* is 17.0149; in LightGBM, it is 16.7914; and in CatBoost, it is 15.3879. Although the values vary slightly, *PFD* remains the most important feature influencing CoD, highlighting the critical role of product flow digitalization across all algorithms. While *LFD* and *IFD* differ in terms of importance ranking, their negative impact on CoD remains significant. Conversely, *CFD* consistently has the weakest influence across all three models, and its pattern of impact is difficult to discern. However, there are some differences among the models. For instance, unlike XGBoost and LightGBM, the CatBoost model ranks *IFD* second, surpassing *LFD*. This change in ranking may be related to the way CatBoost handles the data, as it might be better at capturing more complex patterns within *IFD*, leading to a its greater impact on CoD. Similarly, XGBoost and LightGBM show *LFD* as having a greater impact than *IFD*, possibly because these models are better suited for identifying more direct relationships in features like logistics flows. The differences in how each model processes the data likely account for the variations in feature rankings. Nonetheless, these differences do not affect the overall interpretation of the final results.

4.2.3. Sensitive Analysis of Data

To perform a sensitivity analysis, it is recommended to incorporate approximate data analysis methods. Drawing on the research by Zhou and Li [73], decision tree algorithms with different computational kernels can help ensure the robustness of the results. Given that alternative machine learning algorithms have already been employed in earlier sections to enhance robustness, the subsequent analysis will use methods other than SHAPs for further exploration. To this end, PFI and PDPs can serve as valuable supplements to SHAP-based explainable methods. PFI is model-agnostic, meaning it can be applied to any machine learning model. It assesses feature importance by measuring the drop in model performance and has a lower computational complexity compared to SHAPs, making it suitable for large datasets and complex models. However, PFI cannot capture interactions between features, as it only evaluates the independent effect of a single feature, which may limit its ability to explain nonlinear models as effectively as SHAPs. On the other hand, PDPs visually present the relationship between feature values and model output, typically in two- or three-dimensional plots, making it easier to understand the linear effect of a feature on the target variable. While PDPs have lower computational costs, they may struggle to accurately capture the true impact of features in complex nonlinear models, especially when interactions between features are present. To this end, Figures 5–7 and Table 5 have been generated to display the results of the PFI and PDP calculations. In these figures, the content is divided into two parts: the left side shows the PDP results, illustrating the linear impact patterns of each SCD feature on *COD* in the model; the right side presents the PFI results, highlighting the importance of each SCD feature to *COD* in the model.

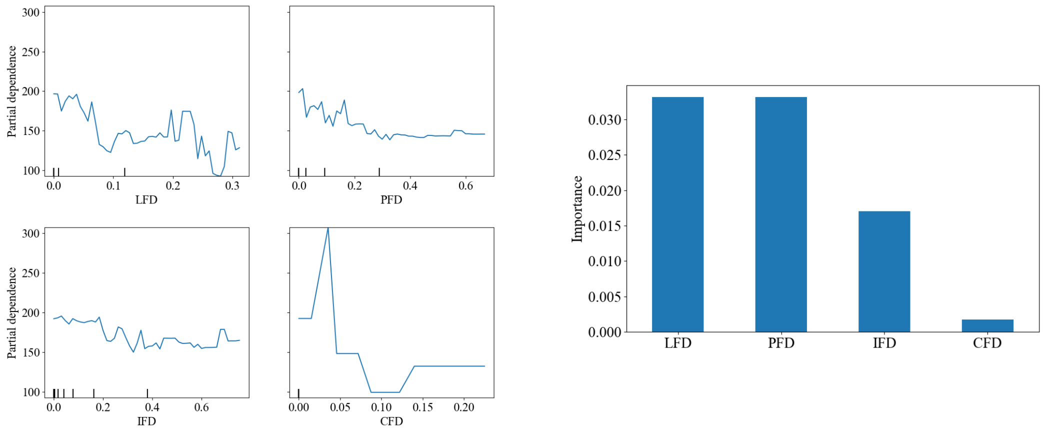

Figure 5. Contributions of SCD features to CoD using PFI and PDPs under XGBoost.

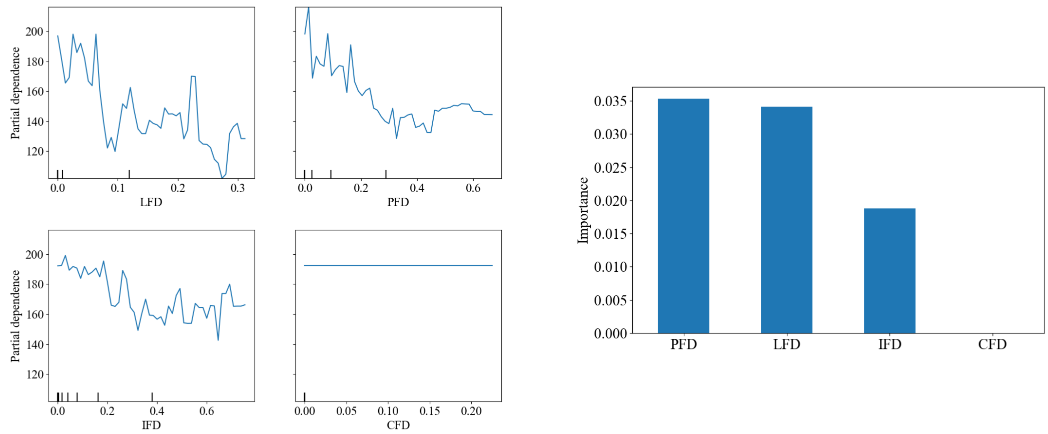

Figure 6. Contributions of SCD features to CoD using PFI and PDPs under LightGBM.

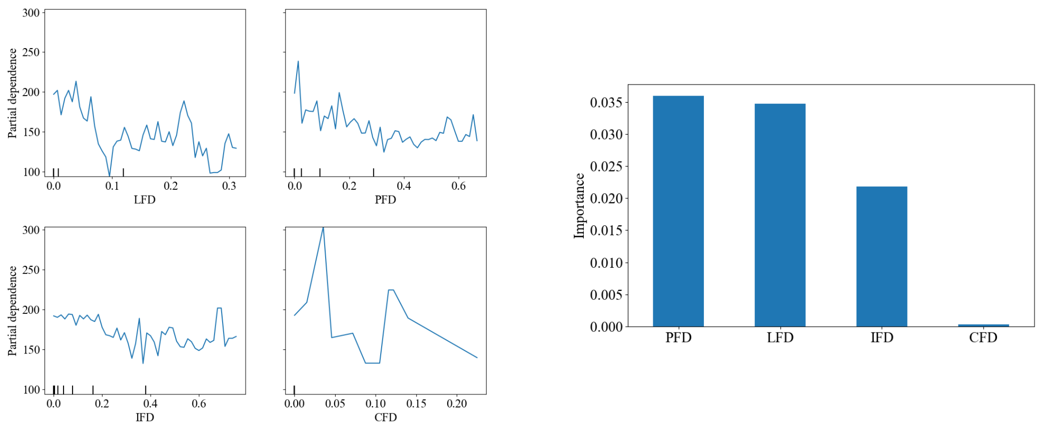

Figure 7. Contributions of SCD features to CoD using PFI and PDPs under CatBoost.

Table 5. Contribution ordering of SCD features to *COD* under PFI.

Feature	XGBoost		LightGBM		CatBoost	
	Importance of PDPs	**Order**	**Importance of PDPs**	**Order**	**Importance of PDPs**	**Order**
LFD	0.0332	1	0.0341	2	0.0347	2
PFD	0.0331	2	0.0353	1	0.0359	1
IFD	0.0170	3	0.0188	3	0.0218	3
CFD	0.0017	4	0.0000	4	0.0006	4

Based on the above figures and table, it is evident that the impact patterns of the various SCD features on CoD remain largely unchanged. From the features' importance calculated by PFI, the XGBoost model results show *LFD* as the most important feature, followed by *PFD*, *IFD*, and *CFD*. In the case of LightGBM, the feature importance ranking remains unchanged, with the order being *PFD*, *LFD*, *IFD*, and *CFD*. CatBoost's PFI results are consistent with those of LightGBM. Furthermore, an analysis of the trends calculated by the PDPs indicates a clear decreasing pattern across all features for all models, except for *CFD* under LightGBM. This suggests that most SCD features contribute to reducing CoD. Overall, it can be inferred that SCD promotes a reduction in CoD. These sensitivity analyses provide robust support for the interpretability of SHAP-based analyses. However, PFI and PDPs have their limitations, and the interpretability of machine learning models derived from these methods should be given less confidence compared to SHAP values. However, PFI and PDPs have their limitations, and the explainability of machine learning models derived from these methods should be considered with less confidence compared to SHAP values, making SHAP the more reliable source for analysis.

4.2.4. Discussion for Data Analysis Results

Relying solely on a data analysis may not sufficiently substantiate the value of the aforementioned viewpoint. Therefore, it is imperative to discuss the above results with those of existing research to provide theoretical support for the data analysis findings and to explain the causal relationship between SCD and its features on CoD.

Product flow digitalization (*PFD*) can lead to a reduction in CoD. The adoption of new technologies in supply chain development, particularly digitalization technologies with interconnection and integration features, has become a focal point today [74]. As a result, enterprises are progressively embracing digitalization in their production, manufacturing, and cargo storage processes, which aligns perfectly with the concept of product flow digitalization. Furthermore, *PFD* can enhance flexibility in the face of limited production capacity. For instance, technologies such as additive manufacturing allow for significantly shorter production and delivery times [75]. This capability for timely production and delivery often translates to improved commercial credit and debt repayment ability [27], which will strengthen the reduction effect on CoD. Additionally, for external debt investors, a company's production capacity is a pivotal factor in their assessment [76]. If a company's production capabilities are not deemed advanced and robust, it is often considered a less attractive investment and may be perceived as lacking the ability to meet its debt obligations. Consequently, *PFD* emerges as a highly influential factor in reducing CoD.

Logistics flow digitalization (*LFD*) also has a positive impact on reducing CoD. A fast and efficient logistics system is an important part of an excellent supply chain, and its importance may be second only to the production capacity of the enterprise for debt investor. The development of this aspect of SCD indicates that enterprises are swiftly incorporating digitalization elements into logistics operations, including transportation and warehousing [64]. This activity enables the enhancement of inventory control and the efficiency of product distribution to consumers, resulting in faster and more cost-effective shipping [75]. For instance, the combined use of geographic information systems (GISs) and big data analysis can significantly support enterprise decision-making, especially during crises such as the COVID-19 pandemic, enabling the optimal utilization of limited resources [77]. Therefore, this progress in supply chain digitalization indicates that enterprises can improve operational efficiency, reduce costs, and offer a better customer experience, resulting in enhanced enterprise performance [78,79]. Based on the signaling theory [56], the proactive development of an enterprise can attract positive attention from external stakeholders. Additionally, the application of *LFD* can enhance the external release effect of such signals, which may subsequently reduce the enterprise's CoD.

Information flow digitalization (*IFD*) can also lead to a reduction in CoD. Information naturally holds a prominent position in SCD as a crucial component. This is also the primary reason why *IFD* is comparable to *LFD*. The main technical components of information flow digitalization encompass information sharing technology or information communication technology. These technologies have promoted the emergence of digitalization waves such as online commerce, reshaping traditional business methods [80]. Specifically, *IFD* facilitates safe and efficient freight operations while improving supply chain visibility, responsiveness, and overall performance [75,81]. These enhancements signify that the enterprise's supply chain is experiencing active development, thereby enabling the release of positive signals regarding its growth to external stakeholders [56]. As a result, it becomes easier for the enterprise to obtain external financing opportunities and lower financing costs.

Capital flow digitalization (*CFD*) exhibits a relatively subdued influence on CoD. This SCD feature has introduced various emerging financing methods, such as supply chain financial platforms, which coexist with traditional financing methods, making the corporate financing environment more complex and variable [82,83]. Due to the differing impact mechanisms and applicable scenarios of these financing methods, their effect on the corporate CoD is difficult to predict and standardize, thus making it challenging to capture their specific impact patterns. Additionally, the infusion of digitalization technology into financial domains, like capital management, introduces novel risks for enterprises [84], and presents challenges to the established financial regulatory system [85]. Within this context, sustained investment in this feature may heighten capital management risks and foster a wait-and-see attitude.

Overall, SCD is expected to reduce CoD. The theoretical discussions regarding the impact of individual SCD features on CoD can be extended to the entire SCD framework. It becomes apparent that SCD also contributes to reducing CoD, as most SCD features exhibit similar effects.

5. Conclusions

5.1. Key Finding and Implications

Reducing debt costs is crucial for maintaining business sustainability, especially as enterprises face mounting financial pressures in today's competitive environment. Additionally, the ongoing globalization and rapid digitalization of supply chain management have exposed managers and professionals to vast amounts of data. This overwhelming influx of information can lead to overload, ultimately resulting in poor decision-making. Therefore, identifying viable SCD development strategies to reduce debt costs, based solely on key operational text data, should be a critical research topic for ensuring the sustainable development of enterprises. To address this, the research initially decomposes SCD into four features from the perspective of the four flows. Subsequently, a series of machine learning models, including XGBoost, LightGBM, and CatBoost, are employed, along with a SHAP-based explanation approach, for an in-depth analysis and mutual verification of the research data. To conduct the sensitivity analysis, PFI and PDPs were incorporated as supplementary explanatory techniques to reanalyze the explainability of these models. Finally, in conjunction with existing research, the obtained data analysis results were discussed to provide a corresponding theoretical basis. After conducting the research, the main conclusions are as follows:

- SCD exerts an overall reducing effect on CoD, primarily due to improvements in supply chain efficiency, cost reduction, and enhanced collaboration. These factors collectively mitigate debt financing risks for enterprises, improve their creditworthiness, and ultimately lower debt financing costs, while also contributing to the long-term sustainability of both financial and operational practices.

- The effects of different SCD features are not exactly the same. Among the four aspects of SCD, *LFD*, *PFD*, and *IFD* show negative impacts on CoD, indicating that focusing on the digitalization of these areas can effectively reduce debt costs, alleviate financing constraints, and promote the overall sustainable development of the company. However, *CFD* fails to exhibit a clear impact on debt costs, suggesting that within the process of SCD, it may not directly influence the company's financial performance as significantly as the other aspects. This may be due to the fact that its introduction creates a more complex and uncertain financing environment, and the potential financial risks associated with further *CFD* development could lead companies to adopt a more cautious approach.
- The various aspects of SCD contribute to varying degrees. *LFD*, *PFD*, and *IFD* contribute effectively to reducing CoD, while *CFD* shows a limited and uncertain impact. Among these, *LFD* exerts the greatest influence among all SCD features, while *CFD* consistently ranks as the least significant. The importance of *PFD* and *IFD* follows that of *LFD*, though their ranks vary depending on the model. This suggests that business managers and other stakeholders should allocate attention proportionately to the different aspects of SCD. Prioritizing areas that can effectively reduce debt costs, improve financing efficiency, and promote the sustainable development of enterprises is essential. This finding reaffirms the significance of the supply chain horizontal deconstruction approach based on the four flows perspective and suggests that future supply chain researchers consider adopting this deconstruction method for other supply chain studies.

Therefore, based on these findings, we propose the following managerial implications for the development of SCD and the practice of reducing CoD to enhance business sustainability:

- Enterprises should acknowledge the complexity and interconnectedness inherent in digital supply chains when formulating their SCD optimization strategies. The four flow framework offers a holistic approach to analyzing SCD, enabling enterprises to understand the digitalization of their supply chains from a horizontal perspective. By adopting this framework, businesses can prioritize their digital investments and allocate resources efficiently across areas such as *PFD*, *LFD*, and *IFD*, with particular emphasis on *PFD*. This strategy has the potential to reduce debt costs and support enterprises in promoting sustainable development at lower costs.
- When considering the *CFD* feature, enterprises need to adopt a cautious approach due to its uncertain impact on CoD. To avoid potential financial risks associated with investment in this area, companies must undertake thorough and comprehensive evaluations before taking any actions related to *CFD*. This ensures that investments in this domain do not inadvertently increase debt costs but rather contribute to maintaining financial health and optimizing the path of supply chain digitalization through prudent and rational assessment.
- The data-driven paradigm and explainable machine learning methodology provide clearer insights for enterprise managers. As enterprises drive SCD, managers should continuously perform cross-verification across multiple models to improve the accuracy and robustness of their analyses, thereby gaining a better understanding of how SCD impacts CoD. This approach enables managers to identify and prioritize the SCD features that most effectively reduce debt costs, ultimately supporting both financial and operational sustainability.

5.2. Contribution

Completing this research can yield a series of contributions, involving enhancements in reducing decision-making resources, business sustainability, and addressing issues across various research paradigms:

- The findings from this study offer valuable insights into the relationship between SCD and CoD, potentially deepening academic understanding of this topic. Unlike previous studies that primarily adopt a vertical perspective focused on suppliers and customers, this research follows Chen et al. [41] in decomposing SCD into four features—logistics flow, product flow, information flow, and capital flow—under the four flows framework, providing a horizontal view of the supply chain. This horizontal perspective allows for a more comprehensive analysis of a company's supply chain structure, helping enterprises to identify which aspects of SCD have the greatest impact on reducing CoD and supporting enterprises in advancing the sustainable development goals.
- Practically, our research provides valuable insights for professionals in the fields of supply chain management, digital transformation, corporate finance, and business sustainability. For instance, in the pursuit of corporate sustainability with a focus on lowering financing costs, managers should prioritize the significant roles of *PFD*, *LFD*, and *IFD* in turn, while carefully analyzing *CFD*. Moreover, our study demonstrates that even with limited data resources, it is possible to uncover the logical relationships between variables. This holds significant relevance for decision-makers who need to make timely decisions with minimal cognitive resources.
- From a methodological perspective, we depart from the traditional hypothesis-based inference commonly used in statistical studies by adopting a data-driven paradigm based on limited text and financial data. This idea uncovers hidden patterns and relationships within the data, offering a more objective view of the functional links between SCD and CoD. It provides a clearer understanding of how specific features of SCD impact CoD from a horizontal perspective. Specifically, this study employs an explainable machine learning methodology to analyze the data, enabling the relationships between variables to be understood with only limited data, thereby conserving decision-makers' cognitive resources. Furthermore, multiple machine learning models and a multi-explanatory approach were used for cross-verification, replacing the traditional single-method analysis. Incorporating multiple models enhances the robustness and accuracy of the results, leading to a more reliable understanding of the impact patterns of SCD on CoD. Finally, building on the data-driven research framework of Zhou and Li [73], we refine it to improve its application. By integrating insights from the existing literature with empirical findings, this study deepens the exploration of how SCD influences CoD, advancing theoretical discussions at the intersection of supply chain management, corporate finance, and sustainable economic development.

5.3. Innovations

Distinguishing itself from previous studies, this research offers several innovative contributions:

- Although our analysis of SCD from the four flows perspective builds upon existing research like Chen et al. [41], prior studies primarily conducted empirical research on SCD from an integrated perspective. In contrast, our study simultaneously analyzes the four distinct SCD features. This approach involved examining the impact of each SCD feature on CoD before extending the analysis to the overall SCD framework. This step-by-step progression in research methodology provides a novel perspective for future scholars.
- By relying solely on text data from annual reports and a limited amount of financial data, our study identifies the relationship between SCD, its features, and CoD. This enables corporate decision-makers to conserve cognitive resources, showcasing an innovative dimension in our approach.
- Unlike traditional data-driven explainable machine learning methodologies [33–38], our research goes beyond merely focusing on feature importance and influence direction. We also integrate existing theories and the literature to explore how and why SCD and its features affect CoD, further enriching the understanding of this relationship.

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