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Research Article

Global Trends and Multidisciplinary Frontiers in Springback Research: A Scientometric Analysis (2010-2025)

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ABSTRACT

Based on 2,352 publications from the Web of Science Core Collection (2010-2025), this study conducts a comprehensive scientometric analysis of the global trends, core topics, and frontier directions in metal stamping springback research using CiteSpace and VOSviewer. Employing bibliometric methods such as keyword co-occurrence, burst detection, and co-citation analysis, it systematically maps the knowledge structure of the field. Keyword evolution analysis reveals a clear technological trajectory: the research focus has shifted from early-stage experimental validation and geometric compensation to advanced constitutive modeling (addressing the Bauschinger effect and anisotropic hardening), hot stamping processes, and more recently, microstructure evolution and artificial intelligence. The national and regional results quantify the contributions of major research centers, identifying China, South Korea, and the United States as the leading countries, driven by their respective national industrial manufacturing strategies. International Journal of Advanced Manufacturing Technology is identified as the journal with the highest publication output, while Materials Science and Engineering: A demonstrates notable citation influence, reflecting the multidisciplinary nature of the field. Despite these advances, this study identifies key technical bottlenecks, including insufficient quantitative characterization of pre-strain and texture evolution in multi-scale models, and a lack of interpretability in data-driven AI methods. This research provides data-driven insights for researchers, process engineers, and R&D managers, indicating that future springback suppression will rely on the deep integration of physical mechanisms and intelligent algorithms to achieve precise control and efficient production.

Keywords: Artificial Intelligence, Finite Element Analysis, Scientometric Analysis, Sheet Metal Forming, Springback.

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INTRODUCTION

Springback is a prevalent and challenging physical phenomenon in the precision manufacturing of metal sheet forming. It is defined as the elastic recovery behavior of the material after the forming load is removed (Carden *et al*., 2002). When a metal sheet undergoes elastoplastic deformation through bending or stretching, the unloading process releases the elastic strain energy stored inside the material, causing the part geometry to deviate from the designed mold shape. Such dimensional deviations directly affect the final product's assembly accuracy, appearance quality, and functional performance, making springback one of the major obstacles to achieving "net-shape" manufacturing (Wagoner *et al*., 2013).

With the global automotive industry accelerating its "lightweighting" strategy to comply with stringent carbon emission regulations, Advanced High-Strength Steels (AHSS) and aluminum alloys are being widely adopted. However, these materials exhibit high yield-to-tensile ratios, and their springback magnitude is often several times greater than that of traditional mild steels, along with significant nonlinear characteristics. This has rendered traditional trial-and-error methods ineffective in mold debugging (Barlat *et al*., 2011; Wagoner *et al*., 2013; Yoshida and Uemori, 2003). Therefore, accurately predicting and effectively compensating for springback has become a key technological bottleneck linking new material development to industrial application.

EVOLUTION OF SPRINGBACK RESEARCH

Over the past few decades, springback research has undergone clear evolution. Early studies relied primarily on physical experiments, such as V-bending and U-bending tests, attempting to establish empirical relationships between process parameters (e.g., punch speed, blank holder force) and springback angle (Kazan *et al*., 2009; Tekaslan *et al*., 2008; Thipprakmas, 2010).

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Although intuitive, these methods lacked generalizability for complex three-dimensional curved surfaces. Subsequently, the advancement of finite element analysis significantly improved prediction accuracy. To enhance simulation precision, researchers introduced complex constitutive models that consider the Bauschinger effect, anisotropic yield criteria, and elastic modulus degradation (Eggertsen and Mattiasson, 2010; Lee *et al*., 2013; Sun and Wagoner, 2011). Despite the improved physical description, the cumbersome parameter calibration process and high computational costs limited their rapid application in industrial settings.

In recent years, computational intelligence methods, particularly Artificial Neural Networks (ANN), have opened new avenues for fast, data-driven springback prediction due to their strong nonlinear fitting capabilities (Baseri *et al*., 2011; Jamli *et al*., 2014; Narayanasamy and Padmanabhan, 2012). For example, some studies have combined ANN with response surface methodology to optimize process parameters (Manoochehri and Kolahan, 2014), or attempted to couple ANN with Crystal Plasticity-Finite Element Methods (CP-FEM) to account for microstructural mechanisms such as texture evolution (Joo *et al*., 2023; Zecevic and Knezevic, 2017).

Despite considerable progress, current research still faces notable limitations and gaps. On one hand, traditional finite element models still rely on simplified assumptions to characterize complex material unloading behavior (Rajput and Paul, 2019). On the other hand, many ANN applications remain at the level of "black-box" data fitting without deep integration with physically interpretable constitutive theories (Jamli and Farid, 2019). Moreover, there is still a lack of quantitative characterization of key internal variables such as pre-strain and microstructural evolution, as well as their mapping relationships to springback. These bottlenecks have led to a large yet somewhat fragmented body of research, lacking a macro-level, systematic perspective to clarify the knowledge structure, identify core evolution paths, and highlight frontier directions.

RESEARCH OBJECTIVES

This study aims to conduct a quantitative and visual analysis of global springback research literature from 2010 to 2025 using scientometric methods, providing a data-driven panoramic overview. The specific objectives include: (1) identifying core countries, institutions, scholars, collaboration networks, and key knowledge dissemination channels in the field; (2) revealing the historical evolution of research hotspots, current focuses, and unresolved technical bottlenecks; (3) through keyword co-occurrence, clustering, and timeline analysis, uncovering the evolution of the field's knowledge structure and its trend toward integration with materials science, mechanical simulation, and intelligent algorithms. This will help guide future research directions and promote springback studies in sheet metal forming toward intelligent prediction, precise control, and efficient production.

METHODOLOGY

Data Collection and Bibliometric Analysis

Bibliometric analysis enables researchers to evaluate and quantify the influence of scientific fields through statistical and quantitative methodologies, with this approach being widely recognized for its high reliability in research domains. In this study, the Web of Science (WoS) platform was utilized for bibliometric analysis, as it houses a vast repository of quantitative data. Additionally, the WoS platform features a well-structured design that facilitates user navigation and retrieval. As noted by Chen (2016), leveraging the WoS platform not only mitigates the risk of data loss but also expedites the conversion process of data across various scientometric analysis tools (e.g., CiteSpace) (Chen, 2016).

The Web of Science Core Collection, specifically encompassing the Science Citation Index Expanded (SCI-EXPANDED, 2010-present) and Social Sciences Citation Index (SSCI, 2010-present), was employed as the data source. The search query was formulated as: TS=(springback OR (stamping OR "sheet metal forming") AND (FEA OR "residual stress")). To ensure comprehensive coverage of all relevant publications on this topic and achieve an inclusive mapping of scientific research, all publication types (i.e., articles, proceeding paper, and review article, among others) were included in the review.

SCIENTOMETRIC ANALYSIS

Scientometrics can clearly map the field of knowledge. Moreover, it evaluates the research progress and performance of researchers, countries, institutions, journals, and documents in specific fields through different networks, and visualizes patterns and trends hidden within large volumes of literature and bibliographic records (Cobo *et al*., 2011). Currently, there are multiple scientometric analysis tools for visualizing and assessing trends and patterns in scientific records. These tools can be divided into dedicated tools (such as CoPalRed and VOSviewer) and non-dedicated tools (such as Pajek and Gephi) (Cobo *et al*., 2012). Depending on the type of analysis required, each tool possesses unique advantages and functions. However, no single software integrates all the functions of raw retrieval data elements, preprocessing, mapping, visualization, description, standardization, and network extraction (Cobo *et al*., 2012). Therefore, previous studies have recommended using multiple scientometric visualization tools (Smith, 2012). Based on this, the present study selected CiteSpace (v.6.3R1) and VOSviewer (v.1.6.20), aiming to obtain highly reliable analysis results.

In this study, CiteSpace (v.6.3R1) was used to generate networks containing nodes and dynamic maps for burst detection and clustering analysis. According to the basic requirements of scientometrics, citation analysis is a key element (Smith, 2012). In terms of the citation analysis required for scientometrics, Web of Science (WoS) can provide users with a high degree of satisfaction. CiteSpace (v.6.3R1) evaluates citation retrieval and related details through in-depth citation retrieval and mapping of research fields.

Scientometric analysis can be divided into three approaches: one-dimensional, two-dimensional, and multidimensional. One-dimensional analysis focuses on numerical indicators (such as citation counts, keywords, number of publications), while two-dimensional analysis examines coded relationships and keyword co-occurrences. Multidimensional analysis includes continuous methods (visualizing data structures through maps) and non-continuous methods (interpretation based on intensity scaling) (Leydesdorff, 2011).

This study employed multiple scientometric techniques: co-word analysis (keyword co-occurrence, citation bursts, clustering), collaboration analysis (country/institution collaboration networks), and co-citation analysis (knowledge domain relationships among authors/journals).

Keyword co-occurrence analysis identifies research keywords and trends (Ding, 2011), while citation burst analysis reveals terms that gained attention through surges in publications/citations during specific periods. Burst detection (via CiteSpace) identifies emerging hotspots, and clustering analysis categorizes nodes (such as keywords) to reveal the structure and evolution of knowledge domains (Chen, 2016).

RESULTS AND DISCUSSION

Research Trends and Analysis of High-Impact Literature

Figure 1 illustrates that a total of 2352 articles related to springback fields in metals were published and indexed in WoS between January 1, 2010, and June 1, 2025. Since 2010, the cumulative number of such articles has sustained rapid annual growth, following the regression curve $y = 194.08e^{\{0.1761x\}}$ ($R^2 = 0.9338$). This trend indicates growing attention toward springback and its promising development potential. Table 1 presents the top 10 most-cited papers.

In 2010, O. Music and others published a paper systematically reviewing the research on the mechanics analysis and application of metal spinning, covering important literatures in English, German and Japanese, focusing on the evolution mechanisms of stress state and strain history of workpieces in processes such as conventional spinning and shear spinning, pointing out that there are knowledge gaps in the evolution of microstructure, residual stress and springback prediction at the present stage, especially the understanding of spinning failure mechanisms (such as fracture and wrinkling) is still insufficient, the toolpath design has not been automated, and meanwhile discussing the innovation potential of new process configurations such as flexible spinning and asymmetric spinning (Music *et al*., 2010). In 2014, A. Pramanik carried out research on the processing problems of titanium alloys, pointing out that characteristics such as low thermal conductivity and high yield strength lead to problems such as chip thickness variation, high thermal stress, high pressure load, springback and residual stress in processing, which easily cause rapid tool wear and deterioration of surface quality, analyzing the applicability of tool materials such as tungsten carbide and cubic boron nitride, and discussing the action mechanisms of solutions such as high-pressure cooling, cryogenic cooling and vibration analysis, for example, high-pressure coolant can increase tool life by three times, cryogenic cooling reduces the cutting temperature through liquid nitrogen spraying, and laser-assisted heating can soften the workpiece to reduce the cutting force (Pramanik, 2014). In 2013, Robert H. Wagoner and others published a paper focusing on the springback, an elastic-driven shape change after forming, summarizing five major research directions after 2006, including plastic constitutive equations (such as Armstrong-Frederick type hardening model), variable Young's modulus (introducing quasi-plastic elastic strain theory), through-thickness stress integration (Gaussian integration method to improve numerical accuracy), magnesium alloys (anisotropic hardening model to solve twinning effect) and advanced high-strength steels (considering age springback and room-temperature creep), pointing out that new constitutive models and numerical methods can significantly improve the accuracy of springback prediction, such as the quasi-plastic elastic model reducing the simulation error to 2.6° (Wagoner *et al*., 2013).

KEYWORD ANALYSIS

Keyword Co-Occurrence Analysis

Keyword analysis, especially of author keywords, provides comprehensive insights into research trends. As they are at the core of an article, they enable in-depth subject exploration (Li *et al*., 2017; Sabour *et al*., 2020). To identify the most popular topics in relevant literature, a modern and comprehensive social network analysis method was employed, leveraging the co-occurrence relationships between keywords. Figure 2 illustrates the network structure using circles and links. The main keywords mentioned in the data collection part are the most frequently recurring ones in VOS viewer. These keywords have been refined for more accurate results.

First, a minimum occurrence threshold of 45 was applied to the author keywords. Additionally, some keywords representing identical concepts (e.g., "finite-element-analysis" and "finite element analysis," "sheet-metal" and "sheet metals") were combined in the analysis. As a result, out of 7226 total author keywords, only 43 were retained for network display after integrating both the occurrence threshold and keyword-merging processes.

The strength of clusters is represented by colors: red, blue, green, and yellow. The red cluster-including keywords like springback, simulation, sheets, prediction, design, and sheet metal forming -is the most influential, with significantly higher homogeneity and interaction than other clusters.

BURST DETECTION IN KEYWORD CO-OCCURRENCE

Analyzing bursts in keyword co-occurrence is crucial for revealing growing research interests. In this study, CiteSpace was used for this analysis, based on Kleinberg's algorithm (Kleinberg, 2003), which is essential for burst detection (Chen, 2014, 2016). This helps track dynamic changes in research interests.

Citation burst analysis shows the citation changes of keywords over specific years, revealing their varying prominence in the literature. According to He *et al.*, (2017), it effectively displays research trend developments and interest changes within certain timeframes (He *et al.*, 2017). In this study, it uncovered the research progress and key changes in Stamping Springback from 2010 to 2025, and helped identify research gaps. Furthermore, this analytical method helps to identify research gaps and neglected areas in literature within a specific time frame. As Pollack and Adler point out, burst analysis can detect the evolution and development of the knowledge system over a period (Pollack and Adler, 2015).

Table 1: Top 10 most cited papers on Stamping Springback research (2010-2025).

Sl. No.	Number Title	Citations	Year
1	A review of the mechanics of metal spinning	292	2010
2	Problems and solutions in machining of titanium alloys	286	2014
3	Advanced Issues in springback	279	2013
4	Hot stamping of ultra-high strength steel parts	271	2017
5	A review of the development of creep age forming: Experimentation, modelling and applications	213	2011
6	Advances and Trends on Tube Bending Forming Technologies	211	2012
7	Single point incremental forming: An assessment of the progress and technology trends from 2005 to 2015	188	2017
8	Complex unloading behavior: Nature of the deformation and its consistent constitutive representation	183	2011
9	Extension of homogeneous anisotropic hardening model to cross-loading with latent effects	182	2013
10	Mechanics of fracture in single point incremental forming	165	2012

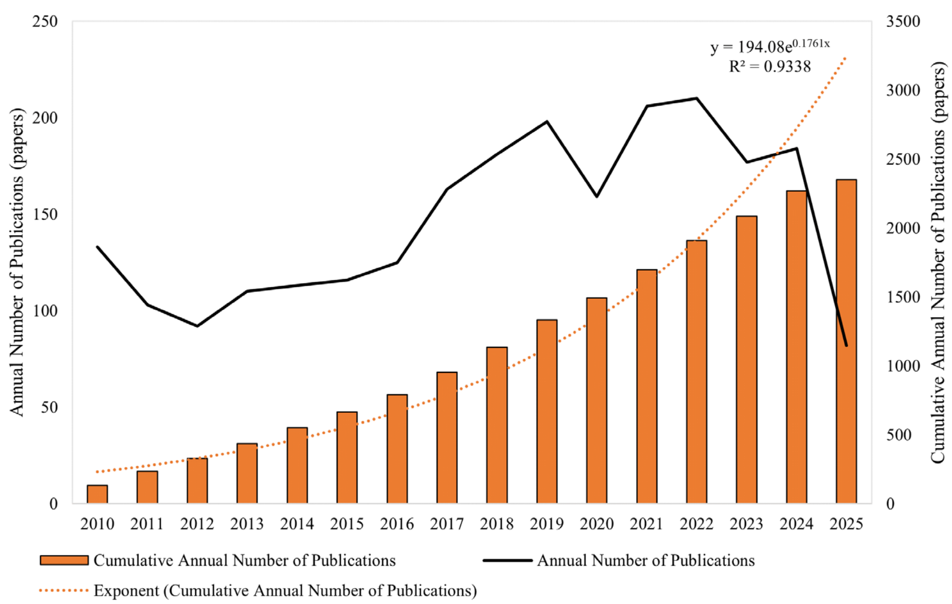

Figure 1: Research Trends in Metal Stamping Springback from 2010 to 2025.

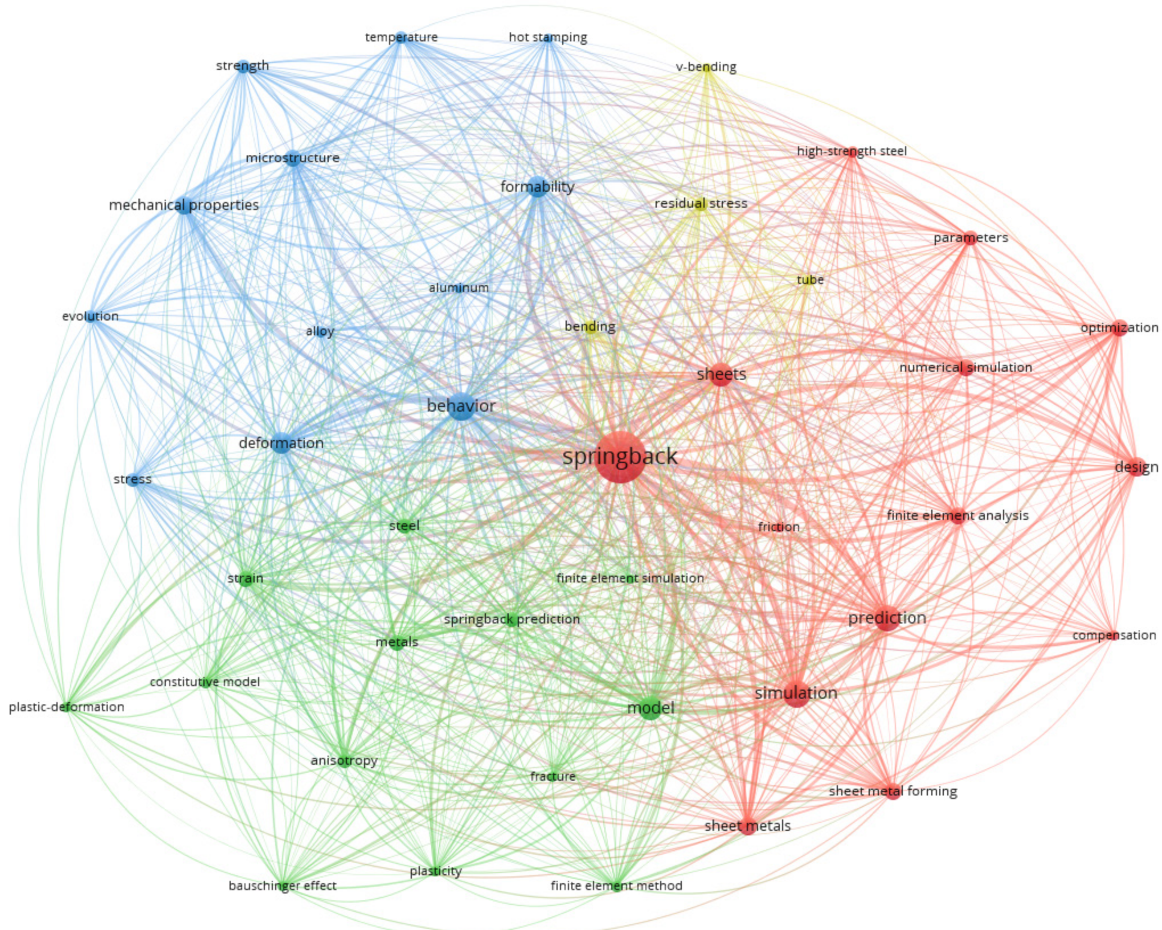

Figure 2: Co-occurrence Relationships Between Author Keywords.

Figure 3, generated by CiteSpace outputs, presents the top 25 keywords with growing interest from 2010 to 2025. Red bars denote citation bursts, and blue bars represent the literature review period of the past decade. The figure is arranged by intensity.

From 2010 to 2015, emerging keywords in this stage included "sheet metal forming", "Bauschinger effect", "finite elements", "response surface methodology", "metal", and "cyclic plasticity". The emerging strength of "sheet metal forming" reached as high as 10.59, indicating that in the early stage of research, there was extremely high attention to the springback problem in the forming process. Scholars were committed to exploring the laws and solutions of springback from the perspective of the overall forming process.

The emerging strength of the "Bauschinger effect" was 7.39. As an important mechanical property of materials, it plays a key role in understanding the mechanism of springback, showing that attention began to be paid to the impact of the material's own properties on springback.

The emergence of numerical methods such as "finite elements" reflected that during this period, the use of computer simulation to study springback became an important trend, laying a methodological foundation for in-depth research later.

From 2016 to 2020, keywords such as "large strain", "plasticity", "sheet metal", "creep age forming", and "hot stamping" emerged. The emergence of "large strain" and "plasticity" showed that research on the springback behavior of materials under complex deformation conditions gradually deepened, no longer limited to small deformation situations.

The appearance of process-related keywords such as "creep age forming" and "hot stamping" indicated that research began to focus on springback problems in specific advanced manufacturing processes, and started to find more targeted springback control strategies according to the characteristics of different processes.

From 2021 to 2025, keywords such as "quality", "performance", "microstructure evolution", "strategy", and "surface roughness" emerged. This reflects that recent research not only focuses on the control of springback itself, but also turns to how to improve the overall quality and performance of the final product by controlling springback. At the same time, it pays attention to the relationship between microstructure changes and springback, as well as formulating more optimized springback compensation strategies.

In the future, research hotspots of "stamping springback" may be reflected in process innovation and comprehensive performance improvement, product life cycle and quality control, and research on lightweight materials and springback characteristics.

KEYWORD CLUSTER ANALYSIS

Cluster analysis is a technique that condenses large amounts of information into smaller, more comprehensible modules. It classifies keywords related to energy performance, making them more organized and manageable. This is achieved by grouping unstructured knowledge bodies (keywords) through algorithms (He *et al*., 2017). The analysis method provides structured units that are easy to understand and explore (He *et al*., 2017). Each cluster contains highly similar related keywords, offering a comprehensive view of the knowledge structure within the research scope.

In this study, CiteSpace was used for cluster analysis, classifying keywords into several groups (Figure 4). Various algorithms are available for cluster analysis, but the Log-Likelihood Ratio (LLR) was chosen because it offers the highest-quality clustering information in terms of uniqueness and coverage (Chen, 2016). The results indicate that the keyword co-occurrence clusters are partially harmonic, making them suitable for identifying patterns within clusters. The harmonic meaning helps find multiplicative or divisive relationships between scores without considering the common denominator.

The clustering timeline map demonstrates the keyword clustering and evolutionary trends of "stamping springback" research from 2010 to 2025. It was drawn by CiteSpace software in advanced mode, with parameters such as g-index (k=15), LRp=3.0, L/N=10, LBY=5, e=1.0, etc. Network characteristics show n=375, E=549; network density Density=0.0078, modularity Q value=0.7743 indicating obvious clustering structure, and average silhouette coefficient S value=0.9149 suggesting high clustering quality.

In terms of the research period

2010-2015 was the initial exploration stage of "stamping springback" research. Relevant studies were scarce, with keywords relatively scattered, mainly focused on the basic concept and goal of "springback compensation", and began to pay attention to factors affecting springback such as "mechanical property".

From 2016 to 2025, research gradually increased, with multiple research hotspots and directions emerging, such as the extension of research on "mechanism", "constitutive model", "anisotropic yield functions", "metal forming", etc. Researchers began to deeply study springback issues from different perspectives such as material properties and deformation mechanisms. Studies also became more refined, forming many stable and in-depth clustering themes such as "finite element analysis", "aluminum profile", "sheet metal forming", etc. Meanwhile, emerging themes

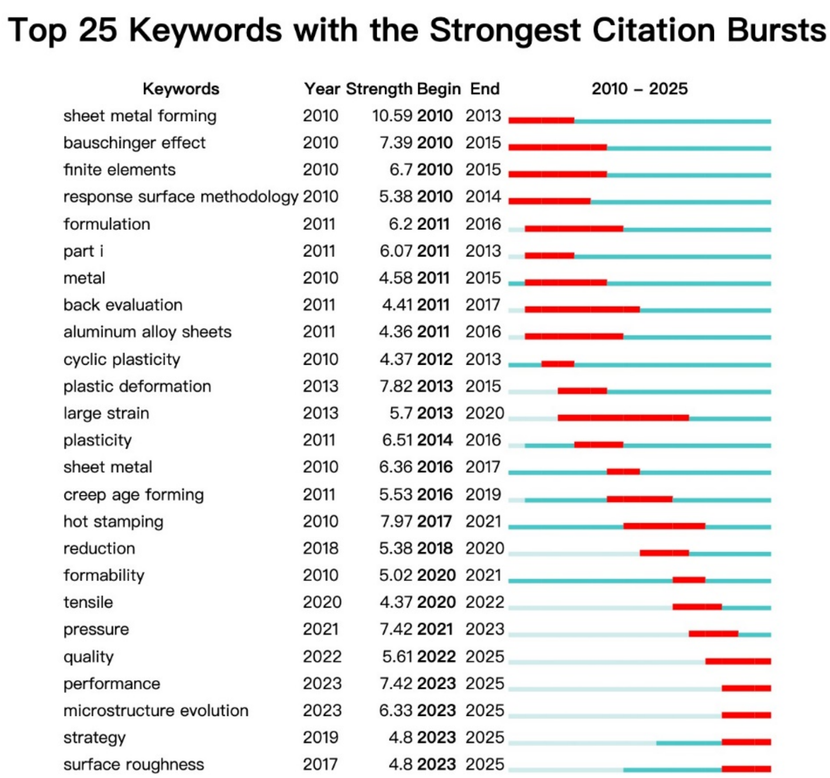

Figure 3: Top 25 Keywords with the Strongest Citation Bursts.

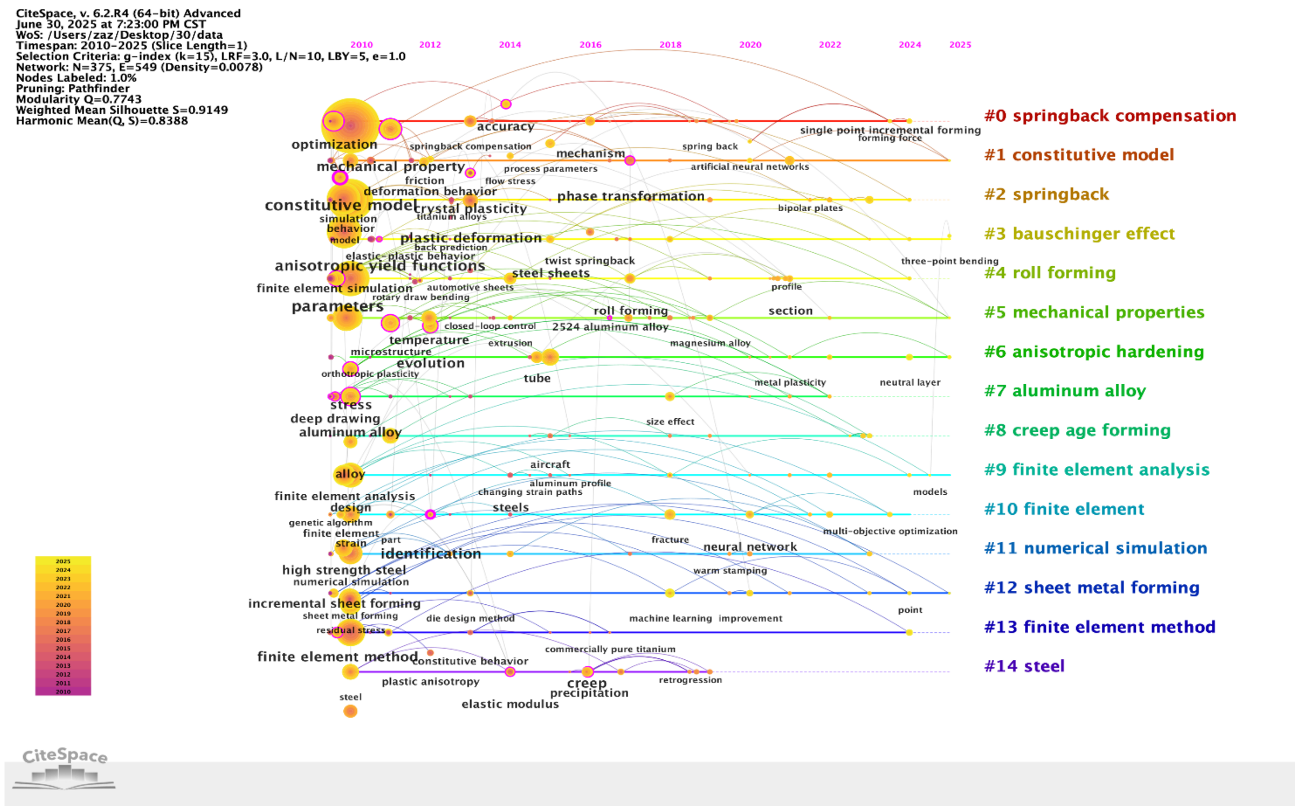

Figure 4: Shows the keyword co-occurrence cluster timeline generated by CiteSpace.

like "artificial neural networks" began to emerge, combining with traditional research to promote the intelligent development of the "stamping springback" field Table 2.

From the perspective of vertical clustering

"Springback compensation" (#0 springback compensation) runs through the entire research period and has always been one of the core themes, indicating that the exploration of springback compensation methods and technologies is a continuous focus in this field, evolving from simple empirical formulas to precise compensation strategies based on complex models and algorithms.

"Constitutive model" (#1 constitutive model) is closely related to the description of material mechanical behavior. It appeared around 2010 and gradually developed. With the deepening understanding of material micro-mechanisms and complex deformation behaviors, establishing more accurate constitutive models is crucial for predicting and controlling springback, involving classic plastic theory models and improved models.

"Springback" (#2 springback), as a basic concept and research object, is closely related to many other keywords. Its research content includes the formation mechanism of springback, quantitative analysis of influencing factors, etc., providing a theoretical basis for subsequent compensation and control. Research has evolved from basic theoretical exploration to practical applications and multidisciplinary integration, and the study of stamping springback issues is continuously deepening.

CO-AUTHORSHIP ANALYSIS

National and Regional Networks

To analyze and reveal the cooperation and contributions of various countries in the field of Stamping Springback, this study constructs a national and regional network. The analysis results of the national/regional network are of great significance for future research to obtain more precise guidance at the geographical level. Scholars can promote the development of this research field by means of cooperation models, and achieve knowledge and information sharing through comparative and collaborative research among countries (see Figure 5). The national network generated by VOSviewer confirms this point.

This study selects co-authorship analysis as the research method, takes countries as the analysis units, and uses the full counting method for statistics. The minimum literature threshold for countries is set at 15 papers, and the minimum number of citations is set at 5 times to obtain a more comprehensive map. Finally, 29 out of 76 countries meet the threshold requirements and are included in the final network Figure 5. The analysis results show that the connection strength among members of the national network is high enough, with only one weakly connected node.

Table 2: The 10 Most Productive Countries in the Dataset.

Ranking	Country	Number of Publications	Proportion	H-index	Total Citations	Average Citations per Publication
1	China	1077	45.791%	49	13748	12.77
2	South Korea	202	8.588%	33	3998	19.79
3	USA	145	6.165%	34	3945	27.21
4	Japan	133	5.655%	30	3217	24.19
5	Germany	132	5.612%	23	1916	14.52
6	France	92	3.912%	22	1545	16.79
7	England	91	3.869%	30	2950	32.42
8	India	91	3.869%	15	910	10
9	Australia	85	3.614%	24	1819	21.4
10	Iran	80	3.401%	22	1193	14.91

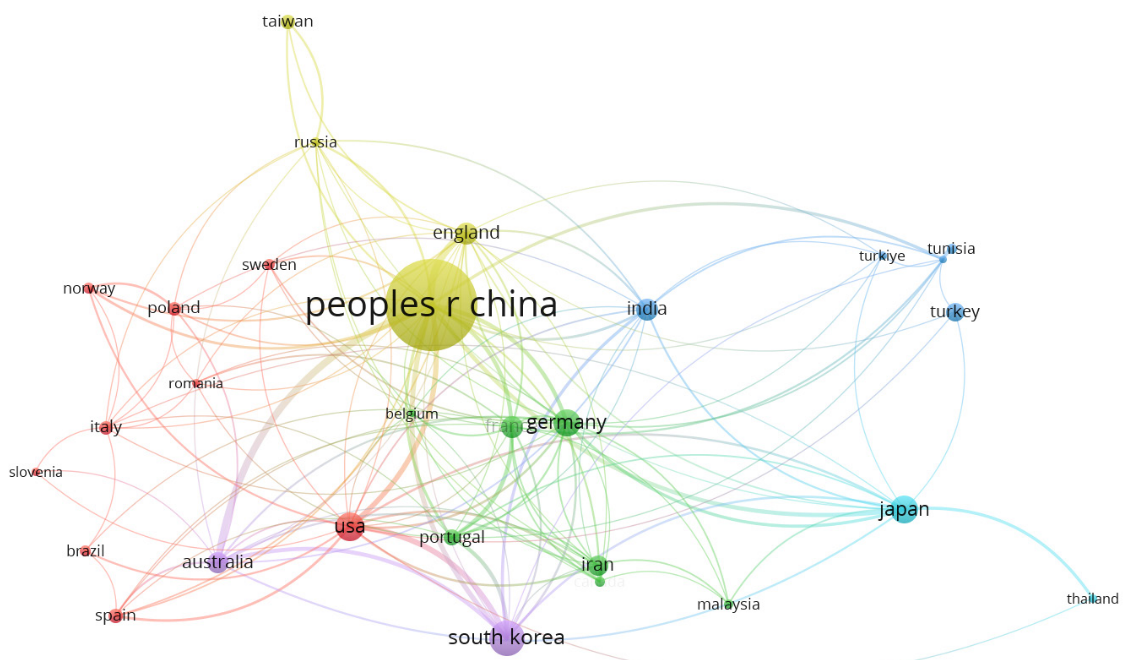

Figure 5: Visualized Collaborative Network of Countries/Regions in Stamping Springback Field Research.

Over the past 15 years, the top ten countries have published 1,699 articles on stamping springback. China ranked first in the number of publications (*n*=1,077), followed by South Korea (*n*=202) and the United States (*n*=145). The differences in publication output across countries are closely related to the strength of their industrial policy support. China's "Made in China 2025" plan (2015) identified advanced rail transportation equipment (Li, 2018), energy-saving and new energy vehicles, among others, as key sectors, providing important driving force for the development of high-precision sheet metal forming and springback control technologies. South Korea's "Manufacturing Innovation 3.0" strategy (2014) aimed to foster growth engines such as smart vehicles and advanced materials, thereby promoting research on forming processes and defect control (Min *et al.*, 2018). The U.S. "Strategy for American Leadership in Advanced Manufacturing" (2018 update) emphasized simulation-based engineering and advanced materials research, offering policy and financial support for the field of precision forming (Min *et al.*, 2018). Japan (*n*=133) and Germany (*n*=132) followed closely, with their research activities also closely aligned with their industrial strengths.

In the country/region collaboration network for stamping springback research, the United States and China are the two nodes with the highest centrality, maintaining close connections with other major research countries. The collaboration link between Australia and China is among the thickest, indicating a strong cooperative relationship between the two countries in this field. Collaborative ties among other countries are relatively limited, and future international cooperation could further promote knowledge exchange and technology sharing.

Research trends in stamping springback vary across countries due to industrial demands. Chinese research primarily focuses on springback control technologies in advanced manufacturing processes, delving into the mechanisms and control methods of springback in high-strength steel sheet forming, with widespread application of simulation technology for prediction and optimization. In contrast, research in Europe and the United States tends to emphasize the springback characteristics of specific materials (such as lightweight alloys) and compensation strategies based on intelligent algorithms. These differentiated directions reflect both the varied research priorities of different countries and the overall pattern of global collaboration in advancing this field.

As shown in Figure 6, among the countries with the highest publication output, the United Kingdom has the largest proportion of international cooperation, with 60 international papers (66%). Australia ranks second with 52 international papers, accounting for 61%.

Organizational Networks

As per prior studies, organizational collaboration via networks boosts scientific output and shapes international research policies (Abramo *et al.*, 2009). Identifying institutions with high engagement benefits any discipline (Ding, 2011), especially for building partnerships and informing decision-makers.

In this study, VOS viewers were used to developing the institutional network. Co-authorship and organizations were chosen as the analysis method and unit. The minimum literature threshold for countries is set at 15 papers, and the minimum number of citations is set at 5 times to obtain a more comprehensive map. Among 1675 organizations, 49 met this criterion.

Seven communities were identified (Figure 7). The first cluster (red) includes AVIC Manufacturing Technology Institute, Baoshan Iron and Steel Co., Beihang University, Dalian University of Technology, Harbin Institute of Technology, Hong Kong Polytechnic University, Imperial College London, Jiangsu University, Northwestern Polytechnical University, Norwegian University of Science and Technology, Shanghai Jiao Tong University, and Xi'an Jiaotong University.

Co-Citation Analysis

The analysis of the frequency with which two papers are simultaneously cited by other documents is called co-citation analysis. Co-citation analysis is one of the successful methods for analyzing the scientific knowledge base (Estrela, 2015; Jacomy *et al.*, 2014). Since papers commonly mentioned in other publications are likely to share related themes, co-citation analysis can assist researchers in identifying hidden patterns and research ideas in the field (Park and Shea, 2020). This study's dataset generated a journal co-citation network and an author co-citation network.

Author Co-Citation Analysis

Over the past 14 years, more than 6512 authors have published papers on springback. Table 3 lists the top ten most productive authors in this thematic field from 2010 to 2025. Their characteristics were extracted through author retrieval in the Web

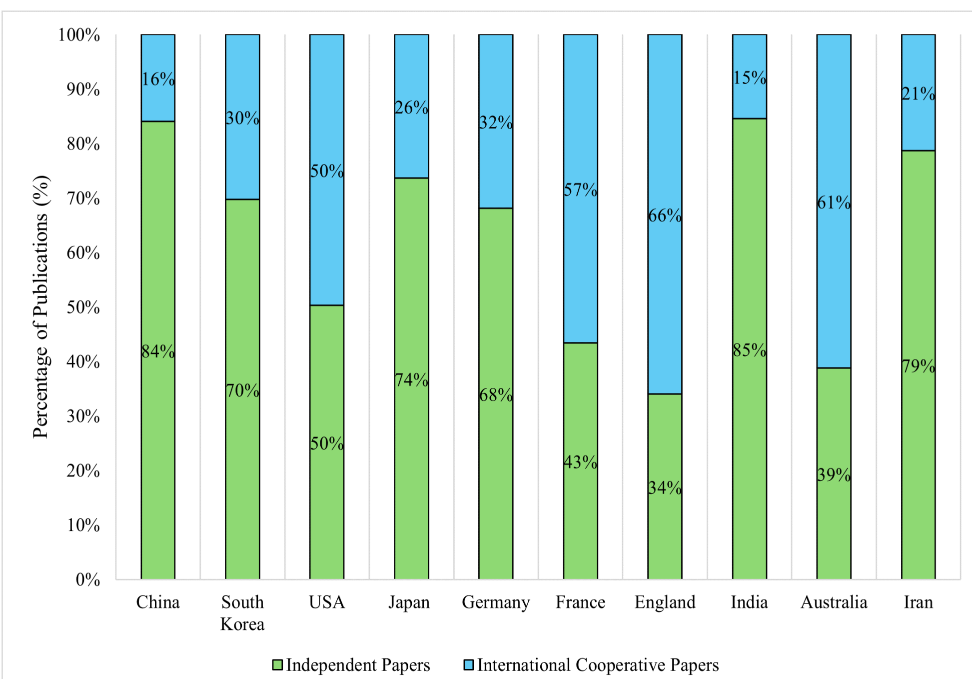

Figure 6: Percentage of independently published and internationally co-authored papers in the top ten countries/regions by publication output.

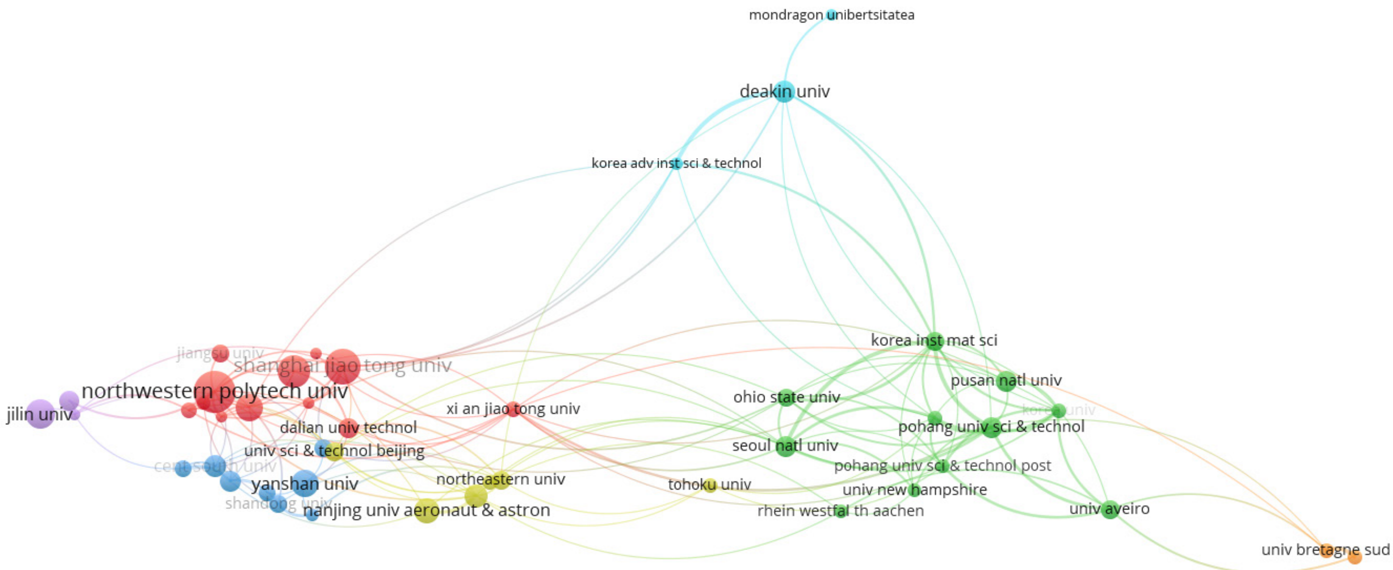

Figure 7: Visualizes the collaborative network of institutions in springback research.

Table 3: The ten most productive authors in the dataset.

Sl. No.	Author Name	Number of Publications	Number of Citations	Average Citations per Publication	H-index
1	Lee, Myoung-Gyu	61	2260	37.05	28
2	Barlat, Frederic	35	1352	38.63	23
3	Yang, He	29	888	30.62	16
4	Li, Heng	27	806	29.85	15
5	Lin, Jianguo	26	1091	41.96	16
6	Zhao, Jun	26	291	11.19	11
7	Zhan, Lihua	24	893	37.21	14
8	Lee, Jinwoo	23	898	39.04	17
9	Tekkaya, A. Erman	19	432	22.74	11
10	Rolfe, Bernard	18	465	25.83	13

of Science. Among the top ten prolific authors, Lee, Myoung-Gyu is highly relevant to this theme. He published a total of 61 papers from 2010 to 2025, with 2260 citations. He is the most cited author and has the highest H-index of 28.

A total of 240 authors have published at least 5 papers. VOS-viewer was used to further filter 69 authors with a threshold of "at least 10 papers" for co-authorship network analysis. As shown in Figure 8, authors finally included in the collaboration map must meet two conditions simultaneously: publishing at least 10 papers and having co-authorship relationships. In terms of the number of papers published by authors, the red and yellow circles represent authors with a relatively large number of publications, who form the core research leaders, including scholars such as Lee, Myoung-gyu and Barlat, Frederic. Meanwhile, they also intuitively show the main connection status among the publishing authors, forming relatively close cooperative groups.

Journal Co-Citation Network

Journal co-citation network analysis helps identify core channels of knowledge dissemination and academic communities within the field. As shown in Table 4, the top 10 journals have published a total of 1,190 papers, accounting for 50.77% of the total publications, and constitute the core knowledge base of this field. These journals are primarily concentrated in materials science and manufacturing engineering, clearly reflecting the multidisciplinary nature of stamping springback research, which involves mechanics, materials science, and process engineering.

The International Journal of Advanced Manufacturing Technology ranks first with 336 publications, representing 14.29% of the total. It serves as a major platform for discussing engineering solutions, process optimization, and case studies. Combined with its high publication volume and stable Journal Impact Factor (JIF=4.2), it can be regarded as one of the most mainstream and active outlets in the field, reflecting the strong engineering application-oriented

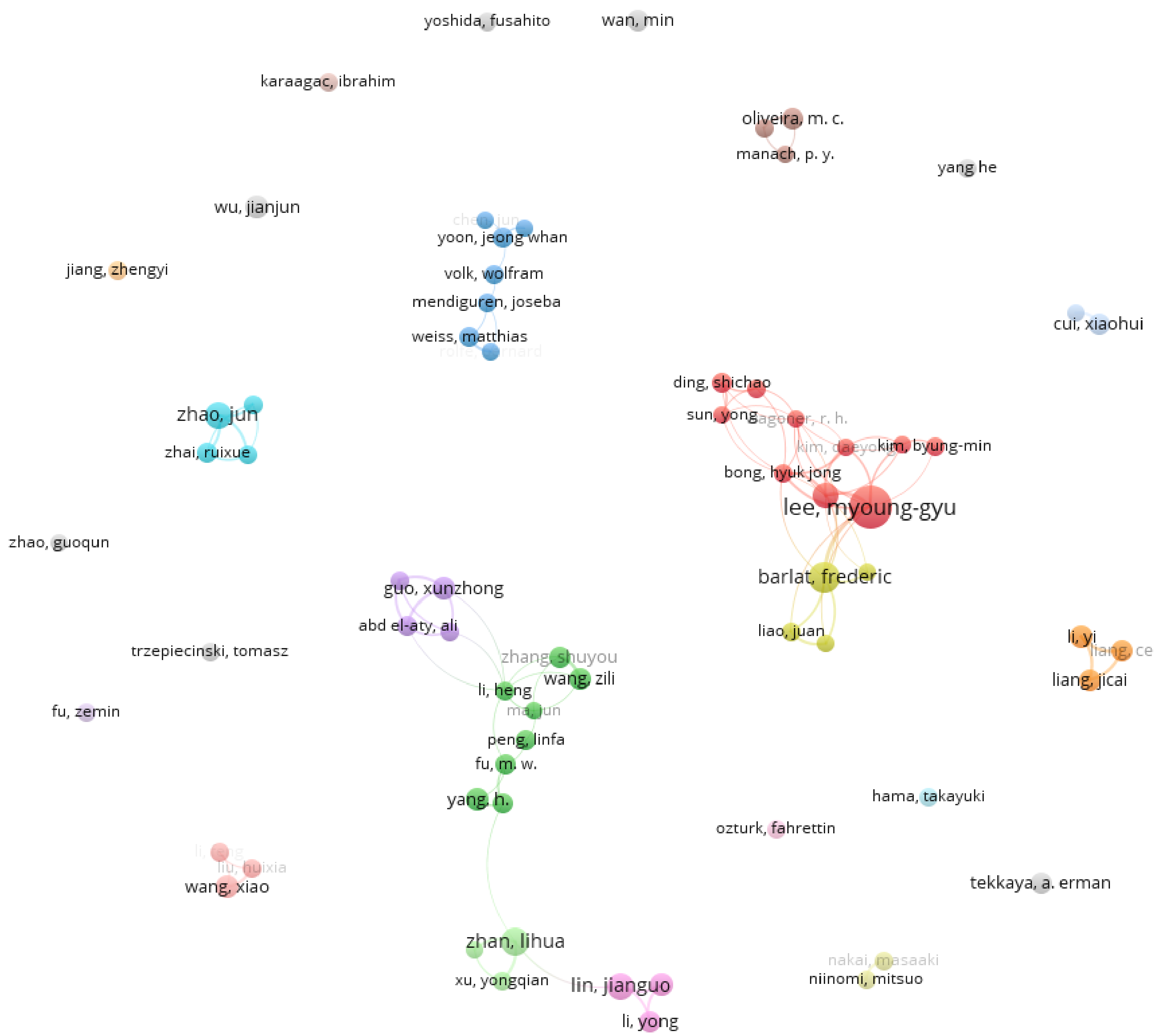

Figure 8: Author Collaboration Based on Co-authorship.

Table 4: Top 10 Journals by Publication Output in the Dataset

Sl. No.	Journal	Number of Publications	Country	Impact Factor	H-index
1	Int J Adv Manuf Technol	336	Germany	4.2	30
2	Int J Mech Sci	105	UK	4.8	40
3	J Mater Process Technol	99	Netherlands	5.3	32
4	Int J Mater Forming	96	France	3.5	27
5	Metals	77	Switzerland	3.2	35
6	Materials	71	Switzerland	3.8	16
7	J Manuf Process	67	USA	4.5	28
8	Mater Des	57	UK	6.3	29
9	Mater Sci Eng A	51	Netherlands	6.977	18
10	Mater Prop Microstruct Perform	46	USA	2.7	32

focus of the research. Notably, Materials and Design (JIF=6.3) and Materials Science and Engineering: A (JIF=6.977) have relatively fewer publications but higher Journal Impact Factors, indicating their significant influence in publishing high-quality research that delves into material mechanisms, constitutive models, and performance characterization.

CONCLUSION

Springback, as a prevalent and highly challenging physical phenomenon in sheet metal forming, continues to constrain the precision of advanced manufacturing. Based on a bibliometric assessment of 2,352 publications from the Web of Science Core Collection spanning 2010-2025, this study systematically presents the global trends, core topics, and frontiers in this field. Early research primarily relied on experimental validation, but the field has since undergone a paradigm shift towards finite element analysis and, more recently, artificial intelligence.

Analysis of spatial distribution and scientific collaboration networks reveals that China, South Korea, and the United States are the most productive research hubs. The publication advantages of these three nations are not coincidental but are closely aligned with their respective national strategies. China leads with 1,077 papers, directly linked to the 'Made in China 2025' initiative prioritizing advanced rail transit and new energy vehicles, which has spurred significant demand for high-precision forming technologies. South Korea's research activity corresponds to its 'Manufacturing Innovation 3.0' strategy, while the United States continues to strengthen its simulation-based engineering approaches. Regarding collaboration, the U.S. and China serve as core nodes in the network, whereas the United Kingdom and Australia exhibit the highest rates of internationally co-authored papers, highlighting the crucial role of cross-border knowledge sharing in tackling complex manufacturing challenges.

The high consistency between the evolution of keyword clusters and industrial demands reflects the multidisciplinary integration in this field. Research hotspots have evolved from early-stage "springback compensation" and macro-level "sheet metal forming" to more refined topics such as "microstructure evolution," "anisotropic hardening," and "hot stamping." This indicates that scholars are deeply integrating solid mechanics and materials science to address the nonlinear challenges posed by Advanced High-Strength Steels (AHSS). This interdisciplinary characteristic is also reflected in the diverse landscape of high-level journals: the International Journal of Advanced Manufacturing Technology, with its advantage in publication volume, serves as the primary platform for engineering applications, while journals such as Materials Science and Engineering: A and Materials and Design anchor engineering solutions in fundamental material mechanisms.

Despite significant progress, current research still faces notable bottlenecks. A key finding is that although AI models are rapidly emerging, they often function as "black-box" data-fitting tools lacking deep integration with physical constitutive theories. Simultaneously, industrial simulations lack characterization methods that quantitatively link micro-scale behaviors-such as pre-strain and texture evolution-to macro-scale springback. Future research could leverage Physics-Informed Machine Learning (PIML) and real-time digital twin monitoring to move beyond static prediction towards dynamic closed-loop control.

This study also has several limitations related to database coverage and time lag. Relying solely on the Web of Science Core Collection may omit engineering papers or non-English publications from Scopus or other regional databases. The inherent time lag in bibliometric indicators means that the latest industrial innovations or patent technologies are not yet fully reflected in citation data.

In summary, the findings of this study provide data-driven decision support for researchers and engineers, clearly indicating that the future of springback suppression lies in the deep integration of multi-scale material mechanics and intelligent algorithms. This approach will ultimately contribute to achieving efficient and precision manufacturing in the automotive and aerospace industries.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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