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CREDIT RISK MANAGEMENT IN FACTORING AND SUPPLY CHAIN FINANCE: A BIBLIOMETRIC ANALYSIS OF SCIENTIFIC PUBLICATIONS

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Abstract

Factoring and supply chain finance (SCF) allow firms, particularly small and medium-sized enterprises, to obtain liquidity against receivables and other trade assets, but they expose financiers to the credit risk of suppliers, buyers and their relationships. This study maps the scientific literature on credit risk management in factoring and SCF through a bibliometric analysis. A Scopus search conducted on 12 October 2026 and screening following the PRISMA 2020 flow yielded 288 articles and reviews published between 1995 and 2025. Performance analysis was combined with science mapping in VOSviewer, including keyword co-occurrence, country co-authorship and co-citation analyses of references and sources. The results show that the field has grown rapidly since 2019, with 87.2% of the documents published in 2019–2025. China dominates research output, while studies from the United Kingdom, the United States and Italy attain higher normalised impact, and operations management and operational research journals are the main publication venues. Three research streams are identified: analytical operations–finance models of risk allocation in capital-constrained supply chains, conceptual and empirical research on SCF adoption and reverse factoring, and machine learning-based credit risk assessment of SMEs. Research attention has shifted from traditional factoring and receivables financing towards SCF, machine learning, blockchain and, most recently, artificial intelligence and sustainability. The accounting, financial reporting and internal control dimensions of these arrangements, the allocation of risk among multiple financiers, and evidence from under-represented regions emerge as the main gaps.

Keywords: factoring, supply chain finance, credit risk management, reverse factoring, bibliometric analysis, VOSviewer.

1. Introduction

Access to working capital remains a persistent constraint for small and medium-sized enterprises (SMEs), and receivables-based instruments have long been used to relax it. Factoring, the sale of accounts receivable to a specialised financial intermediary, allows a supplier to convert invoices into liquidity. Because the factor's exposure depends largely on the creditworthiness of the buyer rather than of the supplier, the instrument can be particularly valuable for informationally opaque small firms in environments with weak creditor protection (Klapper, 2006). Over the past two decades this logic has been extended from bilateral transactions to entire supply chains under the label of supply chain finance (SCF), understood as the inter-company optimisation of financing and the integration of financing processes with customers, suppliers and service providers (Pfohl & Gomm, 2009). Buyer-led solutions such as reverse factoring, in which a creditworthy buyer enables its suppliers to obtain early payment on approved invoices, are among the most widely studied SCF instruments (Lekkakos & Serrano, 2016; Liebl et al., 2016).

Credit risk lies at the core of these arrangements. Because financing is extended against receivables, purchase orders or inventory, the financier's loss depends on the default risk of the supplier, of the buyer and of the trading relationship between them, and information generated within the supply chain can be used to reassess that risk (Moretto et al., 2019). Research on the topic has developed along several lines. Analytical operations–finance models examine how financing schemes, credit guarantees and contracts allocate risk among supply chain members (Kouvelis & Zhao, 2012; Yan et al., 2016; Kouvelis & Xu, 2021). Empirical and case-based studies investigate why and how firms adopt SCF (Wuttke et al., 2013; Caniato et al., 2016). A more recent stream applies machine learning to assess the credit risk of SMEs participating in SCF programmes (Zhang et al., 2015; Zhu et al., 2019).

Several reviews have mapped the SCF field as a whole (Gelsomino et al., 2016; Xu et al., 2018). These reviews treat SCF broadly rather than focusing on credit risk, and they were published before most of the relevant literature appeared: in the dataset analysed in this study, 87.2% of the documents were published between 2019 and 2025. Moreover, research on traditional factoring and research on SCF have largely developed as separate streams, and their links with respect to credit risk management have not been systematically examined. An up-to-date, risk-focused mapping of this literature is therefore warranted.

This study addresses that gap through a bibliometric analysis of Scopus-indexed publications on credit risk management in factoring and SCF. It answers three research questions. RQ1: How have the

volume and impact of research on credit risk management in factoring and SCF evolved, and which sources, countries and documents dominate the field? RQ2: What are the main thematic clusters of this research, and how have research themes shifted over time? RQ3: What intellectual base, in terms of the most co-cited works and sources, does this research build upon?

By combining performance analysis with science mapping (Donthu et al., 2021; Zupic & Čater, 2015), the study provides a structured overview of the field, identifies emerging themes and outlines directions for future research.

2. Materials and methods

2.1. Research design

The study applies bibliometric analysis, which combines performance analysis (the productivity and impact of research constituents) with science mapping (the relationships between them) (Donthu et al., 2021; Zupic & Čater, 2015). The identification and screening of records are reported following the PRISMA 2020 flow diagram (Page et al., 2021), adapted to a bibliometric setting.

2.2. Data source and search strategy

Data were retrieved from Scopus on 12 October 2026. The search covered titles, abstracts and keywords and combined two blocks of terms, one describing the financing instruments and one describing credit risk and its management. Terms referring to mathematical factorisation were excluded, and only complete publication years (up to 2025) were retained. The full query was:

TITLE-ABS-KEY ((“factoring” OR “reverse factoring” OR “supply chain financ*” OR “supply-chain financ*” OR “invoice financ*” OR “invoice discounting” OR “receivable* financ*”) AND (“credit risk*” OR “default risk*” OR “risk management” OR “credit scor*” OR “credit rating*” OR “risk assessment” OR “risk evaluation” OR “default predict*”)) AND NOT TITLE-ABS-KEY (“integer factoring” OR “polynomial factoring” OR “matrix factoring”) AND PUBYEAR < 2026

The search returned 783 documents. Limiting the document type to articles and reviews reduced the set to 510 documents, and limiting the language to English reduced it to 484 documents.

2.3. Screening

The 484 records were screened by title, abstract and keywords against two inclusion criteria: (a) the document addresses factoring in its financial sense, reverse factoring, SCF or related receivables-, order- or inventory-based financing within supply chains; and (b) it addresses credit risk, default risk or risk management in these arrangements. The main source of irrelevant records was the polysemy of the word “factoring”, which also appears in expressions such as “factoring in” (taking into account) and in factor-analysis terminology (e.g., “principal axis factoring”). Records likely to be irrelevant were first flagged by text-pattern matching, and every flagged and borderline record was then verified manually. In total, 196 records were excluded and 288 were retained for analysis (Figure 1). A record-level screening log with the reason for each exclusion is available from the authors on request.

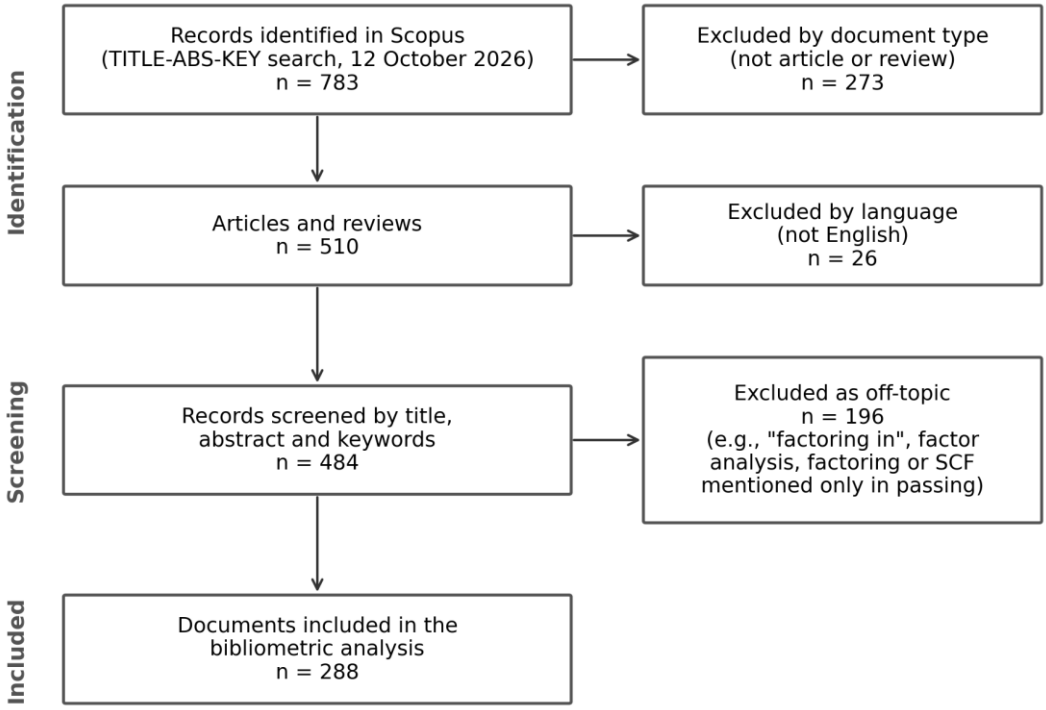


Figure 1. PRISMA flow diagram of the identification and screening of records

2.4. Data cleaning

Two cleaning steps were performed before mapping. First, a thesaurus file was applied to the author keywords to merge synonyms, abbreviations and spelling variants (for example, “supply chain financing”, “SCF” and “supply chain finance (SCF)” were merged into “supply chain finance”, and the variants of “small and medium-sized enterprises” into “SMEs”). Second, the cited references were standardised. In the current Scopus export format, the authors within a cited reference are separated by semicolons, the same character that separates references. In a preliminary run this

led VOSviewer to label references by their last author and to treat formatting variants of the same work (differences in capitalisation, punctuation and abbreviated versus full journal titles) as distinct items. The reference strings were therefore reconstructed, variants of the same cited work were unified, and abbreviated journal titles were replaced with their full forms.

2.5. Analytical techniques

Performance analysis covered the annual number of publications, the number of citations recorded in Scopus on the search date, the mean and median citations per document, the h-index of the dataset, and the most productive sources and countries and the most cited documents. Science mapping was carried out in VOSviewer, version 1.6.21 (van Eck & Waltman, 2010), using full counting, association-strength normalisation and the default clustering resolution (1.00). Four maps were produced: (1) co-occurrence of author keywords (minimum three occurrences), shown as a network visualisation and as an overlay visualisation shaded by the average publication year of the documents in which each keyword appears; (2) co-authorship by countries or regions (minimum two documents), with countries or regions assigned from author affiliations as recorded in Scopus; (3) co-citation of cited references (minimum 10 citations); and (4) co-citation of cited sources (minimum 30 citations).

In the maps, node size reflects the number of occurrences, documents or citations, and node shading reflects cluster membership. Normalised citations, as computed by VOSviewer, equal the number of citations of a document divided by the mean number of citations of all documents in the dataset published in the same year; values above 1 indicate above-average impact relative to publications of the same age.

3. Results

3.1. Overview and annual scientific production

The final dataset comprises 288 documents (282 articles and 6 reviews) published in 164 sources between 1995 and 2025 (Table 1). The documents were written by 751 distinct authors, with an average of 2.94 authors per document; 36 documents are single-authored. Together they have received 7,806 citations, a mean of 27.1 and a median of 11 citations per document, and the h-index of the dataset is 48.

Table 1.

Main characteristics of the dataset

Indicator	Value
Timespan	1995–2025
Documents (articles / reviews)	288 (282 / 6)
Sources	164
Distinct authors	751
Authors per document	2.94
Single-authored documents	36
Total citations	7,806
Mean / median citations per document	27.1 / 11
h-index of the dataset	48
Countries or regions	35
Documents with international co-authorship	64 (22.2%)

Source: authors' calculations based on Scopus data (12 October 2026).

The topic remained marginal until the mid-2010s, with no more than one document per year before 2014 (Figure 2). Output then rose from 4 documents in 2014 to 19 in 2019 and 44 in 2022, stabilised at 32–33 documents in 2023–2024, and reached a peak of 66 documents in 2025. The 2019–2025 period accounts for 251 documents, or 87.2% of the dataset. Documents published before 2019 have a higher mean number of citations (50.4) than those published since 2019 (23.7), which partly reflects the shorter time that recent work has had to accumulate citations.

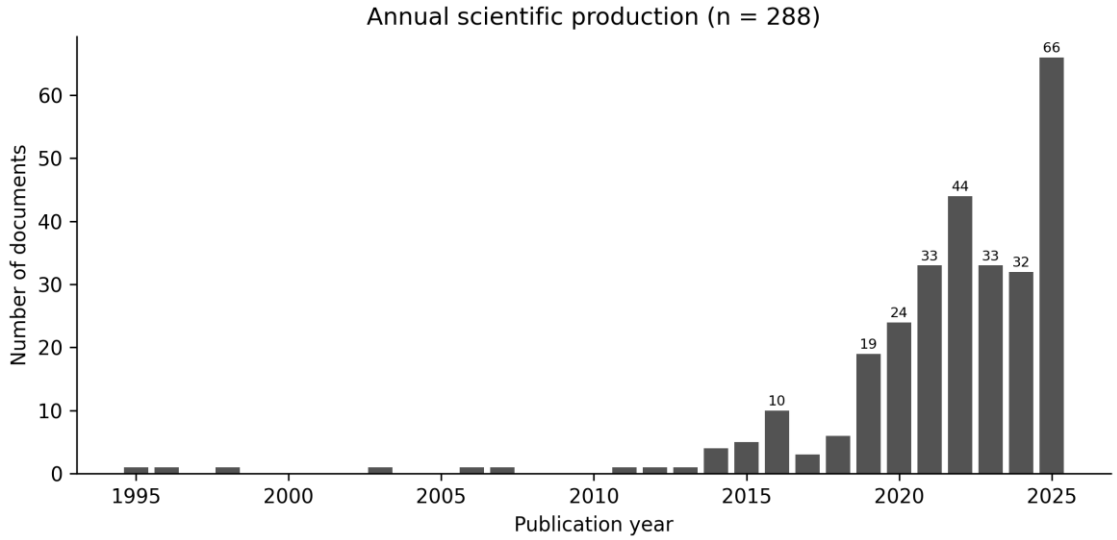


Figure 2. Annual scientific production, 1995–2025 (n = 288)

3.2. Most productive sources

The documents are dispersed across 164 sources, and no single source dominates (Table 2). *Sustainability* published the largest number of documents (19), followed by the *International Journal of Production Research* (10) and *Transportation Research Part E: Logistics and Transportation Review* (9). In terms of citations, the *International Journal of Production Economics* stands out: its 6 documents have received 801 citations. The list is dominated by operations management, operations research and production economics journals, which indicates that the topic has been studied mainly from a supply chain and operations perspective rather than from a banking or accounting perspective.

Table 2.

Ten most productive sources

Source	Documents	Citations
Sustainability	19	383
International Journal of Production Research	10	415
Transportation Research Part E: Logistics and Transportation Review	9	281
Annals of Operations Research	8	320
IEEE Access	8	196
International Journal of Production Economics	6	801
Journal of Intelligent and Fuzzy Systems	5	84
Mathematical Problems in Engineering	5	47
Supply Chain Management: An International Journal	4	356
Industrial Management & Data Systems	4	208

Source: authors' calculations based on Scopus data.

3.3. Countries and international collaboration

Authors affiliated with institutions in 35 countries or regions contributed to the dataset. China is by far the most productive country: authors with Chinese affiliations participated in 213 documents (74.0%), which have received 5,003 citations (Table 3). China is followed at a considerable distance by the United States (27 documents), the United Kingdom (20) and Taiwan (13). Productivity and normalised impact do not coincide, however. The average normalised citation score of Chinese documents (0.90) is below the dataset average, whereas the scores of the United Kingdom (1.98), the United States (1.62) and Italy (1.51) are well above it.

Table 3.

Ten most productive countries or regions

Country or region	Documents	Citations	Avg. normalised citations	Total link strength
China	213	5,003	0.90	62
United States	27	1,675	1.62	22
United Kingdom	20	967	1.98	23
Taiwan	13	291	0.99	20
Italy	11	815	1.51	2
India	10	323	0.89	7
Malaysia	9	124	1.02	15
Hong Kong	7	139	0.72	8
Iran	6	109	1.18	1
Turkey	6	44	0.18	1

Source: VOSviewer co-authorship analysis based on Scopus data. Total link strength is the number of co-authorship links with other countries or regions.

The co-authorship map includes the 23 countries or regions with at least two documents (Figure 3). China occupies the centre of the network, with links to 20 of the other 22 countries or regions and the highest total link strength (62). Its strongest partners are the United States, the United Kingdom, Taiwan and Malaysia. The remaining clusters are small and largely regional, for example Taiwan, Hong Kong, Macao, Malaysia and Thailand; the United Kingdom with India, Singapore, the Philippines and Saudi Arabia; and Italy with Spain and Japan. Italy, despite its high citation impact, is weakly connected (total link strength 2), which suggests that the influential Italian studies, such as Caniato et al. (2016) and Moretto et al. (2019), were produced mainly by domestic research teams. Only 22.2% of all documents involve international co-authorship.

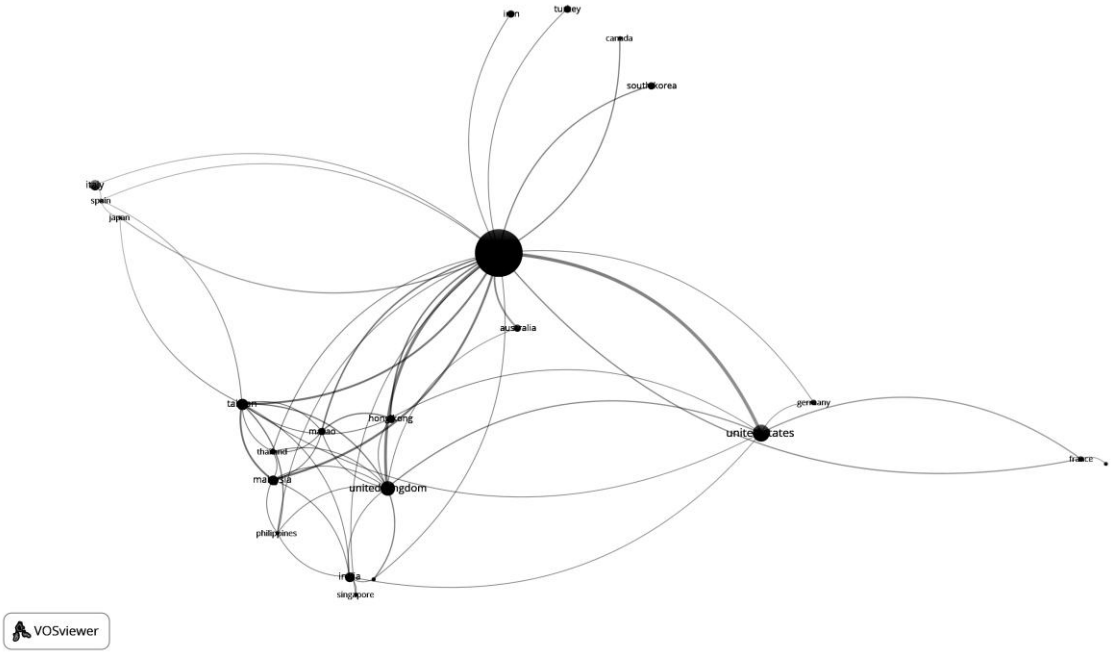


Figure 3. Co-authorship network of countries or regions (minimum two documents; 23 nodes)

3.4. Most cited documents

Table 4 lists the ten most cited documents in the dataset. The most cited one, Zhu et al. (2019), proposes an enhanced hybrid ensemble machine learning approach to forecasting the credit risk of SMEs in SCF and has received 353 citations. It is followed by Caniato et al. (2016), a study of whether SCF solutions address the financing needs of supply chains, and by Klapper (2006), the seminal analysis of factoring as a financing source for SMEs. The list combines three types of contribution: machine learning models for credit risk assessment (Zhu et al., 2019; Sang, 2021; Zhang et al., 2021), analytical models of financing decisions in capital-constrained supply chains (Srinivasa Raghavan & Mishra, 2011; Huang et al., 2020; Kouvelis & Xu, 2021), and empirical or conceptual studies of SCF and factoring (Klapper, 2006; Caniato et al., 2016; Moretto et al., 2019). Fronzetti Colladon and Remondi (2017) apply social network analysis to anti-money-laundering risk in a factoring company.

Table 4.

Ten most cited documents

Rank	Document	Source	Citations
1	Zhu et al. (2019)	International Journal of Production Economics	353
2	Caniato et al. (2016)	Supply Chain Management: An International Journal	270
3	Klapper (2006)	Journal of Banking & Finance	258
4	Fronzetti Colladon & Remondi (2017)	Expert Systems with Applications	186
5	Srinivasa Raghavan & Mishra (2011)	International Journal of Production Economics	184
6	Sang (2021)	Journal of Computational and Applied Mathematics	167
7	Kouvelis & Xu (2021)	Management Science	150
8	Moretto et al. (2019)	Journal of Purchasing and Supply Management	134
9	Huang et al. (2020)	International Journal of Production Economics	132
10	Zhang et al. (2021)	Research in International Business and Finance	128

Source: Scopus, citations as of 12 October 2026.

3.5. Keyword co-occurrence and thematic evolution

Of the author keywords, 50 occurred at least three times and form the co-occurrence network (Figure 4). “Supply chain finance” is the dominant node (156 occurrences; total link strength 209), followed by “credit risk” (32), “SMEs” (26), “blockchain” (24), “risk management” (20) and “credit risk evaluation” (20). “Factoring” occurs 13 times but has a total link strength of only 14, which places traditional factoring at the periphery of the network. VOSviewer identified ten clusters, which can be grouped into the following thematic areas (Table 5).

Table 5.

Clusters of author keywords

Cluster	Keywords	Thematic interpretation
1	capital constraint, credit guarantee, credit scoring, finance, game theory, partial credit guarantee, receivables financing, reverse factoring, Stackelberg game, supply chain management, trade credit	Financing decisions and risk allocation in capital-constrained supply chains (analytical models)
2	artificial intelligence, BP neural network, credit rating, edge computing, Internet of Things, sustainability	Digital technologies for credit rating
3	credit risk, credit risk evaluation, ensemble learning, machine learning, SMEs, SVM	Machine learning-based credit risk assessment of SMEs
4	blockchain, commercial banks, literature review, risk aversion, supply chain finance	Blockchain-enabled SCF and the role of banks
5	bank credit, default risk, moral hazard, online supply chain finance	Default risk and moral hazard in bank-financed and online SCF
6	accounts receivable, factoring, purchase order financing, smart contract	Receivables- and order-based financing instruments
7	risk management, supply chain risk, supply chain risk management, supply risk	Supply chain risk management
8	big data, entropy weight method, risk assessment, sustainable supply chain finance	Multi-criteria risk assessment and sustainable SCF
9	financial risk, risk control, supply chain	Financial risk control in supply chains
10	complex network, evolutionary game, risk sharing	Risk contagion and risk sharing in supply chain networks

Source: VOSviewer co-occurrence analysis of author keywords (minimum three occurrences; thesaurus applied).

Three broad research streams emerge from the clusters. The first (clusters 1, 5, 6 and 10) models how financing schemes, guarantees and contracts distribute default risk among suppliers, buyers and financiers. The second (clusters 2, 3 and 8) develops quantitative tools for credit risk assessment, ranging from multi-criteria methods to machine learning. The third (clusters 4, 7 and 9) links SCF to supply chain risk management and to digital infrastructure such as blockchain.

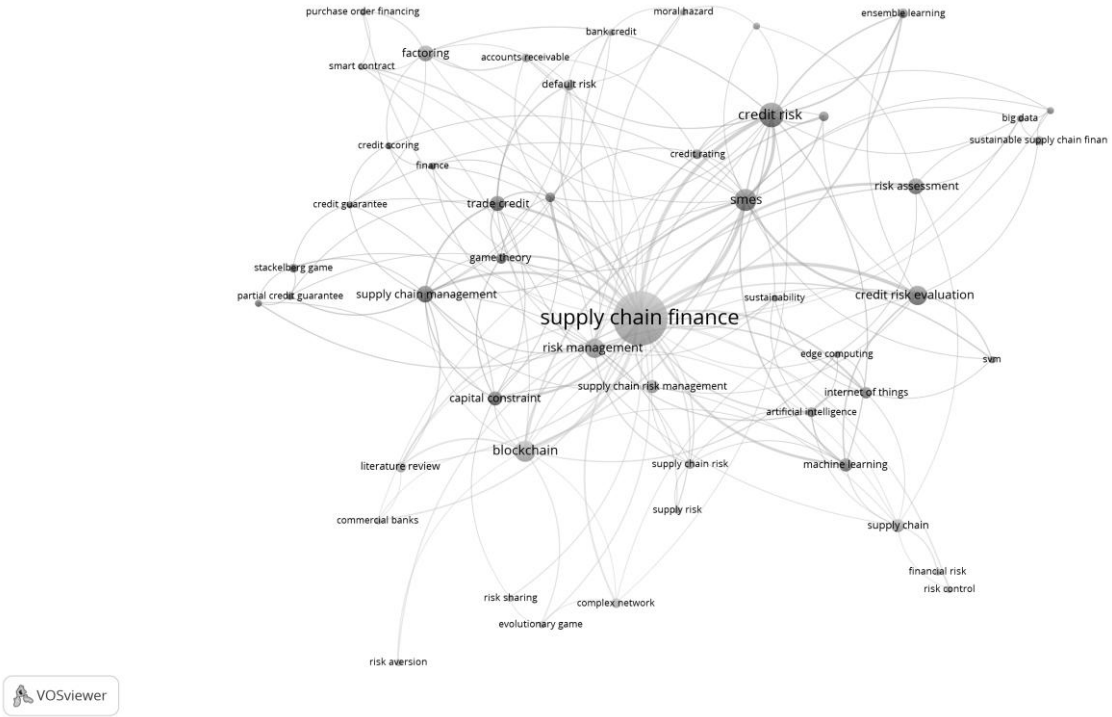


Figure 4. Co-occurrence network of author keywords (minimum three occurrences; 50 nodes; 10 clusters)

The overlay visualisation (Figure 5) shows a clear temporal shift in the themes. The keywords with the earliest average publication year are “accounts receivable” (2012.5), “factoring” (2016.2), “credit scoring” (2016.3) and “SVM” (2018.7), which reflects the origins of the field in receivables financing and classical credit scoring. The most recent themes are “purchase order financing” (2024.3), “commercial banks” (2024.3), “Stackelberg game” (2024.3), “artificial intelligence” (2024.2), “edge computing” (2024.0) and “sustainability” (2024.0), while “blockchain” com-

bines recency (2023.2) with high frequency (24 occurrences). In terms of impact, the keywords with the highest average normalised citations are “ensemble learning” (3.29), “machine learning” (2.84), “smart contract” (2.25), “reverse factoring” (1.99), “credit risk evaluation” (1.89) and “SMEs” (1.82). Data-driven credit risk assessment is therefore the most influential stream relative to the age of its publications.

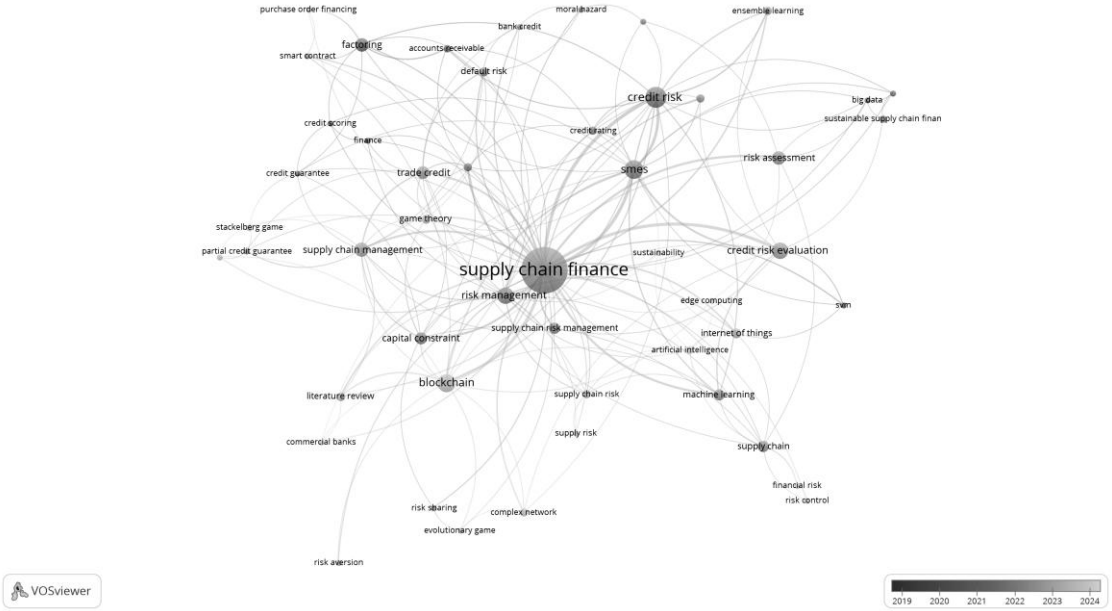


Figure 5.
Overlay visualisation of author keywords by average publication year (darker shades indicate earlier years)

3.6. Intellectual structure: co-citation of references

The co-citation map of cited references includes the 64 works cited at least ten times by the documents in the dataset (Figure 6). The most co-cited works are Zhu et al. (2019; 46 citations), Xu et al. (2018; 34), Wuttke et al. (2013; 32), Lekkakos and Serrano (2016; 31), Yan et al. (2016; 29), Gelsomino et al. (2016; 28) and Kouvelis and Zhao (2012; 28). Xu et al. (2018) has the highest total link strength (291) and is linked to all 63 other works, which makes it the main connecting node of the field. The works form three clusters (Table 6).

Table 6.

Clusters of co-cited references

Cluster	Works	Citations	Representative works	Interpretation
1	29	475	Pfohl & Gomm (2009); Wuttke et al. (2013); Gelsomino et al. (2016); Lekkakos & Serrano (2016); Liebl et al. (2016); Caniato et al. (2016); Xu et al. (2018); Moretto et al. (2019); Klapper (2006)	Conceptual and empirical foundations of SCF, its adoption and reverse factoring
2	27	416	Buzacott & Zhang (2004); Kouvelis & Zhao (2012, 2016, 2018); Jing et al. (2012); Yan et al. (2016); Yang & Birge (2018); Tunca & Zhu (2018); Kouvelis & Xu (2021)	Analytical operations–finance models of capital-constrained supply chains
3	8	160	Zhang et al. (2015); Zhu et al. (2016, 2019); Zhang et al. (2021); Sang (2021)	Machine learning-based credit risk assessment in SCF

Source: VOSviewer co-citation analysis of cited references (minimum ten citations).

Cluster 1 is the largest and contains the conceptual, review and empirical literature. It includes early definitions of SCF (Pfohl & Gomm, 2009), literature reviews (Gelsomino et al., 2016; Xu et al., 2018), studies of SCF adoption (Wuttke et al., 2013; Caniato et al., 2016) and the main empirical studies of reverse factoring (Lekkakos & Serrano, 2016; Liebl et al., 2016). It also contains Moretto et al. (2019) on supply chain credit rating and Klapper (2006) on factoring for SMEs; the latter is located between clusters 1 and 2 on the map. Cluster 2 brings together mathematical models in which a capital-constrained firm chooses between bank and trade credit, or in which a buyer, supplier or bank finances the chain under default and bankruptcy risk (Buzacott & Zhang, 2004; Kouvelis & Zhao, 2012; Yang & Birge, 2018). Kouvelis and Xu (2021), the main analytical comparison of factoring and reverse factoring, belongs to this cluster. Cluster 3 is small but cohesive and consists of studies that predict the credit risk of SMEs in SCF with support vector machines, neural networks and ensemble learning (Zhang et al., 2015; Zhu et al., 2019).

The clusters are clearly separated on the map: cluster 2 occupies one side, clusters 1 and 3 the other, and only a few works, notably Yan et al. (2016), Kouvelis and Xu (2021) and Klapper (2006), lie between them. Works specifically on factoring do not form a cluster of their own; instead they are distributed between the conceptual–empirical and the analytical streams.

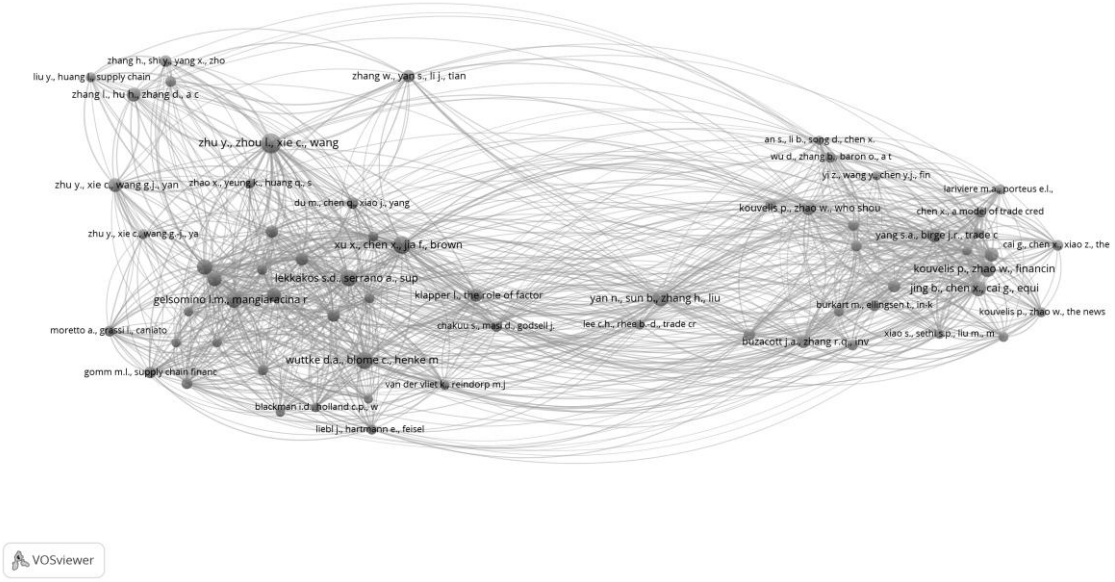


Figure 6. Co-citation network of cited references (minimum ten citations; 64 nodes; 3 clusters)

3.7. Intellectual structure: co-citation of sources

The co-citation map of sources includes the 42 journals cited at least 30 times (Figure 7). The most cited are the *International Journal of Production Economics* (694 citations), the *International Journal of Production Research* (354), *Management Science* (343), the *European Journal of Operational Research* (333), *Manufacturing & Service Operations Management* (257) and *Production and Operations Management* (238). The journals form three clusters. The first cluster, supply chain management, logistics, sustainability and intelligent systems (23 journals, 2,462 citations), is led by the *International Journal of Production Economics*, the *International Journal of Physical Distribution & Logistics Management*, *Sustainability*, *Expert Systems with Applications* and *Computers & Industrial Engineering*. The second cluster, operations management theory and financial economics (11 journals, 1,453 citations), combines *Management Science*, *Manufacturing & Service Operations Management*, *Operations Research* and *Production and Operations Management* with the *Journal of Banking & Finance*, the *Journal of Finance*, the *Journal of Financial Economics*, the *American Economic Review*, the *Review of Financial Studies* and the *Journal of Corporate Finance*. The third cluster, operational research and engineering management (8 journals, 1,321 citations), includes the *European Journal of Operational Research*, the *International Journal of Production Research*, *Omega*, *Transportation Research Part E* and *Annals of Operations Research*.

The source structure mirrors the reference clusters. The analytical stream draws on operations management and financial economics, whereas the conceptual–empirical and machine learning streams draw on supply chain, logistics and information systems journals. Notably, none of the 42 most co-cited sources is an accounting or auditing journal.

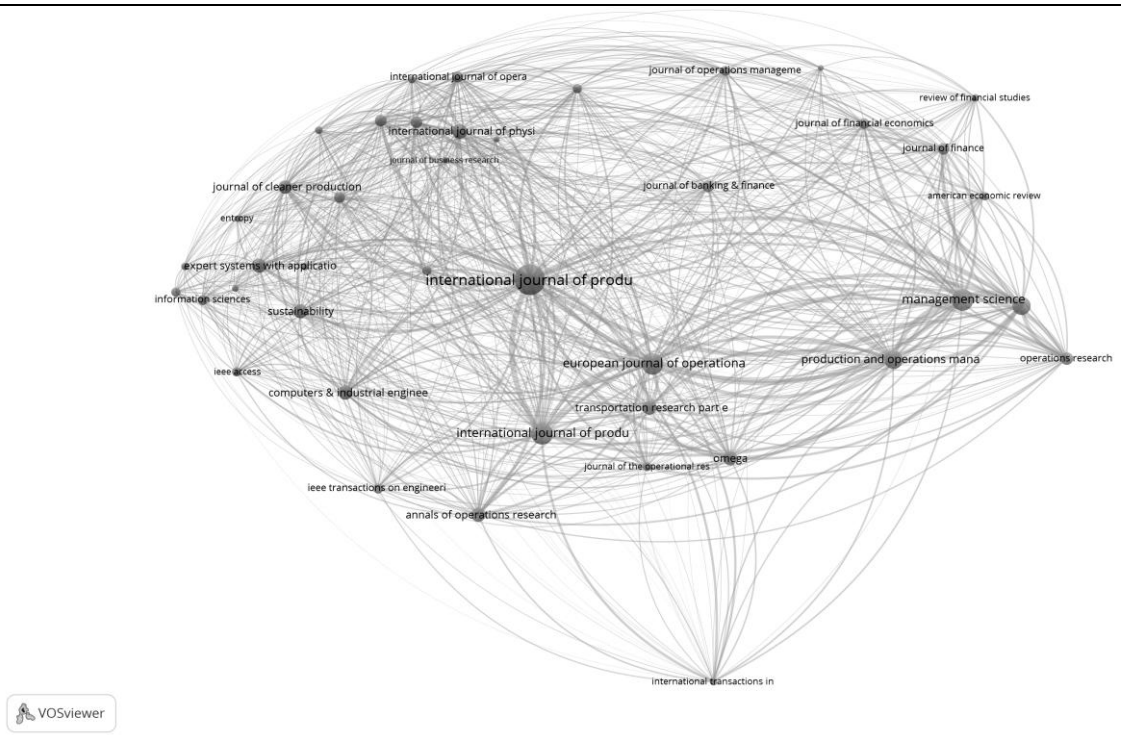


Figure 7. Co-citation network of cited sources (minimum 30 citations; 42 nodes; 3 clusters)

4. Discussion

4.1. Main findings

With regard to RQ1, research on credit risk management in factoring and SCF is a young and rapidly expanding field. Almost nine-tenths of the documents appeared after 2018, and annual output doubled between 2024 and 2025. The field is geographically concentrated: authors with Chinese affiliations took part in about three-quarters of the documents, while work from the United Kingdom, the United States and Italy attains higher normalised citation impact. International collaboration is limited (22.2% of documents). The leading sources and co-cited journals belong to operations management, operational research and supply chain management, which shows that the field has been shaped mainly by supply chain and operations scholars rather than by banking or accounting researchers.

With regard to RQ2 and RQ3, the keyword and co-citation analyses point to the same three research streams. The first is an analytical operations–finance stream, which models how financing schemes, trade credit, guarantees and contracts allocate default risk among suppliers, buyers and financiers (keyword clusters 1, 5, 6 and 10; reference cluster 2). The second is a conceptual and empirical SCF stream, which defines SCF, reviews its instruments and explains adoption, with reverse factoring as its most studied solution (keyword clusters 4 and 7; reference cluster 1). The third is a data-driven credit risk assessment stream, which applies machine learning and multi-criteria methods to evaluate the creditworthiness of SMEs participating in SCF (keyword clusters 2, 3 and 8; reference cluster 3). The third stream is the smallest in the intellectual base but the most influential relative to publication age, with keywords such as “ensemble learning” and “machine learning” showing the highest normalised citations.

The overlay analysis shows how the focus has moved over time. Early work concentrated on accounts receivable, factoring and classical credit scoring. The field then shifted towards SCF, machine learning and blockchain, and the most recent themes are purchase order financing, the role of commercial banks, artificial intelligence, edge computing and sustainability. Traditional factoring, although it is the historical starting point of receivables-based finance (Klapper, 2006), has become a peripheral node in the keyword network, and factoring-specific works do not form a separate co-citation cluster. Factoring is now studied mainly as one instrument within the broader SCF framework, as in the comparison of factoring and reverse factoring by Kouvelis and Xu (2021).

4.2. Gaps and future research directions

The results suggest several directions for future research.

Accounting, reporting and internal control. None of the 50 most frequent keywords and none of the 42 most co-cited sources relates to accounting or auditing. A text search of the 288 documents found no mention of IFRS, expected credit losses or financial reporting, and only one mention of internal control. How factoring and SCF exposures are recognised, measured and disclosed by suppliers, buyers and financiers, how expected credit losses on purchased receivables are estimated, and which internal controls mitigate credit and operational risk in these arrangements remain largely unexplored.

Arrangements with multiple financiers. The literature models financing mainly as a relationship between a firm and a single bank or between supply chain partners. Arrangements in which several financiers share one receivable, such as syndicated factoring or platform-based invoice financing, and the allocation of income and credit losses among them, are not addressed in the dataset; the term “syndicated” does not appear in any document.

Geographical scope. Evidence comes overwhelmingly from China, with few studies from Africa, Latin America or Eastern Europe and none from Central Asian countries. Comparative studies of how institutional and legal environments shape credit risk in factoring and SCF would extend the argument of Klapper (2006) to new settings.

Validation and interpretability of credit risk models. Several of the most cited machine learning studies are based on data on Chinese SMEs (e.g., Zhu et al., 2016, 2019). Testing their transferability to other markets, comparing them with traditional scoring methods and improving their interpretability for credit officers and auditors are natural next steps.

Integration of streams. The separation between the analytical and the empirical clusters suggests that empirical tests of the predictions of operations–finance models, and models calibrated with real transaction data, could connect the two main streams.

4.3. Implications

For researchers, the study provides a map of the main streams, their foundational works and their recent directions, which can guide the positioning of new studies. For practitioners such as factoring companies, banks and SCF platform operators, the results highlight the growing availability of data-driven credit assessment methods and the potential of technologies such as blockchain to reduce information asymmetry. They also show, however, that the accounting and control aspects of these instruments have received little scholarly attention. For regulators and policymakers in emerging markets, the concentration of evidence in a few countries indicates that local evidence is needed before international findings are transferred to domestic factoring markets.

4.4. Limitations

The study has several limitations. It relies on a single database (Scopus) and on English-language articles and reviews, so relevant work in other databases, languages and document types may be missing. The search terms, although broad, may not capture every relevant document, and screening involved judgement despite systematic verification. Citation counts depend on time, which disadvantages recent publications; normalised indicators only partly correct for this. Finally, the maps depend on parameter choices such as thresholds and the thesaurus, and on the standardisation of cited references, which, although carefully performed, may contain residual inconsistencies.

5. Conclusions

This study mapped 288 Scopus-indexed documents on credit risk management in factoring and SCF published between 1995 and 2025. The field has grown rapidly since 2019, is dominated by Chinese authors in volume and by operations management journals in publication venues, and rests on three intellectual streams: analytical operations–finance models, conceptual and empirical SCF research, and machine learning-based credit risk assessment. Over time, attention has shifted from traditional factoring and receivables financing towards SCF, machine learning, blockchain and, most recently, artificial intelligence and sustainability. The main gaps concern the accounting, reporting and internal control dimensions of these arrangements, the allocation of risk among multiple financiers, and evidence from under-represented regions. Addressing these gaps would make the literature more useful for factoring companies, auditors and regulators, particularly in emerging markets.

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