Productive Failure in Education: A Bibliometric Analysis of Research Patterns and Emerging Trends

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https://doi.org/10.17977/2549-7774.005447

Article history
Submitted: 18 June 2026
Revised: 8 September 2026
Accepted: 9 September 2026
Published: 11 September 2026

Keywords
Bibliometric analysis
Educational research
Productive failure
Research trends

Abstract
This study maps the intellectual landscape of productive failure research through a comprehensive bibliometric analysis of 294 documents published between 2006 and 2025, retrieved from the Scopus database. The analysis employed Biblioshiny for descriptive and thematic analysis, and VOSviewer for network visualizations. Findings reveal rapid growth in productive failure research, with the United States, Germany, and Australia as the most productive countries, and Kapur, Rummel, and Loibl as the most influential authors. Thematic analysis identified eight clusters, with core PF concepts and pedagogical strategies dominating the research landscape, while emerging topics include computational thinking, engineering education, and deep learning. Co-authorship analysis revealed a bipolar structure with two primary research groups showing minimal direct collaboration. This study provides the first comprehensive bibliometric mapping of productive failure research, offering researchers and educators a holistic understanding of the field's development, current trends, and research gaps.

1. Introduction

Failure in the learning process is often perceived as something negative that must be avoided. Research indicates that failure in educational settings is frequently stigmatized, leading to avoidance behaviors and negative emotions such as anxiety and self-doubt (Gashaj et al., 2022). These negative perceptions are further reinforced by social and institutional messages that equate failure with incompetence, making it difficult for students to embrace failure as a natural part of the learning process (Hilppö & Stevens, 2020). Educators tend to minimize the possibility of failure by providing full guidance from the outset of instruction. However, this perspective has begun to be questioned as empirical evidence emerges showing that systematically designed failure can actually serve as a catalyst for deep and meaningful learning (Kapur, 2024). When managed appropriately, failure can promote reflection, resilience, and innovation, while enhancing students' ability to persist and improve their understanding (Palominos et al., 2022). This paradox forms the foundation of the productive failure learning approach.

Productive Failure (PF) is an instructional approach in which learners engage in problem-solving tasks before receiving formal instruction, leveraging initial struggle and failure to enhance conceptual understanding, preparation for future learning, and knowledge transfer (Kapur, 2024). This approach originated in secondary mathematics education, where it demonstrated significant benefits for conceptual knowledge acquisition and problem-solving skills (Kapur, 2010). Over time, PF has been adapted to various domains. In science education, PF implemented in virtual learning environments has been shown to improve knowledge transfer and explanatory understanding (Cao & Zhang, 2025). In health professions education, PF has been applied in nursing simulations and clinical training, demonstrating effectiveness in preparing learners for adaptive expertise and future learning (Mylopoulos et al., 2025; Palominos et al., 2022). More recently, PF has been explored in computer science education, although its effectiveness in tertiary settings remains under investigation with mixed results depending on instructional design (Steinhorst et al., 2024). In STEM education more broadly, PF has been shown to support error correction, address misconceptions, and improve learning motivation and project outcomes (Zhou et al., 2025). Despite its demonstrated benefits, the success of PF depends critically on factors such as scaffolding, instructional fidelity, and contextual adaptation, with some studies reporting no significant advantage over direct instruction in specific contexts (Hartmann et al., 2022; Sinha & Kapur, 2019).

Bibliometric analysis has become an essential tool in educational research for identifying research trends, mapping collaboration networks, and revealing underexplored areas in a given field (Gómez et al., 2025; Maral, 2024). Tools such as VOSviewer and Biblioshiny enable researchers to visualize keyword co-occurrences, author

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collaborations, and co-citation networks, providing a comprehensive and quantitative overview of the research landscape (Jing et al., 2024). Compared to traditional narrative reviews, bibliometric analysis offers a more efficient and systematic way to process large datasets, complementing qualitative syntheses with empirical insights into research productivity and impact (Kumar, 2025). Despite the growing body of research on Productive Failure (PF) over the past two decades, no comprehensive bibliometric study has systematically mapped the intellectual structure, publication trends, key contributors, and thematic evolution of PF research. This gap is significant because PF has demonstrated promise in fostering conceptual understanding and knowledge transfer, yet several critical gaps remain in the literature. Most PF studies remain concentrated in secondary mathematics education, with limited exploration in other disciplines such as computer science and advanced tertiary education, where findings have been mixed (Steinhorst et al., 2023, 2024). Furthermore, the emotional and neurophysiological mechanisms underlying PF success remain underexplored (Formaz et al., 2022; Savelson & Muldner, 2021), and variations in design fidelity have been identified as critical factors influencing PF effectiveness (Sinha & Kapur, 2019). The application of PF in clinical learning environments and advanced STEM courses also remains underdeveloped (Mylopoulos et al., 2025). Therefore, a bibliometric mapping of PF research is urgently needed to provide a holistic overview of the field, identify research gaps, and guide future investigations. The novelty of this study lies in its two-decade time span (2006–2025) and its multi-tool bibliometric approach, encompassing descriptive analysis (using Biblioshiny), co-authorship analysis, co-occurrence analysis, and co-citation analysis (using VOSviewer).

Based on the aforementioned gaps, this study aims to conduct a comprehensive bibliometric analysis of Productive Failure research spanning the period from 2006 to 2025. Specifically, this study seeks to achieve four main objectives: (1) to describe publication and citation trends in PF research over the past two decades, (2) to identify the most productive and influential authors, sources, and countries contributing to the field, (3) to map the thematic structure and evolution of research topics through keyword co-occurrence analysis, and (4) to uncover the intellectual foundations of Productive Failure through co-citation analysis. By providing a holistic overview of the PF research landscape, this study is expected to identify research gaps, inform future research directions, and offer practical implications for educators and instructional designers seeking to implement PF in various learning contexts.

2. Method

2.1. Research Design and Flow

This study employed a bibliometric approach to systematically map the intellectual landscape of Productive Failure research. Bibliometric analysis is a powerful tool for understanding and advancing educational research, offering several key advantages: it identifies emerging and dominant research themes through keyword co-occurrence and citation patterns, maps global collaboration networks among countries and institutions, and visualizes the intellectual structure of a field by clustering related research themes and identifying influential works (Nurazmi et al., 2025). Compared to traditional narrative reviews, bibliometric methods complement qualitative syntheses by quickly identifying theoretical pillars, influential studies, and knowledge gaps, saving researchers significant time (Kumar, 2025). Bibliometric analysis has been widely applied across various educational contexts, including STEAM education (Nurazmi et al., 2025), virtual reality in schools (Kasperiuniene & Faiella, 2023), artificial intelligence in education (Akinlar, 2025), and learning analytics (Yuan et al., 2026). Tools such as VOSviewer, and Biblioshiny enable researchers to visualize co-authorship networks, keyword co-occurrence, and thematic clusters (Kasperiuniene & Faiella, 2023). Figure 1 presents the overall flow of the research procedure, which consisted of five main stages: (1) data retrieval from Scopus, (2) data screening and filtering, (3) data export, (4) bibliometric analysis using multiple tools, and (5) interpretation of findings.

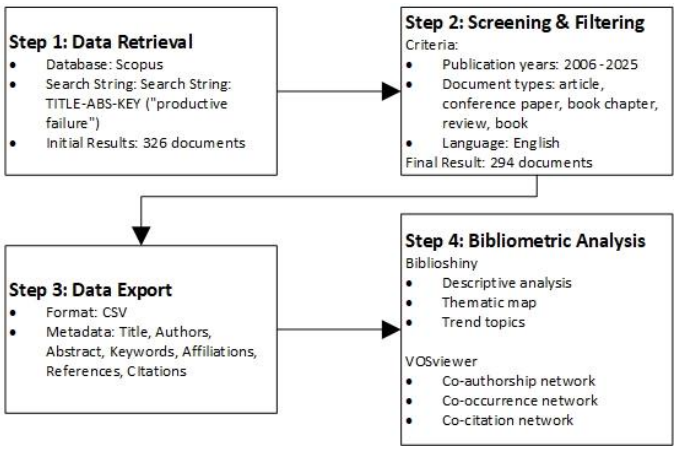


Figure 1. Research Workflow

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2.2. Data Collection

Data were retrieved from the Scopus database. Scopus was selected due to its comprehensive coverage of peer-reviewed literature in the social sciences, education, and psychology (Baas et al., 2020). The following search string was applied: `TITLE-ABS-KEY ("productive failure")`. The initial search yielded 326 documents.

2.3. Data Screening and Filtering

To ensure the relevance and quality of the data, several inclusion criteria were applied. First, the publication years were limited to 2006 to 2025 to capture two decades of research on Productive Failure since its introduction by Kapur (2006). Second, document types were restricted to articles (ar), conference papers (cp), book chapters (ch), reviews (re), and books (bk). Third, only documents written in English were included. After applying these criteria, a total of 294 documents were retained for further analysis. Table 1 presents the distribution of document types in the final dataset. Table 1 shows that articles constituted the majority of documents (n=169, 57.5%), followed by conference papers (n=93, 31.3%), book chapters (n=18, 6.1%), reviews (n=11, 3.7%), and books (n=4, 1.4%).

Table 1. Distribution of Document Types

Document Type	Frequency	Percentage
Article	169	57.5%
Conference paper	92	31.3%
Book chapter	18	6.1%
Review	11	3.7%
Book	4	1.4%

2.4. Bibliometric Analysis Procedures

The analysis proceeded in four stages, employing complementary tools to address the research objectives. Bibliometric analysis procedures using Biblioshiny and VOSviewer are well-established for mapping co-authorship, co-occurrence, and co-citation networks in educational research (Sharma et al., 2024). First, descriptive analysis was conducted using Biblioshiny, the web-based interface of the bibliometrix R package. This stage generated main information about the dataset, including timespan, number of sources and documents, annual growth rate, average citations per document, total references, author counts, collaboration indices, and document type distribution. Annual scientific production was also calculated to identify publication trends over time.

Second, co-authorship analysis was performed using VOSviewer to examine collaboration patterns among authors and countries. This analysis identifies research clusters and international collaboration structures, revealing the social structure of the research community (Anas et al., 2025). Third, co-occurrence analysis was conducted using VOSviewer to map the conceptual structure of the field. Author keywords were extracted, and a co-occurrence matrix was constructed. The resulting network visualization reveals dominant research themes and their interrelationships (Sharma et al., 2024). Fourth, co-citation analysis was performed using VOSviewer to uncover the intellectual foundation of Productive Failure research. This technique measures how frequently two references are cited together, revealing seminal works and their conceptual relationships (Du et al., 2024).

2.5. Analysis Tools

Three complementary tools were employed to perform the bibliometric analysis. First, Biblioshiny, the web-based interface of the bibliometrix R package, was used for descriptive analysis, thematic mapping, thematic evolution, and trend topics analysis (Sharma et al., 2024). Second, VOSviewer was used to construct and visualize co-authorship networks, co-occurrence networks, and co-citation networks (Anas et al., 2025). Third, Python in a Jupyter Notebook environment was used for data processing and visualization customization. All visualizations were generated using native plotting functions in Biblioshiny and VOSviewer.

3. Results and Discussion

3.1. Main Characteristics of the Dataset

Table 2 presents the main characteristics of the dataset. The analysis covered 294 documents published between 2006 and 2025 across 172 different sources. The annual growth rate of 20.93% indicates that productive failure research has experienced rapid expansion over the past two decades, reflecting increasing scholarly interest in productive failure. The average of 25.65 citations per document suggests that PF research has made a substantial impact in the field, indicating that despite its relatively recent emergence, PF has garnered considerable scholarly attention.

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A total of 674 authors contributed to the 294 documents, with an average of 3.24 co-authors per document. Notably, only 47 documents (16.0%) were single-authored, demonstrating that collaborative research dominates the field. This high proportion of collaborative publications suggests that PF research is characterized by a collective effort to establish and refine its theoretical framework, which is particularly significant given that PF is a relatively young field. International co-authorships accounted for 24.15% of all publications, indicating meaningful cross-border collaboration and confirming that PF has achieved global recognition across different research communities. The corpus contained 718 author keywords, providing rich material for thematic analysis. These descriptive statistics provide the foundation for the subsequent analyses by confirming that the PF corpus is sufficiently large and diverse for meaningful bibliometric mapping of its intellectual structure, research patterns, and emerging trends.

Table 2. Main Information of the Dataset

Description	Results
Timespan	2006 – 2025
Sources	172
Documents	294
Annual growth rate	20.93%
Average citations per document	25.65
Author's keywords	718
Authors	674
Single-authored documents	47 (16.0%)
Co-Authors per document	3.24
International co-authorships	24.15%

3.2. Publication and Citation Trends

Figure 2 illustrates the annual scientific production of productive failure research from 2006 to 2025. The publication trend reveals three distinct phases. The first phase (2006–2013) was characterized by low and fluctuating growth, with an average of 5.1 publications per year and a peak of 8 publications in 2012. The second phase (2014–2019) witnessed accelerated growth, with publications increasing from 13 in 2014 to 22 in 2019, averaging 17.3 publications per year. The third phase (2020–2025) showed the most rapid expansion, with publications reaching a peak of 37 in 2025, averaging 26.8 publications per year. Notably, after reaching a peak of 29 publications in 2021, the field experienced a gradual decline to 23 publications in 2024. However, this downward trend was reversed in 2025, which recorded the highest annual output over the entire two-decade period. The overall upward trajectory, with an annual growth rate of 20.93% as reported in Table 2, confirms that productive failure research has experienced significant growth over the past two decades, particularly in recent years.

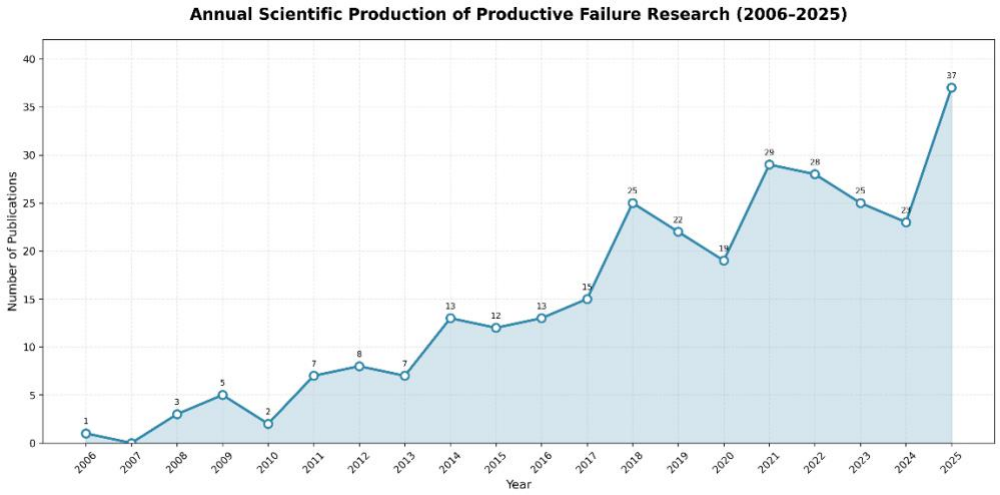


Figure 2. Annual Scientific Production of Productive Failure Research (2006–2025)

3.3. Most Relevant Sources, Authors, and Documents

Table 3 presents the top 10 most productive sources in productive failure research. Instructional Science ranked first with 26 publications, followed by the Proceedings of the International Conference of the Learning Sciences (ICLS) with 17 publications, and Learning and Instruction with 9 publications. The presence of both journals and conference proceedings reflects that PF research is disseminated through both peer-reviewed journal articles and conference presentations, indicating an active and dynamic research community. Other notable sources include Thinking Skills and Creativity (7 publications), Educational Psychology Review (6

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publications), Educational Technology Research and Development (6 publications), and Lecture Notes in Computer Science (LNCS) (6 publications). The latter indicates growing interest in PF within computer science education. CSCL Conference Proceedings contributed 5 publications, while Frontiers in Education and Interactive Learning Environments contributed 4 publications.

Table 3. Top 10 Most Relevant Sources

Rank	Source	Publications
1	Instructional Science	26
2	ICLS Proceedings	17
3	Learning and Instruction	9
4	Thinking Skills and Creativity	7
5	Educational Psychology Review	6
6	Educational Technology Research and Development	6
7	Lecture Notes in Computer Science (LNCS)	6
8	CSCL Conference Proceedings	5
9	Frontiers in Education	4
10	Interactive Learning Environments	4

Table 4 displays the top 10 most productive authors in PF research. Kapur M emerged as the most productive author with 39 publications, followed by Rummel N (29 publications) and Loibl K (16 publications). The dominance of Kapur is expected given his role as the originator of the productive failure framework (Kapur, 2006, 2008, 2016, 2024). Rummel and Loibl's high productivity reflects their extensive contributions to understanding the mechanisms and boundary conditions of PF (Loibl et al., 2017; Loibl & Rummel, 2014). Other productive authors include Jacobson MJ (11 publications), Hartmann C (10 publications), Roll I (9 publications), DeCaro MS (8 publications), Sinha T (7 publications), Song Y (7 publications), and Kalyuga S (6 publications). The concentration of publications among this core group indicates the existence of a cohesive research community centered around the PF paradigm.

Table 4. Top 10 Most Relevant Authors

Rank	Author	Publications
1	Kapur M	39
2	Rummel N	29
3	Loibl K	16
4	Jacobson MJ	11
5	Hartmann C	10
6	Roll I	9
7	DeCaro MS	8
8	Sinha T	7
9	Song Y	7
10	Kalyuga S	6

Table 5 lists the top 10 most globally cited documents. Kapur's (2008) article "Productive failure" published in Cognition and Instruction ranked first with 735 citations, followed by "Designing for Productive Failure" (Kapur & Bielaczyc, 2012) with 494 citations, and "Examining Productive Failure, Productive Success Unproductive Failure, and Unproductive Success in Learning" (Kapur, 2016) with 389 citations. The concentration of Kapur's works in the top ranks confirms his foundational role in establishing and developing the PF framework. Other highly cited documents include Loibl, Roll, and Rummel's (2017) theoretical synthesis (239 citations), Kapur's (2010) empirical study (210 citations), and Kapur's (2012) variance study (195 citations). Notably, Kalyuga and Singh's (2016) article on cognitive load theory (184 citations) and Loibl and Rummel's (2014) study on knowledge gap awareness (172 citations) also rank highly, indicating the field's engagement with adjacent theoretical frameworks and empirical mechanisms.

Table 5. Top 10 Most Global Cited Documents

Rank	Title	Author, Year	Citations	Source
1	Productive failure	Kapur, 2008	735	Cognition and Instruction
2	Designing for Productive Failure	Kapur & Bielaczyc, 2012	494	Journal of the Learning Sciences
3	Examining Productive Failure, Productive Success, Unproductive Failure, and Unproductive Success in Learning	Kapur, 2016	389	Educational Psychologist
4	Productive failure in learning math	Kapur, 2014	315	Cognitive Science
5	Towards a Theory of When and How Problem Solving Followed by Instruction Supports Learning	Loibl, Roll, & Rummel, 2017	239	Educational Psychology Review

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Rank	Title	Author, Year	Citations	Source
6	Productive failure in mathematical problem solving	Kapur, 2010	210	Instructional Science
7	Productive failure in learning the concept of variance	Kapur, 2012	195	Instructional Science
8	Rethinking the boundaries of cognitive load theory	Kalyuga & Singh, 2016	184	Educational Psychology Review
9	Knowing what you don't know makes failure productive	Loibl & Rummel, 2014	172	Learning and Instruction
10	Understanding Difficulties and Resulting Confusion in Learning: An Integrative Review	Lodge et al., 2018	161	Frontiers in Education

Table 6 presents the top 10 corresponding author countries. The United States ranked first with 39 publications, followed by Germany with 29 publications, Australia with 20 publications, and Singapore with 17 publications. The high percentage of multiple country publications (MCP) for Germany (37.9%), Singapore (35.3%), and China (41.7%) indicates strong international research collaboration in PF research. Canada and Switzerland each contributed 15 publications, with MCP rates of 20.0% and 26.7% respectively. China, despite ranking seventh in total publications (12 articles), showed the highest MCP rate (41.7%), suggesting that Chinese researchers actively engage in international collaborations. The United Kingdom (5 publications), Georgia, Hong Kong, and Israel (4 publications each) completed the top 10.

Table 6. Top 10 Corresponding Author Countries

Rank	Country	Publications	MCP %
1	United States	39	10.3%
2	Germany	29	37.9%
3	Australia	20	25.0%
4	Singapore	17	35.3%
5	Canada	15	20.0%
6	Switzerland	15	26.7%
7	China	12	41.7%
8	United Kingdom	5	0.0%
9	Georgia	4	0.0%
10	Hong Kong	4	25.0%

Note: MCP = Multiple Country Publications (international co-authorships)

3.4. Thematic Structure: Keyword Analysis

The analysis of author keywords revealed the core thematic structure of productive failure research. Table 7 presents the top 20 most frequent keywords in the dataset. As expected, "productive failure" was the most frequently occurring keyword (156 occurrences), which is consistent with the search strategy employed for data collection. Beyond the primary keyword, several distinct thematic clusters emerged.

"Students" ranked second with 69 occurrences, followed by "problem solving" (40 occurrences), "teaching" (25 occurrences), "education" (24 occurrences), and "learning" (24 occurrences). These keywords reflect the educational context in which PF research is situated. The prominence of "engineering education" (22 occurrences) and "e-learning" (20 occurrences) indicates the expansion of PF research beyond traditional mathematics education into engineering and online learning contexts. Other notable keywords include "collaborative learning" (16 occurrences), "curricula" (16 occurrences), "problem-solving" (16 occurrences), and "instructional design" (12 occurrences). The presence of "scaffolding" (9 occurrences), "exploratory learning" (9 occurrences), "problem-based learning" (9 occurrences), and "cognitive load theory" (8 occurrences) reflects the theoretical and pedagogical foundations that inform PF research. The keyword "failure" (11 occurrences) and "conceptual knowledge" (10 occurrences) further emphasize the dual focus on failure as a learning mechanism and conceptual understanding as a primary outcome.

Table 7. Top 20 Most Frequent Keywords

Rank	Keyword	Occurrences
1	productive failure	156
2	students	69
3	problem solving	40
4	teaching	25
5	education	24
6	learning	24
7	engineering education	22
8	e-learning	20
9	collaborative learning	16
10	curricula	16
11	problem-solving	16

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Rank	Keyword	Occurrences
12	instructional design	12
13	failure	11
14	conceptual knowledge	10
15	learning designs	10
16	mathematics	10
17	scaffolding	9
18	exploratory learning	9
19	problem-based learning	9
20	cognitive load theory	8

Beyond individual keywords, the analysis of discipline-specific terms reveals the educational contexts in which productive failure has been applied (Table 8). General education keywords (education, teaching, learning, curricula, instructional design, pedagogy) totaled 105 occurrences, reflecting the broad educational foundation of PF research. Online and digital learning contexts (e-learning, virtual reality, game-based learning) ranked second with 37 occurrences, indicating the growing integration of PF with technology-enhanced learning environments. Engineering education (29 occurrences), computer science education (18 occurrences), mathematics education (17 occurrences), medical and health education (17 occurrences), and science education (8 occurrences) represent the primary disciplinary domains where PF has been empirically investigated. Language education appeared only once ("language learning"), suggesting that productive failure has received very limited attention in language learning contexts, representing an underexplored area for future research.

Table 8. Distribution of Educational Disciplines in Productive Failure Research

Discipline	Keywords (occurrences)	Total Occurrences
General Education	education (24), teaching (25), learning (24), curricula (16), instructional design (12), pedagogy (4)	105
Online/Digital Learning	e-learning (20), virtual reality (7), game-based learning (6), simulation (4)	37
Engineering Education	engineering education (22), stem education (4), stem (3)	29
Computer Science Education	computer science (5), computational thinking (6), programming (3), computer science education (4)	18
Mathematics Education	mathematics (10), mathematics education (7)	17
Medical/Health Education	medical education (6), clinical competence (6), nursing education (2), pharmacy education (3)	17
Science Education	science education (5), physics education (3)	8
Language Education	Language learning (1)	1

Figure 3 illustrates the evolution of research foci through trend topics analysis based on the median year of occurrence for each keyword. The analysis reveals three distinct temporal phases in the development of productive failure research.

The first phase (2009–2015) represents the early development of the field. Keywords from this period include "research" (median 2009), "virtual reality" (2010), "inquiry learning" (2012), and "invention activities" (2014). These terms reflect the foundational period when researchers were establishing the conceptual basis of PF and exploring its initial applications. The presence of "virtual reality" in this early phase is notable, indicating that technology-enhanced learning environments have been considered as a context for PF since its early development.

The second phase (2016–2020) marks a period of expansion and consolidation. Keywords from this period include "collaborative learning" (2016), "prior knowledge" (2016), "science education" (2016), "worked examples" (2017), "e-learning" (2018), "learning systems" (2018), "problem solving" (2019), and "scaffolds" (2019). The emergence of "collaborative learning" and "scaffolds" reflects growing attention to the instructional mechanisms that support PF effectiveness. The presence of "worked examples" (median 2017) indicates theoretical dialogue between PF and example-based learning research. "E-learning" and "learning systems" (median 2018) suggest the increasing integration of PF with digital learning environments.

The third phase (2021–2025) represents the most recent developments and emerging trends. Keywords from this period include "productive failure" (2021), "student" (2021), "problem-based learning" (2021), "human" (2022), "teaching" (2022), "failure (mechanical)" (2022), "engineering education" (2023), "curricula" (2023), "male" (2023), and "deep learning" (2024). The appearance of "engineering education" and "failure (mechanical)" confirms the expansion of PF into engineering disciplines. The emergence of "deep learning" (median 2024) as the most recent keyword is particularly noteworthy, suggesting potential future directions for PF research in the context of artificial intelligence and advanced learning technologies. The shift from early

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methodological and theoretical development toward applied contexts (engineering education, e-learning) and specialized topics (psychology, deep learning) confirms the maturation and diversification of productive failure research as a field.

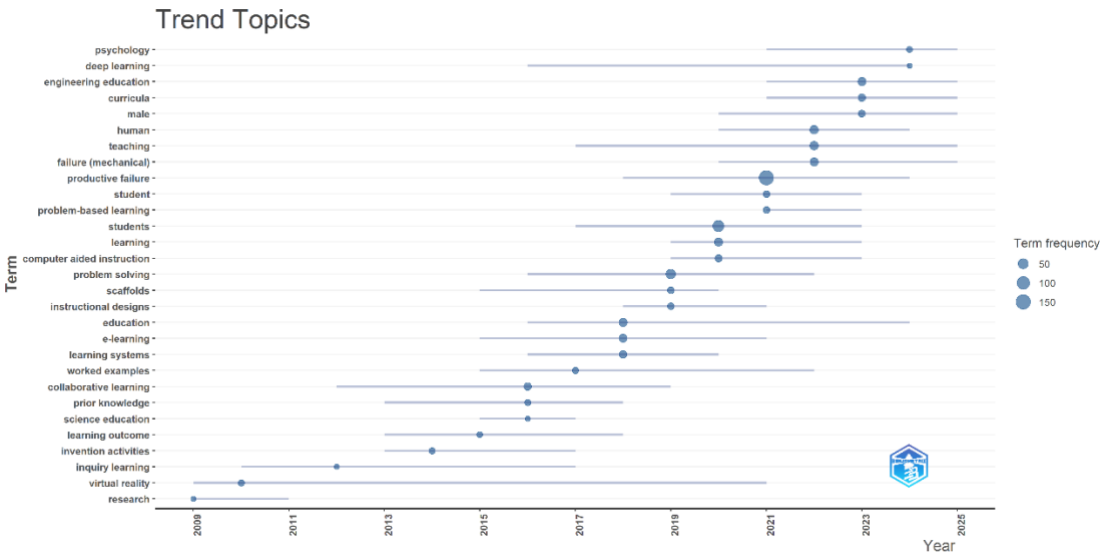


Figure 3. Trend Topics in Productive Failure Research (2009–2025)

3.5. Thematic Structure: Thematic Map and Co-occurrence Network

3.5.1. Thematic Map

The thematic map analysis was conducted using Biblioshiny to identify the conceptual structure of productive failure research based on two dimensions: centrality (relevance of a theme) and density (development of a theme). Figure 4 presents the resulting thematic map, while Table 9 summarizes the five thematic clusters ranked by their Callon centrality and density values. The productive failure cluster had the highest density (58,168) but moderate centrality (7,125), while the students cluster showed the highest centrality (12,147) with high density (87,045). The human cluster demonstrated the highest density (128,114) with moderate centrality (6,247).

Table 9. Thematic Clusters Based on Centrality and Density

Cluster	Callon centrality	Callon Density	Rank Centrality	Rank Density	Frequency
productive failure	7,125	58,168	4	1	330
students	12,147	87,045	5	3	636
human	6,247	128,114	3	5	346
problem-based learning	4,508	75,034	2	2	71
game-based learning	1,319	102,444	1	4	30

The thematic map revealed the positioning of five clusters across four quadrants. The game-based learning cluster (Callon centrality 1,319; density 102,444) was located in the niche themes quadrant (upper-left). This quadrant contains themes with high density but low centrality, indicating that this theme is well-developed internally but has low relevance to the main research themes, representing a specialized sub-domain within PF research. The human cluster (centrality 6,247; density 128,114) was positioned on the upper-middle line between the niche and motor themes quadrants. This position suggests that research on human factors in education has moderate centrality and the highest density among all clusters, bridging specialized and mainstream topics in PF research.

The productive failure cluster (centrality 7,125; density 58,168) was positioned in the basic themes quadrant (lower-right). This quadrant contains themes with high centrality but low density, indicating fundamental concepts that are essential to the field but have not yet developed into dense internal networks. This position confirms that the core concept of PF and its relationship with cognitive load theory serve as foundational theoretical pillars that are highly relevant and connected to many other research topics. The problem-based learning cluster (centrality 4,508; density 75,034) was located in the emerging or declining themes quadrant (lower-left). This quadrant contains themes with low centrality and low density, suggesting that the integration of problem-based learning and computational thinking may represent either an emerging research direction or a declining topic within PF research.

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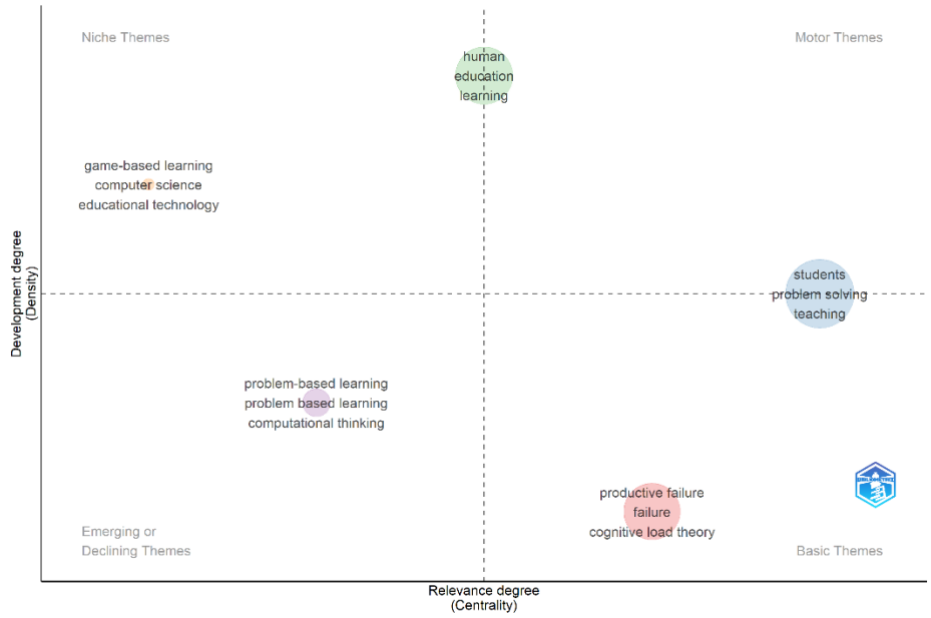


Figure 4. Thematic Map of Productive Failure Research

3.5.2. Co-occurrence Network

To further explore the thematic structure, a keyword co-occurrence analysis was performed using VOSviewer. Of the 719 author keywords, 28 met the threshold of a minimum of five occurrences. Figure 5 visualizes the co-occurrence network, and Table 10 summarizes the eight thematic clusters identified from the analysis.

Table 10. Thematic Clusters Identified from Keyword Co-Occurrence Analysis

Cluster	Theme	Keywords	Number of items
1	Core Productive Failure and Collaboration	collaborative learning, education, game-based learning, productive failure, science education	5
2	Pedagogical Strategies	creativity, failure, problem-based learning, problem-solving, scaffolding	5
3	Computational Thinking	computational thinking, debugging, design-based research, mathematics education	4
4	Cognitive Foundations	cognitive load theory, inquiry learning, invention activities, worked examples	4
5	Adaptive Expertise	adaptive expertise, instructional design, preparation for future learning	3
6	Mathematics Problem Solving	mathematics, problem solving, vicarious failure	3
7	Invention and Discovery	exploratory learning, invention	2
8	Instructional Approaches	direct instruction, learning from errors	2

Cluster 1 (core PF and collaboration) contains "productive failure" as its central node, along with "collaborative learning," "education," "game-based learning," and "science education." Productive failure's central position in the network confirms its foundational role in the field. This cluster represents the core of PF research, emphasizing collaborative and game-based learning contexts in science education. Cluster 2 (pedagogical strategies) includes "failure," "problem-solving," "scaffolding," "creativity," and "problem-based learning." This cluster reflects the pedagogical mechanisms that support PF, highlighting the role of scaffolding and problem-based learning in helping students learn from failure. Clusters 1 and 2 were positioned adjacent to each other in the network, reflecting the strong conceptual integration between core PF concepts and pedagogical strategies.

Cluster 3 (computational thinking) comprises "computational thinking," "debugging," "design-based research," and "mathematics education." This cluster indicates the emerging application of PF in computer science education and mathematics education, with a focus on debugging as a form of productive failure. Cluster 4 (cognitive foundations) consists of "cognitive load theory," "inquiry learning," "invention activities," and "worked examples." This cluster represents the theoretical dialogue between PF and cognitive load theory, as well as connections to invention-based learning approaches. Clusters 2 and 4 were positioned adjacent to each other in the network, reflecting the strong conceptual integration between pedagogical strategies and cognitive

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theories in PF research. This adjacency suggests that researchers often draw upon cognitive load theory to explain the effectiveness of scaffolding and problem-based learning within the PF framework.

Cluster 5 (adaptive expertise) includes "adaptive expertise," "instructional design," and "preparation for future learning." This cluster reflects the long-term goals of PF, emphasizing the development of adaptive expertise and preparation for future learning. Cluster 6 (mathematics problem solving) comprises "mathematics," "problem solving," and "vicarious failure." This cluster represents the traditional domain of PF research, highlighting its origins in mathematics education and the concept of learning from others' failures. Cluster 7 (invention and discovery) includes "exploratory learning" and "invention," representing related instructional approaches that share similarities with PF. Cluster 8 (instructional approaches) comprises "direct instruction" and "learning from errors," representing the pedagogical contrast between direct instruction and productive failure approaches.

The co-occurrence network confirms the thematic map findings while providing more detailed cluster differentiation. The central position of "productive failure" and its strong connections to various clusters confirms its role as the foundational concept in the field. The presence of specialized clusters (computational thinking, cognitive load theory, adaptive expertise) indicates the maturation and diversification of productive failure research across multiple theoretical and applied domains.

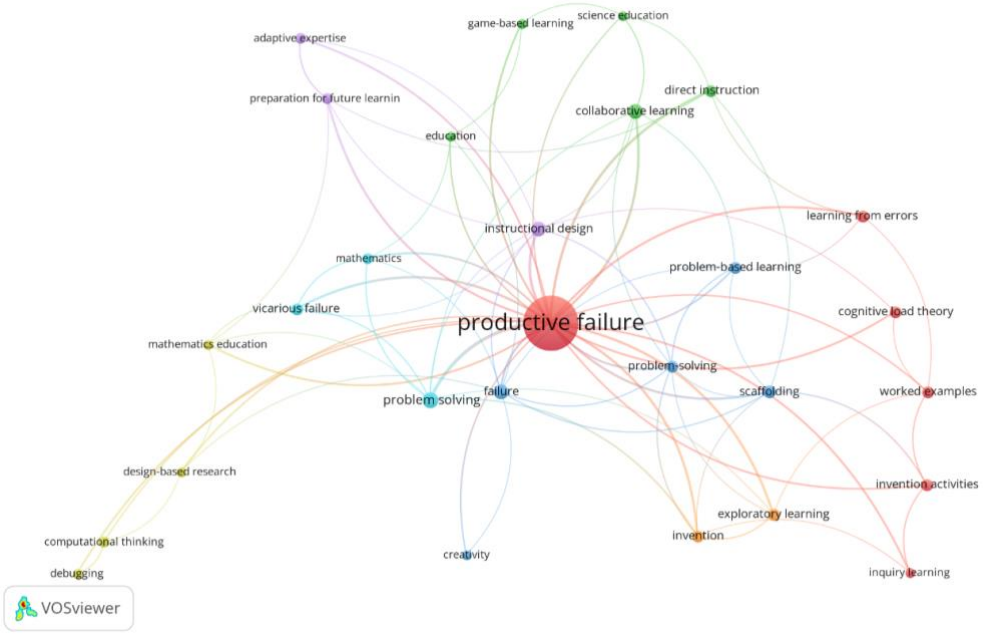


Figure 5. Co-occurrence Network of Author Keywords in Productive Failure Research

3.6. Collaboration Networks

3.6.1. Co-authorship Network

The co-authorship analysis was performed using VOSviewer to examine collaboration patterns among productive failure researchers. Of the 674 authors in the dataset, 16 met the threshold of a minimum of five publications. After removing isolated authors, 13 authors formed a connected network consisting of four clusters. Figure 6 visualizes the co-authorship network, and Table 11 summarizes the four clusters.

Table 11. Co-authorship Clusters Identified from VOSviewer Analysis

Cluster	Color	Authors	Number of items
1	Red	Brand, C; Loibl, K; Mazziotti, C; Roll, I; Rummel, N	5
2	Green	Kapur, M; Sinha, T; Song, Y; Trninic, D	4
3	Blue	Hartmann, C; van Gog, T	2
4	Yellow	Jacobson, MJ; Lai, PK	2

The co-authorship network reveals a bipolar structure with two central figures acting as primary hubs: Rummel, N in the left cluster and Kapur, M in the right cluster. Their node sizes are the largest in the network, reflecting their high productivity and extensive collaboration with other researchers. Cluster 1 (red, center-left) centers on Rummel, N and includes Loibl, K, Brand, C, Mazziotti, C, and Roll, I. This cluster demonstrates

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intensive and interconnected collaboration, with Rummel-Loibl having the strongest link. This group has been instrumental in investigating the cognitive mechanisms and boundary conditions of productive failure. Cluster 2 (green, center-right) centers on Kapur, M, the originator of the productive failure framework, and includes Sinha, T, Song, Y, and Trninic, D. This cluster represents the foundational research on PF, with Kapur-Sinha showing a strong collaborative link. Song and Trninic also maintain connections to Kapur, indicating an active research group.

Cluster 3 (blue, left) consists of Hartmann, C and van Gog, T. This cluster shows strong connections to the Rummel group, particularly Hartmann-Rummel and van Gog-Rummel. Hartmann also has connections to Loibl (3) and Brand (3), indicating that this cluster serves as a bridge within the left network. Cluster 4 (yellow, right) comprises Jacobson, MJ and Lai, PK. This cluster is connected to the Kapur group through links from Jacobson-Kapur (2) and Jacobson-Lai (4). Notably, this cluster has an earlier average publication year (2015-2017) compared to other clusters, suggesting their foundational contributions to PF research in virtual learning environments.

Crucially, the network reveals minimal direct collaboration between the two primary research groups. Only a peripheral link connecting Roll, I (cluster 1) to Kapur, M (cluster 2) exists. This suggests that productive failure research has developed through two relatively independent "schools of thought": one centered on Kapur (focusing on foundational PF mechanisms in mathematics) and another centered on Rummel (focusing on collaborative learning and cognitive mechanisms). This polarization presents an opportunity for future research to integrate findings from both research traditions.

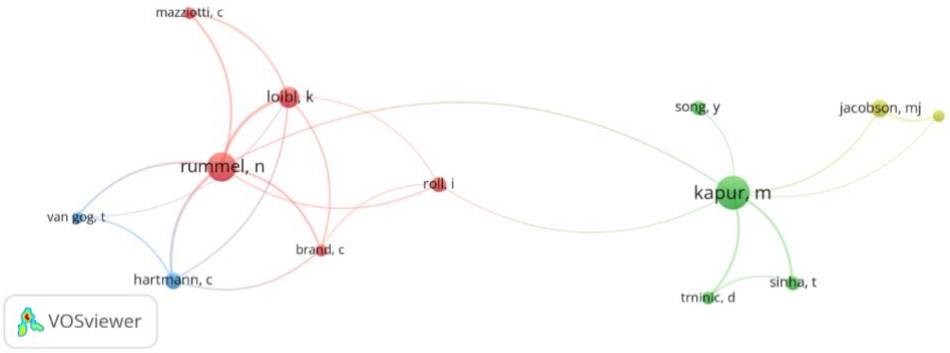


Figure 6. Co-authorship Network of Productive Failure Researchers

3.6.2. Co-authorship by Country

The co-authorship analysis by country was performed to examine international collaboration patterns in productive failure research. Of the countries represented in the dataset, 11 met the threshold of a minimum of one document. These 11 countries formed a connected network consisting of four clusters. Figure 7 visualizes the co-authorship network by country, and Table 12 summarizes the four clusters.

Table 12. Co-authorship Clusters by Country

Cluster	Color	Countries	Number of items
1	Red	Australia, China, Germany, Netherlands, United Kingdom	5
2	Green	Canada, United States	2
3	Blue	Hong Kong, Singapore	2
4	Yellow	Israel, Switzerland	2

The co-authorship network reveals a core-periphery structure with two dominant countries acting as primary hubs: the United States and Germany. Their node sizes are the largest in the network, reflecting their central roles in facilitating international collaboration. Cluster 1 (red) is the most geographically diverse cluster, led by Germany as a secondary hub. Germany has established strong collaborative links with the Netherlands and Switzerland, while also maintaining connections to Australia, China, and the United Kingdom. The Netherlands and Australia also serve as important connectors within this cluster, bridging European and Asia-Pacific research communities. Cluster 2 (green) comprises the United States and Canada. The United States serves as the primary global hub, with strong collaborative links to Canada, Germany, Australia, and Singapore. The United States also maintains connections to Switzerland and the United Kingdom. This cluster's central position in the network confirms the United States' role as the main nexus for international PF research collaboration.

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Cluster 3 (blue) consists of Singapore and Hong Kong, representing a specific Asia-Pacific collaboration cluster. Singapore shows proactive connections to the United States, Australia, Switzerland, and China. Hong Kong maintains connections to Singapore, Switzerland, and the United States. Cluster 4 (yellow) comprises Switzerland and Israel. Switzerland serves as an important peripheral bridge, connecting to Germany, the United States, Singapore, and Israel. This cluster demonstrates how smaller research nations can integrate into the global PF research network through strategic collaborations.

The network reveals that international collaboration is highly concentrated among a few dominant countries. The United States and Germany account for the majority of collaborative links, indicating that PF research is primarily driven by these two research superpowers. Countries such as China, Australia, and Singapore serve as important regional hubs but remain dependent on connections to the United States and Germany for global integration.

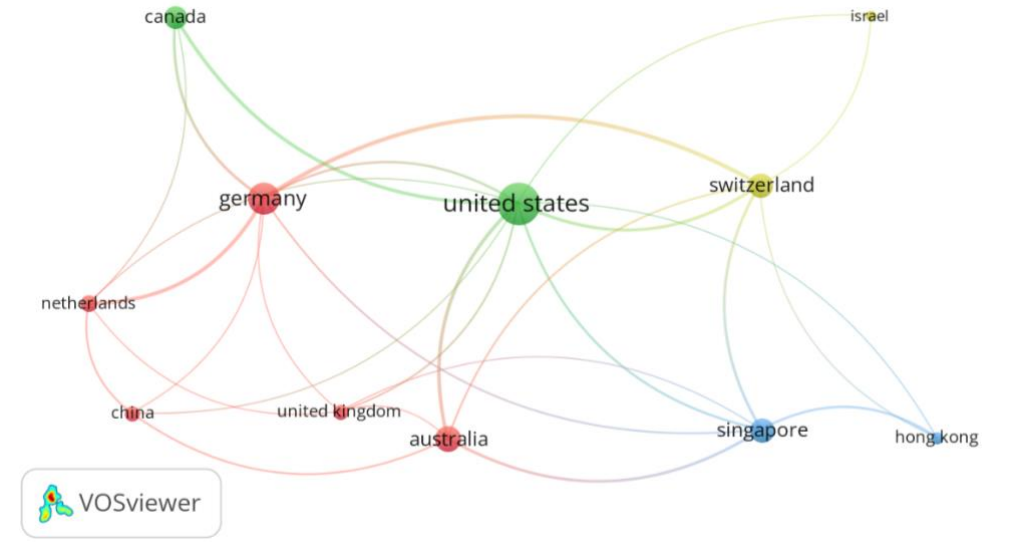


Figure 7. Co-authorship Network of Productive Failure Research by Country

3.7. Co-citation Network

The co-citation analysis was performed to uncover the intellectual foundation of productive failure research. This technique measures how frequently two references are cited together, revealing seminal works and their conceptual relationships. Of the 10,262 cited references in the dataset, 19 met the threshold of a minimum of 20 citations. These 19 references formed a connected network consisting of three clusters with 164 links. Figure 8 visualizes the co-citation network, and Table 13 summarizes the three clusters.

Table 13. Co-citation Clusters Identified from VOSviewer Analysis

Cluster	Theme	Key References	Number of items
1	Productive Failure Core	Kapur (2008, 2010, 2011, 2014, 2016); (Kapur & Bielaczyc, 2012); Loibl et al. (2017)	8
2	Instructional Design and Invention	Kapur (2008, 2012, 2014); Kapur & Bielaczyc (2012); Glogger-Frey et al. (2015); (Loibl & Rummel, 2014)	7
3	Theoretical Foundations	Schwartz & Bransford (1998); Kirschner et al. (2006); VanLehn et al. (2003); Schwartz & Martin (2004)	4

The co-citation network reveals three distinct clusters representing the intellectual structure of productive failure research. Cluster 1 (red) is the largest cluster, dominated by Kapur's seminal works on productive failure, including his foundational 2008 article, his 2014 article on learning math, his 2016 theoretical synthesis, and his 2021 meta-analysis. This cluster also includes Kapur & Bielaczyc's (2012) design framework and Loibl et al.'s (2017) theoretical synthesis. The central position of Kapur's works in this cluster confirms his role as the primary architect of the productive failure framework. Cluster 2 (green) connects Kapur's works with research on invention activities and instructional design. Key references include Kapur (2008, 2012, 2014), Kapur & Bielaczyc (2012), Glogger-Frey et al. (2015) on "Inventing a Solution and Studying a Worked Solution Prepare Differently for Learning from Direct Instruction", and Loibl & Rummel (2014) on "Knowing What You Don't Know Makes Failure Productive". This cluster demonstrates the strong conceptual integration between productive failure and invention-based learning approaches. Cluster 3 (blue) represents the theoretical foundations that underpin productive failure research. This cluster includes Schwartz & Bransford's (1998) "A

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Time for Telling," which established the preparation for future learning framework; Kirschner et al.'s (2006) critique of minimal guidance, representing the direct instruction perspective; VanLehn et al.'s (2003) work on tutoring and impasse-driven learning; and Schwartz & Martin's (2004) work on inventing to prepare for future learning.

The dense interconnections between Cluster 1 and Cluster 2 indicate a strong theoretical consensus among researchers working on productive failure and invention-based learning. The connections between Cluster 1 and Cluster 3 reveal that productive failure research is grounded in broader learning sciences theories, particularly preparation for future learning and the debate between direct instruction and discovery learning.

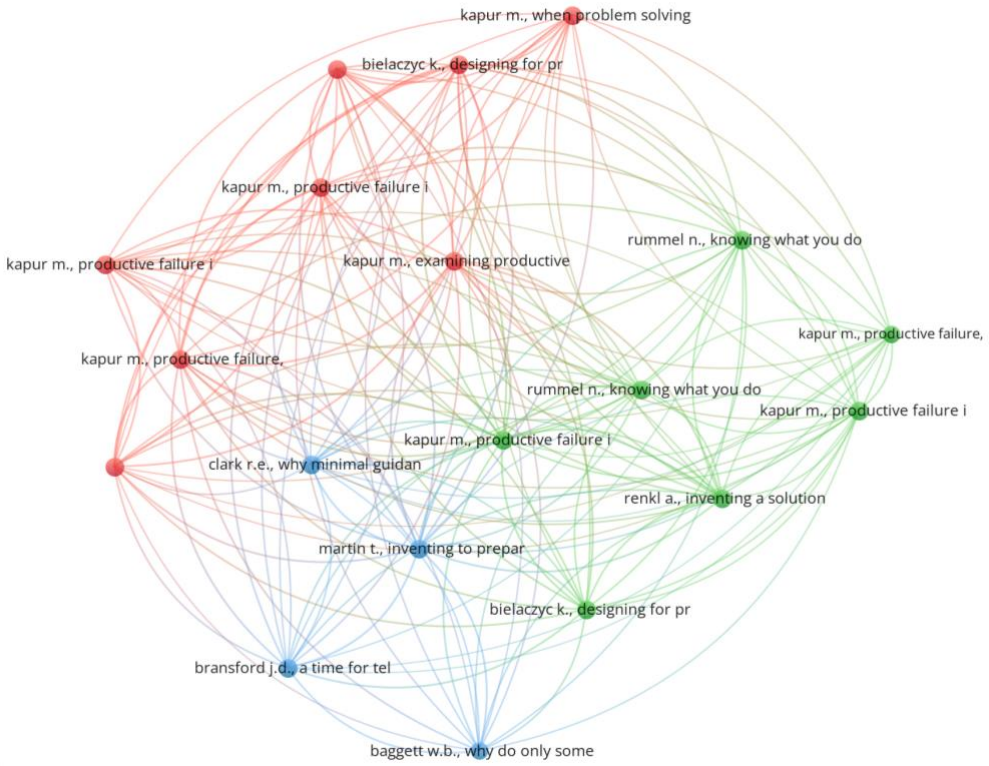


Figure 8. Co-citation Network of Productive Failure Research

4. Conclusion

This bibliometric examination of 294 papers on productive failure (2006–2025) reveals three primary conclusions. First, PF research has had significant expansion (20.93% annual growth rate), evolving from basic theoretical advancements to varied applications across fields, notably in engineering education and computer science. Second, this field shows an integrated yet fragmented framework of thought, although Kapur's foundational works serve as the theoretical basis, two largely independent research groups have emerged (one focused on Kapur and the other on Rummel), with minimal collaboration between them hindering theoretical synthesis. Third, the thematic analysis reveals neglected areas, particularly in language education, as well as rapidly evolving fields such as computational thinking and deep learning, which offer promising prospects for future research.

Limitations of this study include reliance on a single database (Scopus), which may exclude relevant publications indexed elsewhere, and the inherent limitations of bibliometric methods in capturing qualitative aspects of research impact. Future research should prioritize: (1) expanding PF applications to underexplored domains, particularly language education and advanced STEM contexts; (2) integrating emerging technologies such as artificial intelligence and deep learning into PF instructional designs; and (3) fostering greater collaboration between the two primary research communities to advance theoretical integration and empirical validation across diverse educational contexts. As PF continues to gain recognition across diverse educational settings, its potential to transform instructional practices through systematically designed failure experiences remains substantial, offering educators a powerful pedagogical approach for fostering deeper conceptual understanding and adaptive expertise.

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Author Contributions

All authors contributed equally to this paper. All authors have read and approved the final manuscript.

Funding

No funding support was received.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declaration on AI Use

The authors declare that no artificial intelligence (AI) or AI-assisted tools were used in the preparation of this manuscript.

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