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A Comparative Bibliometric Analysis of Emotional Intelligence in Leadership Performance

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Abstract. *This paper provides an overview of a comparative bibliometric analysis of research on emotional intelligence in leadership performance using multiple analytical tools. Historically, bibliometric research evolved from simple citation analysis into a complex discipline that intersects with AI and ethics. As publications are continuously growing in complexity and in volumes, bibliometric analysis is increasing in importance to identify research trends, assess impact, and undercover new directions. While its methodologies provide deep insights into the evolution of knowledge, an overreliance on metrics without critical assessment can reinforce biases and hinder innovation. In this evolving context, the research assesses analysis results of well-known bibliometric tools (VOSviewer, Biblioshiny); and compare the results with the outcome of analysis performed with AI technology (Scholar GPT). Both VOSviewer and Biblioshiny offer capabilities which complement each other in supporting bibliometric research. Although AI tools in bibliometric research are controversial and still evolving, they can be considered for addressing productivity challenges which also arise in the research field due to the increased number of publications. This paper's outcomes re-emphasize the importance of selecting the right research methodology and tools based on each research project's requirements. In conclusion, future bibliometric research should consider hybrid models that combine quantitative precision with qualitative focus, while tools will have to balance high processing demands, increased accuracy and relevancy. Bibliometrics will continue to model progress through innovation and research objectivity.*

Keywords: emotional intelligence, leadership performance, knowledge dynamics, comparative study. VOSviewer, Biblioshiny, Scholar GPT.

Introduction

Bibliometric research is an important and powerful scientific method used by scientists to understand trends and the impact of current studies or to discover unexplored avenues across various disciplines. This methodology is adopted more and more due to its capability to process large quantities of data using bibliometric software (VOSviewer, CitaSpace, Biblioshiny, SciMAT, Gephi, Pajek, HistCite) and databases (Web of Science (WoS), Scopus, Google Scholar, PubMed, IEEE Xplore). The existence of Big Data and Artificial Intelligence tools (Scholar GPT, ChatGPT, DeepSeek, Copilot) increased the importance of bibliometric research in the context of constant rise in publications available and the need to boost productivity, influence and dissemination of information. The use of it expanded outside academia, being used by companies activating in the publishing industry.

Although in its early stages, bibliometric research in Emotional Intelligence in Leadership Performance noted an increase in number of publications and citations since 2021, with a pick in 2023, being a focus area for Business Economics and Psychology related studies.

Furthermore, exploring publications in Business Economics where Artificial Intelligence (Scholar GPT) was mentioned, only 12 references were found in Web of Science database (query https://www.webofscience.com/wos/woscc/summary/fa1874f0-88c0-4a17-87e8-

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22ca44cc7ce7-0149afe8f7/relevance/1). Regional analysis displays an even distribution of interest in the subject globally.

While previous bibliometric studies explored independently Leadership Performance or Emotional Intelligence, research is limited in exploring the performance and effectiveness of AI tools, like Scholar GPT, in comparison with well-established and more traditional bibliometric tools, such as VOSviewer or Biblioshiny, in discovering trends in leadership research. This study filles this gap by assessing the effectiveness, accuracy and usability of AI-driven and traditional bibliometric tools in analyzing emotional intelligence in leadership performance publication, while identifying future research trends within this domain.

The tool selection process described within the Methodology section confirmed VOSviewer and Biblioshiny as suitable for this study for their strong visualization and statistical capabilities. Scholar GPT was included due to its accessibility and NLP (Natural Language Processing) capabilities, as an AI-based tool to evaluate feasibility in generating bibliometric analyses. Other tools like SciMAT and CiteSPace were not included due to their installation complexity and steep learning curves, making them less practical for this study.

The following research questions will be explored within the present analysis:

RQ1: How has the publication landscape on emotional intelligence in leadership performance evolved over time? A comparative bibliometric analysis of trends, impact, and thematic shifts using popular bibliometric tools and unconventional AI tools.

RQ2: Are Artificial Intelligence (Scholar GPT) bibliometric analysis results comparable with popular bibliometric tools (VOSviewer, Biblioshiny)?

RQ3: Can Artificial Intelligence (Scholar GPT) be used to increase productivity in bibliometric research?

The analysis consists of a qualitative analysis performed with VOSviewer, version 1.6.20, and Biblioshiny version 4.4.2 and Scholar GPT, using the same Web of Science database query output file ("WoS_data_15022025") generated following the process described in detail in the Methodology section. Data was validated and sanitized according to the process outlined in the the same section. The resulting file was processed using an R-based script into a new and curated Web of Science file (WoS_cleaned_23022025.txt"). VOSviewer version 1.6.20 was released on October 31, 2023. VOSviewer is a software tool for constructing and visualizing bibliometric networks. These networks may for instance include journals, researchers, or individual publications, and they can be constructed based on citation, bibliographic coupling, co-citation, or co-authorship relations." (Centre for Science and Technology Studies (CWTS), 2025) "Bibliometrix provides various routines for importing bibliographic data from SCOPUS, Clarivate Analytics' Web of Science, Dimensions, The Lens, PubMed and Cochrane databases, performing bibliometric analysis and building data matrices for co-citation, coupling, scientific collaboration analysis and co-word analysis." (Aria & Cuccurullo, 2025). Bibliometric insights collected through methods and techniques which map relationships between academic papers based on citations (Citation Networks) or groups papers sharing common references indicating thematic similarities (Bibliometric Coupling) are important within this study as they illustrate the impact of current publications within the field of study.

"Scholar GPT, available in the ChatGPT Store, is an advanced AI tool tailored for nonprofit organizations that require reliable research and data analysis capabilities. This tool aids in navigating the vast landscape of academic literature, reports, and datasets, providing curated insights and summaries that support evidence-based decision-making." (CharityGPT, 2025).

While Scholar GPT provides fast analysis via user friendly interface through NLP (Natural Language Processing) capabilities, the results can be influenced by biases introduced by training data and algorithms. Unlike traditional bibliometric tools, AI-generated bibliometric insights may not always be reproducible due to the variability of prompts interpretation, needing human oversight when applied in bibliometric research.

The article covers literature reviews of the evolution of bibliometric research and segways into emotional intelligence in leadership with focus on leadership styles, a bibliometric tools comparative analysis (VOSviewer, Biblioshiny, Scholar GPT), research data selection and validation processes, applied research methodology and concludes with the research findings and limitations. Future-related research possibilities within the emotional intelligence in leadership are also included in the last chapter of this paper.

Literature review

The evolution of bibliometric research

Bibliometric analysis has emerged as a quantitative transformative method of analyzing scientific data, examining patterns in authorship, citation, keywords and collaboration. Throughout the past seven decades, bibliometrics has provided insights into the impact of research and dynamics of knowledge dissemination (Garfield, 1955; Prichard, 1969).

The bibliometrics research is founded on Garfield E. work in citation analysis. The developed the concepts of "Science Citation Index" (Garfield, 1955) and "Social Science Citation Index" (Garfield, 1973). "Bibliometric mapping" (Small, 1999) and "Co-citation analysis" (Small, 1977, 1973) are key methods for analyzing and visualizing scientific literature which are used in study trends, evaluating scientific impact, and informed science policy, contributing to the development of tools for bibliometric mapping and network analysis (e.g. VOSviewer, CiteSpace). "Triple helix model" (Leydesdorff, 2001) explains how innovation emerges from interactions between academia, industry and government, influencing the bibliometric research methods introducing measures to quantify collaboration, co-authorship and interdisciplinary research, being used in analyzing scientific output, citation trends and collaboration networks impact between institutions.

Bibliometric analysis evolved towards a holistic understanding (Østergaard, 2008) of how bibliometric indicators can be applied to assess research performance, with implications in both policy and funding decisions.

"Altmetrics" (alternative metrics) (Priem et al, 2010) was introduced as an alternative approach to traditional cited-based metrics like h-index and impact. Altmetrics captures the social impact of research quantifying the impact of the research by tracking social media, news, blogs, policy documents and more, on various online platforms. Compared to the traditional citation metrics focusing on academic impact, altmentrics focuses on public engagement, policy influence and media coverage, offering real time feedback on research engagement, broader impact measurement. Although this approach is fast paced it has its limitations as it might provide attention measurement, not necessarily an indication of the quality or rigor of the research. It is also criticized for the lack of standardization as methods of calculating and interpretation are not yet standardized. In addition, platform bias can influence popularity, affecting the real engagement indicators. The influence of bias in academia was previously explained as "Matthew Effect in Science" (Merton, 1968), highlighting the accumulation of advantage, unequal distribution of credit and reinforcement of inequality. In the domain of bibliometrics this can be also translated as an artificial increase in citation of well-known authors or from prestigious publications, compared with less well-known authors, where quality of the work is comparable. Also, high-profile researchers are likely to be invited to collaborate on projects, increasing their reputation and visibility, compared with early career researchers.

"Citation Network Methodology" (Waltman & Van Eck, 2012) introduced the new methodology for creating publication-based citation networks, representing relationships between publications based on citation links. Unlike the traditional approaches focusing on journal level and author level networks, this method highlights the importance of individual publication as a node in the network. This methodology leverages concepts from network science and bibliometrics to uncover patterns of influence, collaboration and the evolution of research trends, being incorporated in VOSviewer to facilitate user-friendly bibliometric analysis.

Artificial intelligence technologies such as machine learning or natural language processing (NLP) enhanced traditional bibliometric methods, enabling researchers to combine quantitative with qualitative results (Wang et al., 2023). The combination of bibliometric (Aria & Cuccurullo, 2017) and Latent Dirichlet Allocation (LDA) (Blei et al., 2003) illustrated how AI is used to enrich traditional bibliometric indicators with content-based insights.

The Smart Local Moving (SLM) algorithm (Walman & Van Eck, 2013) provides an efficient method for detecting communities in large citation networks, while Chen (2017), reviews how various AI technologies transform scientific research.

Impactful bibliometric research overview

From the beginning of 2021, bibliometric research focused on Management, Psychology Multidisciplinary and Business areas. Sharma and Tiwari (2022) bibliometric research in business and management key trends from 2002 to 2022, revealed that although transformational leadership, organizational behavior and cultural intelligence, more recent trends were aligned with social intelligence competences. Mindfulness, COVID-19 impact on leadership and AI integration in business management are highlighted by the study as emerging themes (Sharma and Tiwari, 2022). Another relevant study on literature review in the leadership field focused on leadership behavior in project management practices. The study assessed leadership behavior, underlying the increasing importance of interpersonal skills and people-focused leadership styles in complex circumstances (Rehan et al., 2024). The study found that relationship-building, communication, and emotional intelligence, are needed for effective leadership contrasting with traditional task-oriented styles (Rehan et al., 2024).

Bratianu and Paiuc (2023) presented in their comparative bibliometric study the importance of emotional intelligence and cultural intelligence in multicultural leadership. The study focused on cultural differences between United States of America and Romania. The study includes a bibliometric analysis using VOSviewer and a quantitative analysis based on 604 questionnaires from managers in the USA and Romania, processed with SPSS software. The analysis concluded that effective multicultural leadership and organizational performance are influenced by both Emotional Intelligence (EQ) and Cultural Intelligence (CQ). The research confirmed that Emotional Intelligence can predict Cultural Intelligence, both being vectors for culturally diverse leadership (Bratianu & Paiuc, 2023).

Zhou et al. (2024) study highlights the importance of Emotional Intelligence in leadership, especially in leadership effectiveness, job performance and organization behavior. Developed based on Scopus literature review, the paper illustrated United Stats and United Kingdom as leaders in this research field, indicating that future research trends will explore Emotional Intelligence in diverse cultural settings, different industries and the importance of leadership development programs.

Li and Bitterly (2024), compared human with Artificial Intelligence (AI) management impact within a field study of 400 delivery riders in Mainland China and three experiments with a total 2350 participant. The study suggests that AI management is perceived as less benevolent than human management, negatively impacting trust, especially in circumstances where individuals are seeking empathy from their managers (Li& Bitterly, 2024). The paper concludes that employees prefer human management in contexts in which emotional understanding is essential (Li& Bitterly, 2024). The study contributes to the literature on trust, emotions and AI adoption, emplacing the role of emotional context and trust in emerging AI management.

As business settings are continuously changing, bringing new challenges for the leaders to face, the need for understanding of EI's role in leadership is increasing. The shift to a new setup where teams are geographically dispersed and digitally connected unveils a new domain where emotional intelligence plays a crucial role, defined by virtual leadership. Emotional intelligence is a fundamental skill for leaders in building trust, mage conflict, enhance communication to create the safe environment needed for emotional resilient and high performing virtual teams, enabling organizational success in digital era.

Emotional Intelligence influence on Leadership styles

As seen in the previous subchapter, leadership is a central topic of research in management and organizational studies. Various leadership styles have been discussed in the past decades, each focusing on specific leaders approaches in meeting organizational goals. Among these, Transformational Leadership and Servant Leadership gained attention due to their focus on leaders' emotional intelligence, ethical behaviour and leaders' development and succession.

Leadership research shifter from task-oriented models (e.g., transactional leadership) to more people-centric approaches with focus on emotional and ethical dimensions. Early leadership theories, such as Trait Theory and Behavioural Theory, were criticized for their focus on leaders' behaviour and lack of attention to the relational and emotional aspects of leadership.

Contingency Theories explored the role of the context for the effective leadership, however, only until Transformational Leadership (Bass, 1985) and Servant Leadership (Greenleaf, 1977) leadership research started to focus on the emotional and ethical influences on leadership performance. These styles changed the focus from managing to leading people, transforming leadership.

Transformational leadership (Bass, 1985) is extensively examined in leadership studies. This leadership style focuses on individuals' needs and values to inspire and motivate others. Transformational leaders exhibit key behaviors related to motivation, inspiration, innovation, and mentoring. Research has linked transformational leadership to positive organizational outcomes, such as increased employee satisfaction, higher performance, and greater organizational commitment (Bass & Avolio, 1994). Emotional Intelligence (EI) is seen as crucial for transformational leadership, as it enables leaders with high EI to effectively inspire and motivate others by understanding their own and others' emotions (Goleman, 1995).

Servant leadership (Greenleaf, 1977) prioritizes the leader's role in serving others and addressing their needs, contrasting with traditional leadership models that emphasize the leader's authority. Servant leaders are known for their empathy, listening and awareness capabilities, stewardship, and supportiveness. Research links servant leadership with increased trust, higher employee engagement, and better organizational culture (Liden et al., 2008). Servant leadesrhip also requires emotional intelligence for relationship building and fostering supportive work environments (Barbuto & Wheeler, 2006).

Emotional intelligence (EI) (Goleman, 1995), refers to the ability to recognize, understand, and manage one's own emotions and those of others. EI has been identified as a critical factor in effective leadership, particularly in people-centric styles like transformational and servant leadership. Leaders with high EI are capable of building trust and positive rapport with others, foster positive relationships, manage conflicts, inspire and motivate others with empathy.

Research has shown that EI enhances the effectiveness of both transformational and servant leaders. For example, transformational leaders with high EI are more effective at inspiring and motivating their disciples (Wong & Law, 2002). Similarly, servant leaders with high EI are better able to empathize with their disciples and create a supportive work environment (Barbuto & Wheeler, 2006).

These two leadership styles are influential in contemporary research. Both emphasize the importance of emotional intelligence, ethical behavior, and leadership development. While transformational leadership focuses on inspiring and motivating disciples to achieve organizational goals, servant leadership prioritizes serving others and creating a supportive work environment. Future research should continue to explore the intersection of emotional intelligence and leadership styles, particularly in the context of emerging challenges such as remote work, digital leadership and ESG (Environmental, Social and Governance) regulatory framework.

Methodology

Bibliometric research relies on specialized tools to generate various analyses to support scientists to evaluate the impact, structure and evolution of research fields. As research data is constantly evolving, bibliometric analysis tools are essential for modern research evolution due to their powerful analytic and visualization capabilities, combined with reproducibility.

This research study is focused on identifying the qualitative and quantitative differences between well-established bibliometric tools (VoSviewer, Bibliometrics) and AI tools (ChatGPT) in performing bibliometric analysis in emotional intelligence in leadership performance domain.

Different tools, both traditional bibliometric and AI-based tools, were compared based on their analytical capabilities, visualization strengths, usability, accessibility and user friendliness, combined with reproducibility and transparency. A summary of the assessment made is presented in the table below (Table 1).

Feature	VOSviewer	Biblioshiny	SciMAT	CiteSpace	Scholar GPT (AI)
Primary Functionality	Network visualization	Statistical bibliometric analysis	Thematic evolution mapping	Trend detection & citation burst analysis	AI tool with bibliometric capabilities
Data Sources	Web of Science, Scopus, PubMed	Web of Science, Scopus, Dimensions	Web of Science, Scopus	Web of Science, Scopus	Any data input

Feature	VOSviewer	Biblioshiny	SciMAT	CiteSpace	Scholar GPT (AI)
Visualization Capabilities	Excellent	Basic	Strong	Advanced	Limited
Ease of Use	Moderate (requires installation)	Easy (web-based, few installation commands)	Moderate (some learning curve)	Complex (Java setup required)	Very easy, Natural Language Processing (NLP)

Table 1. Comparative analysis of bibliometric tools used in the research

Source: Author' own research.

Based on these findings, VOSviewer and Biblioshiny were selected for this study due to their strong visualization and statistical capabilities. Scholar GPT was included due to its accessibility and user friendliness capabilities, as an AI-based tool to evaluate feasibility in generating bibliometric analyses in the context of the current study. Other tools like SciMAT and CiteSPace were not included due to their operating complexity and steep learning curves, making them less practical for this study.

This research was conducted solely by the author, including data collection, processing and validation. While collaborative verification was not possible, self-validation techniques were used in this research (manual cross checking, versioning control, re-running analysis, cross-checking with other bibliometric tools) to ensure accuracy and reliability of the findings.

Research Data Collection

As the effectiveness of bibliometric analysis is directly related to the quality of data used for research, data collection is an important stage of any bibliometric research, including this one. To ensure accuracy and relevancy during this stage PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method was used. This approach is a deep-rooted framework for conducting and reporting systematic and meta-analysis in literature review. The PRISMA method involves a four-phase process: identification, screening, eligibility, and inclusion. A key feature of PRISMA is the use of a flow diagram to document the study selection process, which enhances clarity and accountability. Page et al. (2021) provides the latest recommendations for conducting systematic PRISMA 2020 reviews and emphasizes the importance of transparency and reproducibility in research.

For this study, the Web of Science database was selected due to its structured and curated content, despite the criticism of its biases for well-known publications and authors. During the data collection process, the database was queried following the process steps outlined below, also described in Figure 3:

1. Web of Science Database search string was applied (ALL=(emotional intelligence) AND ALL=(leadership performance), with an output of n=1223 results;
2. Language filter was applied as a subsequent filter, with an output of n=1195 results.
3. Document filter was used to limit the data selection with output of n=1182 results.
4. The last filter was used to exclude non conclusive results from 2025, final query resulted in n=1167 results.

The Web of Science query used for data collection is accessible using the following link: https://www.webofscience.com/wos/woscc/summary/29817d0b-06f5-4faa-8a65-73aaca69ca1c-0149ab77a0/relevance/1

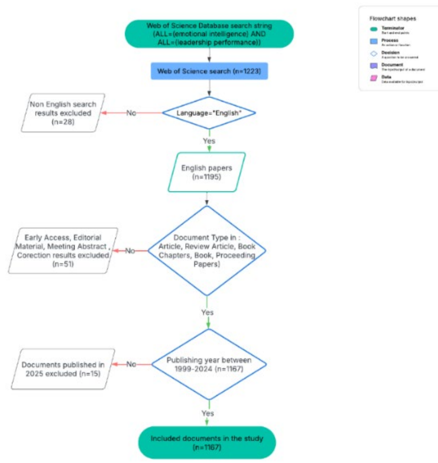

Figure 1. Study data collection methodology (flow chart)

Source: Author' own research.

Selected data was then exported in "Plain Text File" format, choosing Record Content as "Full Record and Cited References" to preserve all data attributes for an enhances quality. Due to the database export limitation, the results were exported in batches of 500 entries and later-on manually collated in a single file named "WoS_data_15022025". Final file was checked for duplicate entries and missing DOI, procedure and results are presented within the following subchapters of this research.

Research Data Validation

To ensure data accuracy, information generated during the collection phase was checked for duplications and missing Digital Object Identifier (DOI), using Bibliometix R scripts detailed in the Appendix of this paper. Analysis results (Figure 2) illustrated only two duplicates ("ALBARG, ABBAS N.","AB HAMID MR, 2017, J P HYS CONF SER, V890, DOI 10.1088/1742-6596/890/1/012163"), most probably introduced during manual processing of the file, and 123 missing DOIs (10,7% of total number of 1167 records). All records having missing DOIs were registered in Web of Science database after 2000, when standard was introduced (Gorraiz et al., 2016).

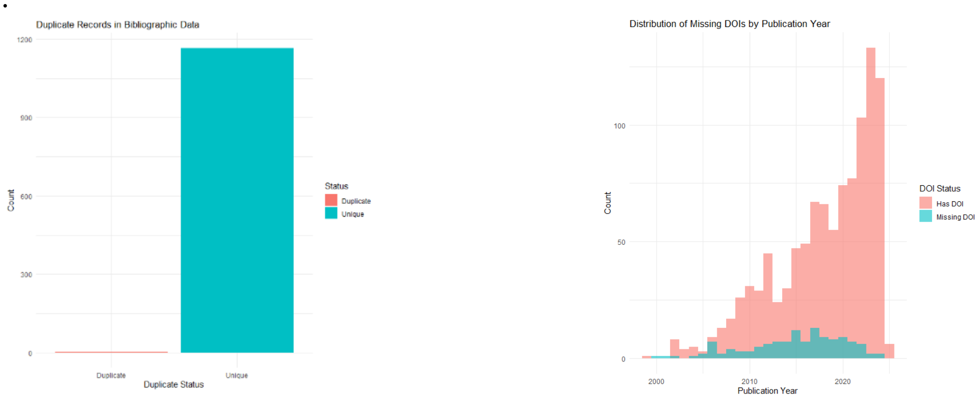

Figure 2. Bibliometric data validation analysis: duplicate status and missing DOI yearly distribution

Source: Author graphs generated with R scripts.

As entries with missing DOI were evenly distributed (Figure 2) it was decided to remove them without introducing biases. Web of Science export file ("WoS_data_15022025") was processed to remove duplicates and missing DOIs using a R-based script (detailed in Appendix). Output file "WoS_cleaned_23022025.txt" was generated and imported in Biblioshiny. After importing, the tool recognized 1043 entries and no missing DOI was listed. R-based scripts were run for curated file "WoS_cleaned_23022025.txt" to check the file validity. Results showed that all duplicates and missing DOIs were removed (Figure 3). Further checks were attempted by importing the file into Web of Science database for crosschecking, actions were not completed due to technical limitations imposed by the researcher profile.

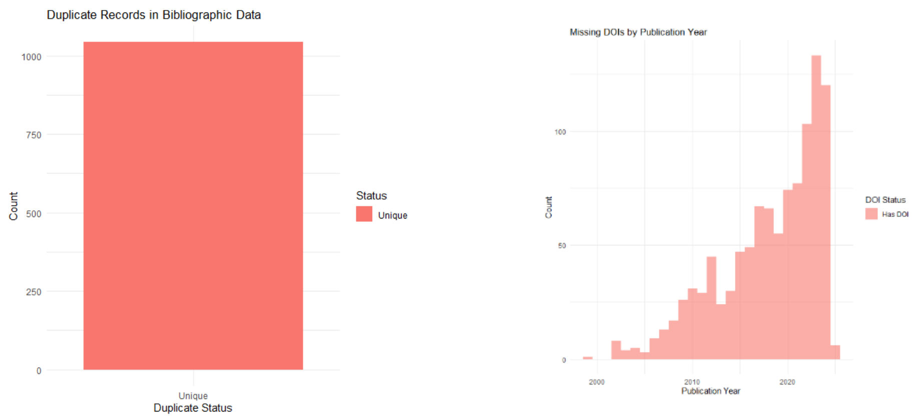

Figure 3. Bibliometric data validation analysis: duplicate status and missing DOI yearly distribution after data sanitization

Source: Author graphs generated with R-based scripts.

Further, bibliometric analysis was conducted using Biblioshiny, VOSviewer and Scholar GPT using the validated file ("WoS_cleaned_23022025.txt") to generate comparative bibliometric research of trends, impact and insights

Evolution of Emotional Intelligence Research in Leadership Performance: Trends

The generation of trends in publication landscape on emotional intelligence in leadership was accomplished with tools such as Biblioshiny, VOSviewer and Scholar GPT, results are presented in Figure 5, Figure 6 and Figure 7. Further details about the process of generating the results using Scholar GPT (Figure 7), prompts used, and results are outlined in the paper Appendix.

The bibliometric analysis results evaluating the evolution over time of the publication landscape on emotional intelligence in leadership performance, conclude that 2023 was the most prolific publication year in this domain, especially after the COVID-19 pandemic ended, when digital leadership emerged, and leadership had to evolve in the context of hybrid and remote working. The downward trend seen in 2024 may be influenced by the delay in indexing publications in the Web of Science database, rather than lack of interest in this subject. This is confirmed by the upward trending number of papers indexed in Scopus in 2024 (7637) compared to 2023 (5778), as illustrated below (Figure 4).

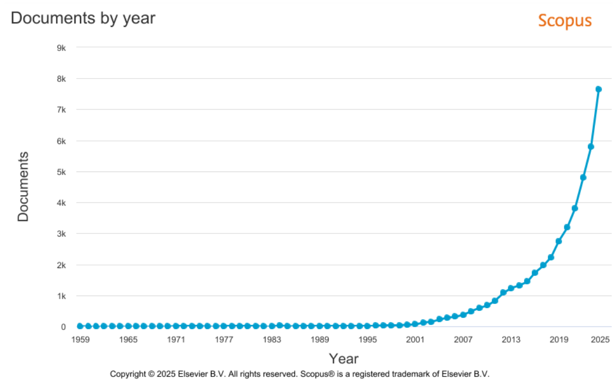

Figure 4. Publication landscape on emotional intelligence in leadership performance evolution over time: Scopus

Source: Scopus Documents by year Report

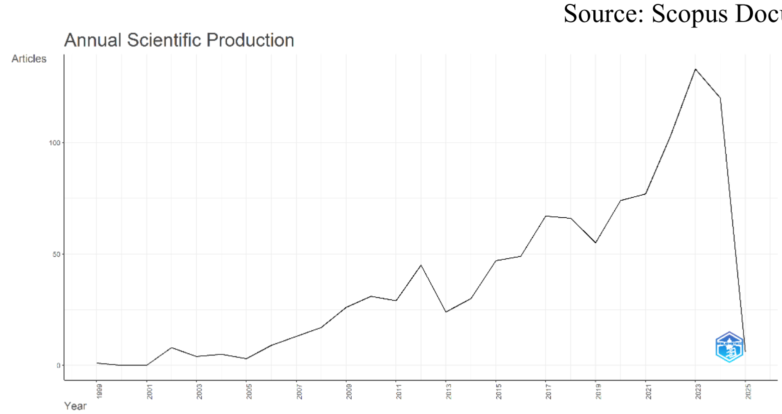

Figure 5. Publication landscape on emotional intelligence in leadership performance evolution over time: Biblioshiny

Source: Biblioshiny Annual Scientific Production Report.

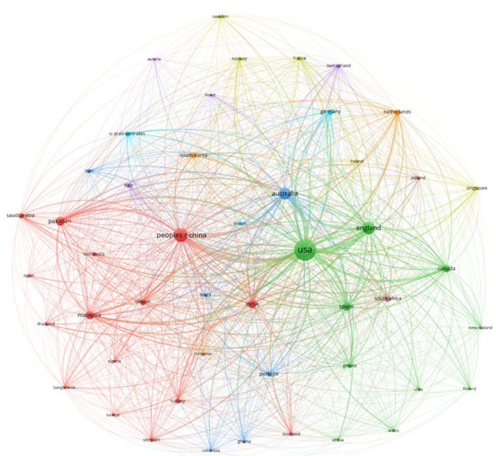

Figure 6. Publication landscape on emotional intelligence in leadership performance evolution over time: VOSviewer

Source: VOSviewer Overlay Visualization Bibliographic Coupling Countries Report.

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Due to the complexity of VOSviewer tool there is no simple method to extract a trend line given a specific criterion. For this purpose, the closest option used was Overlay Visualization Bibliographic Coupling Countries Report (Figure 6), resulting in unmatching timelines and unclear research pick in publications trends. In conclusion, VOSviewer is posing limitations for simple trends analysis, however creating visually impacting graphs.

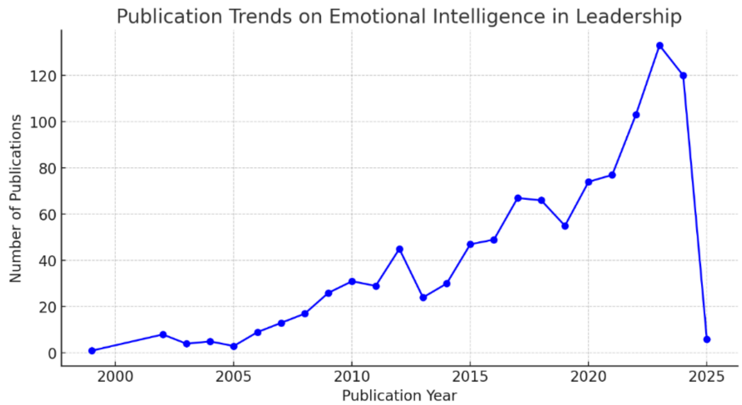

Figure 7. Publication landscape on emotional intelligence in leadership performance evolution over time: Scholar GPT

Source: Scholar GPT Report.

On the other hand, Scholar GPT can generate similar results as Biblioshiny, without the complexity of installing and running any software. Several considerations should be made regarding the ethical use of Artificial Intelligence in research, which are detailed in the results sections and will be explored in future research.

Comparing all three bibliometric analysis outputs it can be observed that Figure 5 and Figure 7 are very similar, meeting the research question objectives and qualitative criteria. This similarity highlights Scholar GPT capabilities in executing trend analysis in bibliometric research.

Evolution of Emotional Intelligence Research in Leadership Performance: Impact

Same process was used for generating the bibliometric analysis on the impact in the evolution of Emotional Intelligence research in Leadership Performance, using Biblioshiny, VOSviewer and Scholar GPT, results are presented in Figure 8, Figure 9 and Figure 10. Further details about the process of generating the results using Scholar GPT (Figure 10) are outlined in the paper Appendix.

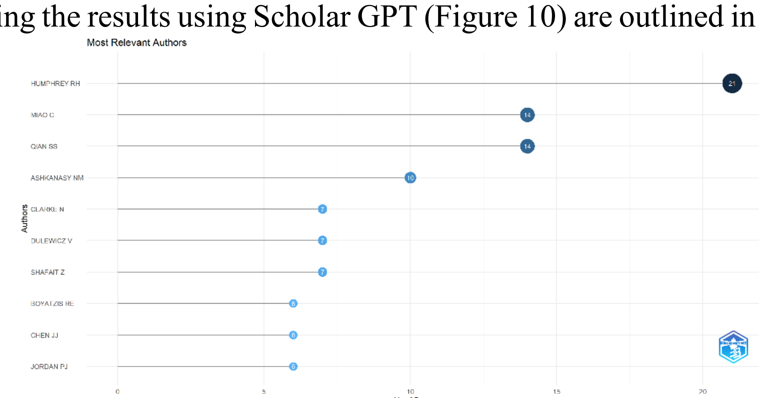

Figure 8. Bibliometric impact of Emotional Intelligence Research in Leadership Performance: Biblioshiny

Source: Biblioshiny Most Relevant Authors Report.

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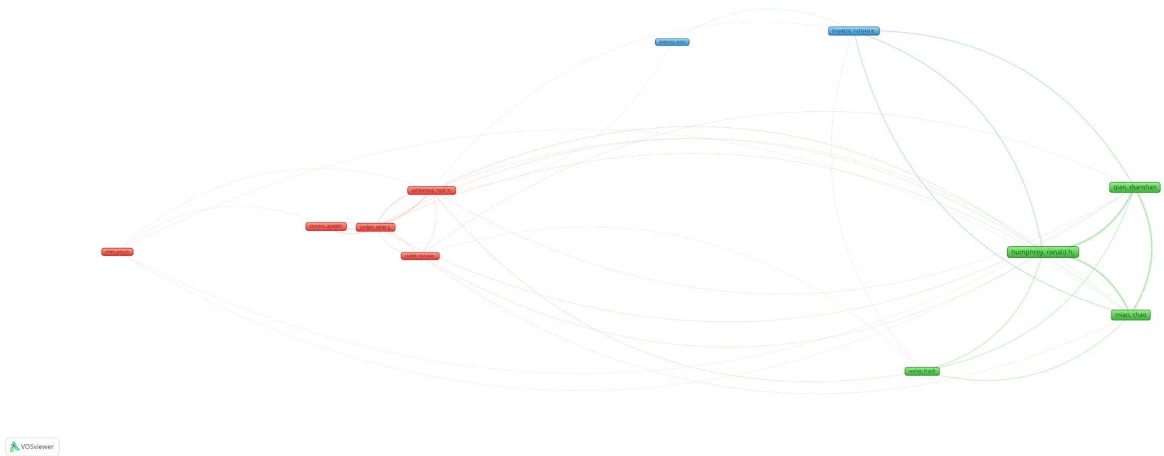

Figure 9. Bibliometric impact of Emotional Intelligence Research in Leadership Performance: VOSViewer

Source: VOSviewer Author Citation Report.

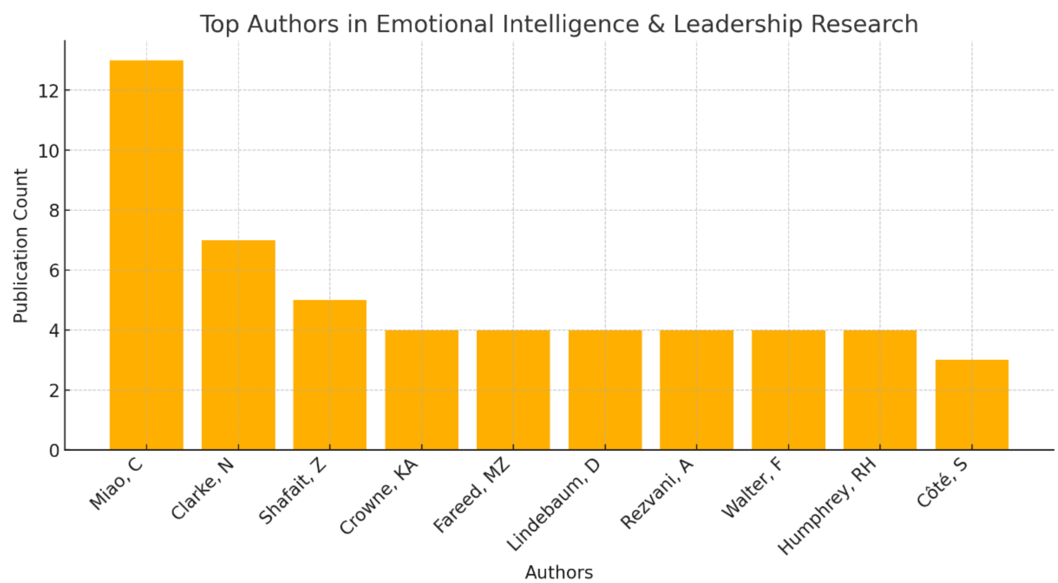

Figure 10. Bibliometric impact of Emotional Intelligence Research in Leadership Performance: Scholar GPT

Source: Scholar GPT Most Citated Papers Report.

The bibliometric analysis conducted concluded that HUMPHREY Roland H is the most prolific author in the field with 21 documents. This research outcome is illustrated in Biblioshiny and VOSviewer analysis output (Figure 8 and Figure 9). VOSviewer tool complexity and focus on visually impacting graphs doesn't provide a simple report to identify the author with the highest number of publications, this can be observed based on the strength links and cluster size in Figure 9. Scholar GPT results are not matching (Figure 10), the Artificial Intelligence model delivered a comparable, but different result (Top Authors in Emotional Intelligence & Leadership Research).

This highlights the need for human intelligence intervention in reviewing Artificial Intelligence analysis results and assessing appropriately in the context of the research.

In conclusion, VOSviewer is posing limitations for simple bibliometric analysis, however supporting researchers by delivering visually impacting graphs. Scholar GPT results were inconclusive.

Evolution of Emotional Intelligence Research in Leadership Performance: Insights

In the last and most complex stage of the research, the bibliometric analysis focused on identifying the insights for future researches in Emotional Intelligence in Leadership Performance. In completing this stage of the research, Factorial Analysis Word Map Report was selected in conducting the assessment using Biblioshiny.

The Word Map provides a visual representation of relationships between research themes from the Keyword Plus field exported from Web of Science. The X-axis (Dim 1) represents the most significant variance in the dataset, while the Y-axis (Dim 2) captures the second most significant variance. Central terms in the map signify widely connected and frequently occurring research topics, while peripheral terms may indicate emerging research areas.

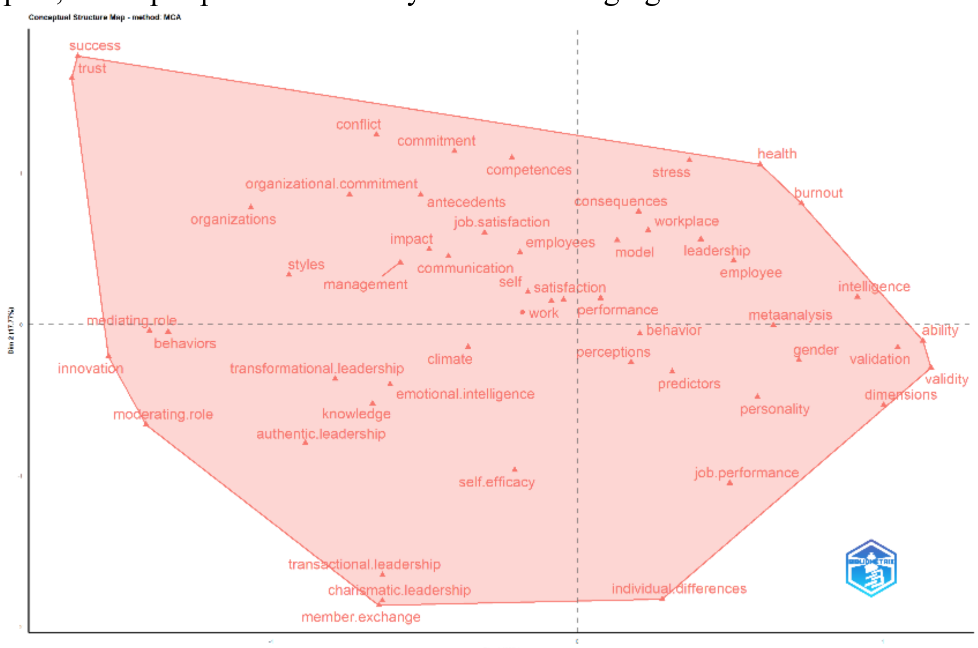

Figure 11. Bibliometric insights of Emotional Intelligence Research in Leadership Performance: Biblioshiny

Source: Biblioshiny Factorial Analysis Word Map Report

Distant elements represent less connected or niche topics, showing potential research gaps or specialized fields. From the analysis results (Figure 11) four clusters of words representing different research themes can be observed:

- Cluster 1 (top left) “trust”, “success” are closely related and linked together, indicating emerging themes around leadership effectiveness and employee trust.
- Cluster 2 (bottom left) “moderating role”, “innovation” and “mediating role”, suggests themes around leadership role in mediating and moderating innovation.

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- Cluster 3 (bottom right) “transactional leadership”, “charismatic leadership” and “member exchange”, emphasis the impact of leadership styles in the field of emotional leadership in leadership performance.
- Cluster 4 (top right) “health”, “burnout”, “stress”, are illustrating the emerging theme of emotional intelligence in leadership well-being.

The presence and grouping of leadership styles (“Authentic Leadership” and “Transformational Leadership”) within the centre of the red polygon in Figure 11, is illustrating a growing emphasis on ethical leadership and trust. This suggests that future studies may explore how emotional intelligence can influence leaders’ ability to navigate corporate ethics and social responsibility challenges, especially in the context of the current ESG (Environmental, Social and Governance) regulatory framework. Grouping of “behaviour”, “performance”, “perceptions”, “work”, “satisfaction”, emphasise the importance of emotional intelligence within the workspace to facilitate leadership success. In conclusion, the research filed can be structured in four major thematic research direction within the emotional intelligence in leadership domain: leadership styles and their impact on employees and job satisfaction, leadership impact on workspace outcomes with focus on organizational climate, psychological needs/traits with focus on leadership wellbeing and innovation and emotional intelligence in transformational leadership with focus on leadership as mediators and innovators.

Research of bibliometric insights conducted with VOSViewer focused on Citation Author Keywords Network Visualization analysis (Figure 12). This type of analysis examines the relationship between frequently cited articles and the keywords used by their authors, illustrating research trends, influential themes, and the evolution of topics. This representation is a graph where nodes (circles) represent keywords and highly cited authors or articles, while edges (lines) indicate connections between frequently cited works and shared keywords. The size of a node reflects its frequency in high-impact studies, with larger nodes representing more frequently used keywords. Additionally, clusters (colors) group related topics into distinct research themes, helping to identify key areas of study and emerging trends within the field.

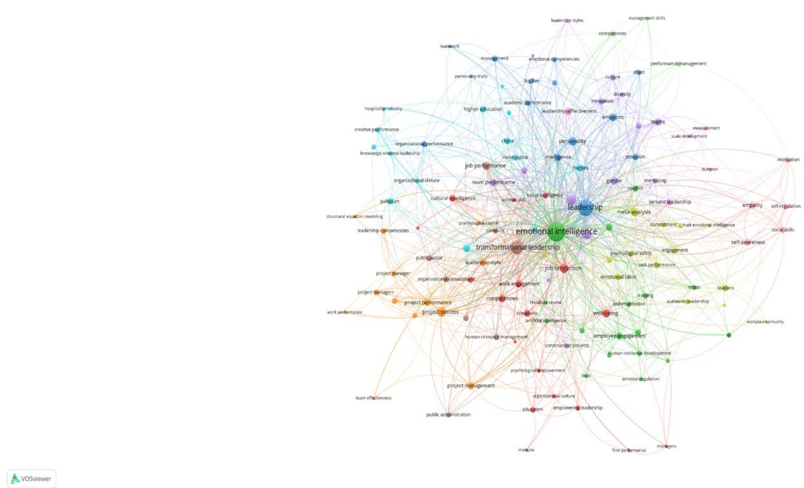

Figure 12. Bibliometric insights of Emotional Intelligence Research in Leadership Performance: VOSViewer

Source: VOSviewer Co-Occurrence Author Keywords Network Visualization Report.

Four clusters can be distinguished, in the order of their importance, listed them based on the cluster size: Green Cluster (Emotional Intelligence, Management Skills, Performance Management), Red Cluster (Transformational Leadership, Work Engagement, Job Satisfaction, Well-Beeing), Blue Cluster (Leadership, Organizational Performance, Academic Performance, Personality), Orange Cluster (Project Management, Leadership Competences) , Yellow Cluster (Meta-Analysis, Counterproductive Work Behavior, Leaders, Authentic Leadership) and Purple Cluster (Performance, Teams, Team Performance. Organization). "Emotional Intelligence", "Leadership" and "Transformational Leadership" are the core of the network indicating high relevance. In this analysis it can also be noticed an increase in interest for the leadership styles ("Servant Leadership", "Authentic Leadership"), which also correlates with the previous findings from the analysis performed with Biblioshiny and the results of the literature review.

Results of the research conducted with Scholar GPT in evaluating bibliometric insights are presented in the Appendix of this paper. Results given by Scholar GPT "the most frequently used terms include emotional intelligence, leadership style, performance, and transformational leadership." (Scholar GPT, 2025) are aligned with the results provided by the conventional bibliometric analysis tools, such as Biblioshiny and VOSviewer. In conclusion, for this complex task, researchers can use conventional and AI-driven tools to capture the nuances of the future of scientific trends in areas of interest. The comparative analysis performed using Scholar GPT on different data sets doesn't show an improvement in training and results provided by the AI-based tool, Scholar GPT. Detailed analysis results are presented withing the paper Appendix.

In conclusion, the bibliometric analysis shows a shift from the traditional task-oriented leadership styles to more people-centric approaches, highlighted by the presence of transformational leadership and innovation in the analysis results. The findings also underline the increased focus on emotional intelligence core competences (empathy, self-awareness and emotional regulation) in transformational leadership.

Results and discussions

This complex bibliometric analysis was performed on two parallel streams, one focused on analyzing bibliometric traditional and AI-driven tools performance in supporting research endeavors, while the other stream focused on completing a complex bibliometric analysis in identifying future trends in Emotional Intelligence in Leadership Performance.

Findings of the current study detailed in the above chapter are summarized below.

RQ1: How has the publication landscape on emotional intelligence in leadership performance evolved over time? A comparative bibliometric analysis of trends, impact, and thematic shifts using popular bibliometric tools and unconventional AI tools. The present bibliometric analysis performed using tools such as VOSviewer, Biblioshiny, and AI-powered platforms like Scholar GPT, illustrates an increased interest in emotional intelligence (EI) in leadership performance, showcasing an increased number of publications since 2021, registering a pick in 2023. Although initial research was more focused on foundational leadership theories, research evolved towards emerging leadership styles (Transformational and Servant Leadership) and Emotional Intelligence (EI) implication. Recent studies explored the practical application of leadership in addressing current demands: corporate leadership, ethical decision-making and employee engagement. The new thematic evolution, observed through keyword analysis, indicates a growing academic interest in topics at the intersection of psychology, management, and organizational behavior domains. A shift from general leadership concepts to applied leadership styles related challenges, showcasing how Emotional Intelligence (EI) can influence leaders' ability to navigate corporate ethics and social responsibility challenges, especially in the context of the current ESG (Environmental, Social and Governance) regulatory framework.

RQ2: Are Artificial Intelligence (Scholar GPT) bibliometric analysis results comparable with popular bibliometric tools (VOSviewer, Biblioshiny)? The findings of the current bibliometric study confirmed that AI tools provide rapid analysis while presenting limitations in generating complex analysis like those provided by traditional bibliometric software, which offer detailed bibliometric mapping with co-citation, co-authorship, and keyword analyses. Traditional bibliometric tools require technical expertise for software installation. Artificial Intelligence (AI) has proven effective in steeping the learning curve and provides adequate support in reviewing R-scripts for the statistical analysis required in the data validation phase. The implications of AI in bibliometric analysis have further expanded research capabilities while introducing ethical concerns, swaying into future research themes within bibliometric research.

RQ3: Can Artificial Intelligence (Scholar GPT) be used to increase productivity in bibliometric research? AI in bibliometric analysis improves efficiency and outcomes but also introduces biases. Models like Scholar GPT may inherit biases from training data and algorithms, potentially distorting research results. These models sometimes prioritize frequently cited sources, reinforcing the "Mattew Effect" (Merton, 1968), amplifying well established research and institutions voices neglecting emerging and niche studies or research institutions which are not historically recognized for scientific contribution. Language, especially English, contributes to this bias, as AI trained models were primarily trained on English language. Another critical challenge in AI-driven bibliometric analysis is the lack of reproducibility compared with the traditional bibliometric tools (VOSviewer, Biblioshiny). AI-based tools operate on "black-box" trained models and algorithms, not allowing the researcher to check the results generation process and validate the results, limiting transparency and reproducibility. Bibliometric tools with established algorithms offer fixed and transparent processes, enabling researchers to trace and manually verify the analysis results. Additionally, it is important to consider ethical issues, data privacy concerns, and potential inaccuracies of AI tools. To address these biases and ensure reliability, combining AI with traditional research methods is recommended, as human oversight is essential in achieving accurate, ethical, and transparent bibliometric analysis. In summary, AI tools can act as an integrated assistant to handle simpler search tasks, but quantitative accuracy and complex visualization still require specialized bibliometric software. A key finding from this study reveals that AI- based tools can be used to steep the learning process in bibliometric research. Graphical analysis presented in Research Data Validation subchapter was created with support from Scholar GPT in reviewing and correcting R-based scripts. This massively contributed to the reduction of time spent on validating the data using traditional Excel tools and manual analysis.

Based on the study outcomes, below bibliometric research guidelines can be summarized and recommended to researchers in their endeavors to perform future bibliometric analysis and accomplish their research objectives:

- For data collection it is recommended to use structured databases (Web of Science, Scopus) to generate data for their studies. It is also recommended that comparative analysis of data sources validate preliminary research assumptions regarding quantitative aspects of the research (e.g. number of entries, categories).
- To ensure transparency of data collection it is recommended to follow PRISMA guidelines and provide insights into data collection procedures for research reproducibility purposes.

- To ensure research validity and transparency, data validation and data sanitization procedures are required. Whenever possible, peer reviewing is required. Alternatively, self-validation methods are available using statistics. Some guidelines into how to use R-scripts to validate data can be found in the paper Appendix.
- To balance efficiency and depth of the bibliometric analysis adopt a hybrid approach combining traditional bibliometric tools (e.g. VOSviewer, Biblioshiny) with AI-driven tools (e.g. Scholar GPT), always cross-checking the results and validating them in the research context.
- To mitigate potential biases firstly identify the potential biases introduced by the methodology used or any unconscious biases which might be present, critically evaluate the research results, especially AI-generated results. AI- tools can be also used to criticize assumptions and research outcomes, generated results can be of use for research especially in the case of research completed without peer review.
- When presenting research findings, it is essential to contextualize bibliometric results within established theoretical frameworks and research context. Research outcomes should be logically sound and should fit in the context.
- Researchers should also address limitations (e.g. technical, contextual) of their work and establish the correct context of their work. Ethics should also be considered when presenting findings.

In conclusion, bibliometric analysis should consider its inherited time lag between the research publication and its subsequent citation, which results in possible misrepresentation of emerging fields or reduced number of citations. To counteract this limitation, the use of altmetrics or perioding follow-up assessments can be used to outline a more comprehensive evaluation of emerging research trends. Researchers should also consider limitations introduced by personal biases during data collection phase. Choosing filters and keywords potentially influenced by their professional background, bibliometric analysis accuracy can get altered. As a countermeasure, standardized selection process should be used to refine bibliometric analysis raw data.

As this study is limited to publications indexed in Web of Science database, future research can expend to Scopus and Google Scholar to illustrate a more ample view on emotional intelligence in leadership performance field of study. Future studies should consider researching emotional intelligence in the context of leadership performance in addressing corporate ethics and social responsibility challenges in the new ESG (Environmental, Social and Governance) regulatory framework. Digital leadership and cross-cultural leadership are emerging research topics given the complexity of the current remote and hybrid working environments, combined with global footprints of firms.

In summary, the bibliometric analysis presented in this paper illustrates an increased focus on emerging leadership skills required to navigate complex ESG (Environmental, Social and Governance) regulatory framework. AI-powered bibliometric analysis accelerates research workflows but lacks the depth of traditional tools like VOSviewer and Biblioshiny, therefore a hybrid approach combining AI for thematic analysis and traditional bibliometrics is the most effective strategy.

As Emotional Intelligence continues to shape leadership research, it is crucial that future explorations outcomes will translate into practical guidelines to drive leadership effectiveness and adaptability to constant evolution of the business environment.

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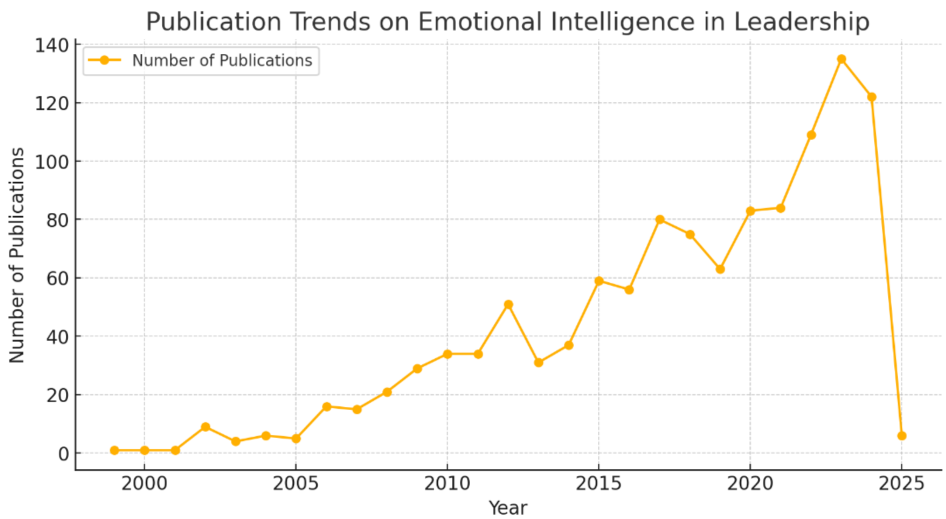
Appendix

<table>
<tr><td>Author's Scholar GPT Prompt 1: How has the publication landscape on emotional intelligence in leadership performance evolved over time? Create full bibliometric analysis of trends, impact, and thematic shifts. Use the attached data for this purpose. ("WoS_data_15022025")</td></tr>
<tr><td>Updated Emotional Intelligence in Leadership Data
<table>
<tr><th>Document Type</th><th>Authors</th><th>Title</th><th>Source</th></tr>
<tr><td>J</td><td>Desai, D</td><td>Emotional intelligence - the moderator of leadership styles and</td><td>NMIMS MANAGEMENT REVIEW</td></tr>
<tr><td>C</td><td>Yao, YH</td><td>The Influence of Emotional Intelligence on Job Performance: Moderating</td><td>2009 INTERNATIONAL CONFERENCE ON MANAGEMENT SCIENCE & ENGINEERING</td></tr>
<tr><td>J</td><td>Weinberger, LA</td><td>Emotional Intelligence, Leadership Style, and Perceived Leadership</td><td>ADVANCES IN DEVELOPING HUMAN RESOURCES</td></tr>
</table>
I have successfully extracted and displayed the updated dataset on emotional intelligence in leadership performance. Next, I will perform a full bibliometric analysis, covering:

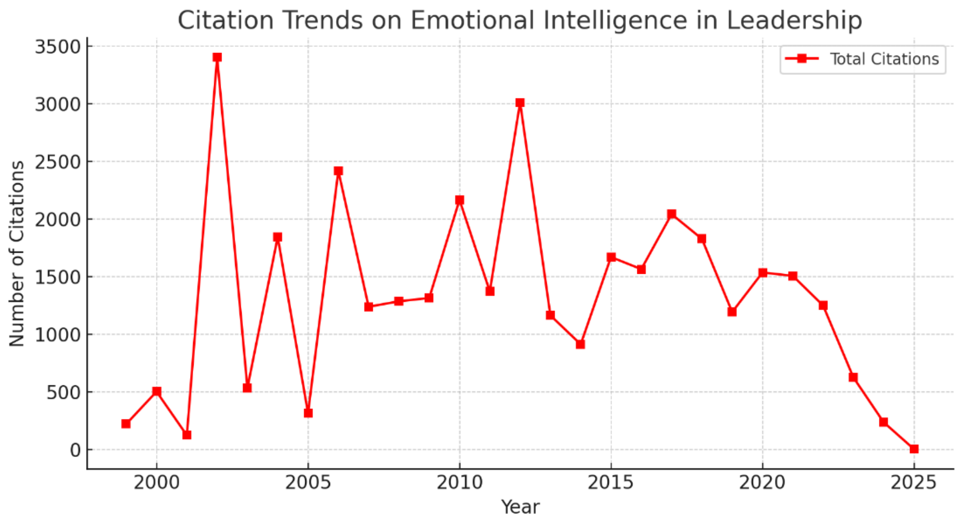
Publication Trends - Evolution of research output over time.
Citation Impact - Highly cited papers and their influence.
Keyword Analysis - Identifying key research themes.
Authorship and Collaboration Networks - Leading researchers and institutions.
Thematic Evolution - Changes in research focus over time.

I'll proceed with the analysis now.
Publication Trends on Emotional Intelligence in Leadership

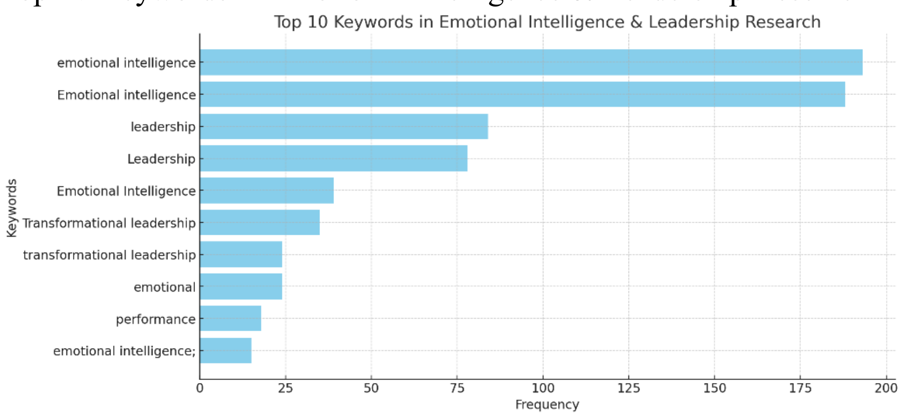


Citation Trends on Emotional Intelligence in Leadership</td></tr>
</table>

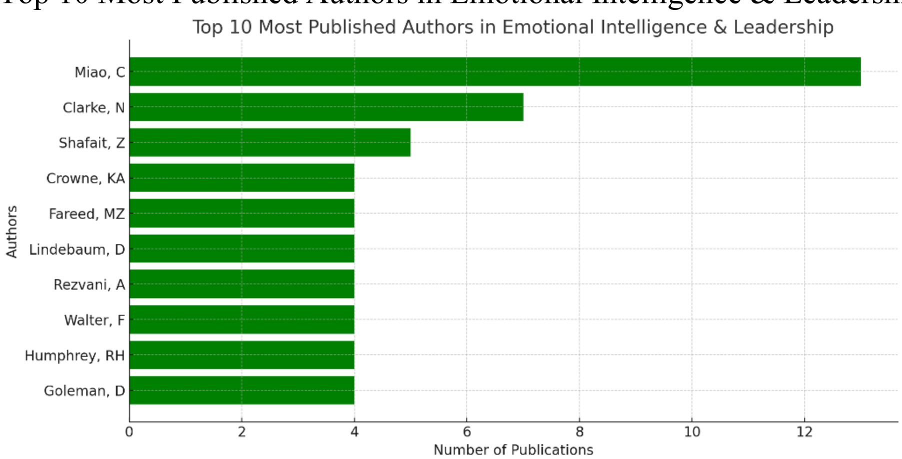
DOI: 10.2478/picbe-2025-0063, pp. 783-813, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025



Top 10 Keywords in Emotional Intelligence & Leadership Research



Top 10 Most Published Authors in Emotional Intelligence & Leadership



DOI: 10.2478/picbe-2025-0063, pp. 783-813, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025

Top 10 Highly Cited Papers

	Title	Authors	Source
502	Emotional intelligence: A meta-analytic investigation of predictive	Van Rooy, DL	JOURNAL OF VOCATIONAL BEHAVIOR
587	Scale development and construct clarification of servant leadership	Barbuto, JE	GROUP & ORGANIZATION MANAGEMENT
1035	Job Demands-Resources theory and self-regulation: new explanations and	Bakker, AB	ANXIETY STRESS AND COPING
242	Emotional intelligence, cognitive intelligence, and job performance	Côté, S	ADMINISTRATIVE SCIENCE QUARTERLY

Thematic Evolution of Keywords

	1990	2000	2010
group cohesiveness;	0	1	0
communications technology	0	1	0
leadership;	0	1	2
leadership self-efficacy	0	1	0
trait emotional intelligence	0	1	1

I have completed the full bibliometric analysis on emotional intelligence in leadership performance using the updated dataset. The findings include:

1. **Publication and Citation Trends**
   - Research output has increased significantly, especially from the 2000s onward.
   - Citations peaked around 2010–2015, indicating key influential works were published during this period.
2. **Keyword Analysis**
   - The most frequently used terms include *emotional intelligence*, *leadership style*, *performance*, and *transformational leadership*.
   - Thematic shifts show increasing interest in *task performance* and *HRD (Human Resource Development)* in recent years.
3. **Authorship and Collaboration**
   - The most prolific authors in the field were identified, with multiple contributions from leading researchers.
   - Prominent institutions include NMIMS University, University of Lausanne, and Harvard Business Review.
4. **Top 10 Highly Cited Papers**
   - The list of most influential studies shows citation counts reaching over 1700 for key publications, highlighting their impact on the field.
5. **Thematic Evolution**
   - The field evolved from focusing on *emotional intelligence* in leadership in the 1990s to broader applications in *performance* and *HRD* in the 2010s.

Let me know if you need further interpretation or additional analysis!

Author's Scholar GPT Prompt 2: How has the publication landscape on emotional intelligence in leadership performance evolved over time? Create full bibliometric analysis of trends, impact, and thematic shifts. Use the attached data for this purpose. ("WoS_cleaned_23022025.txt")

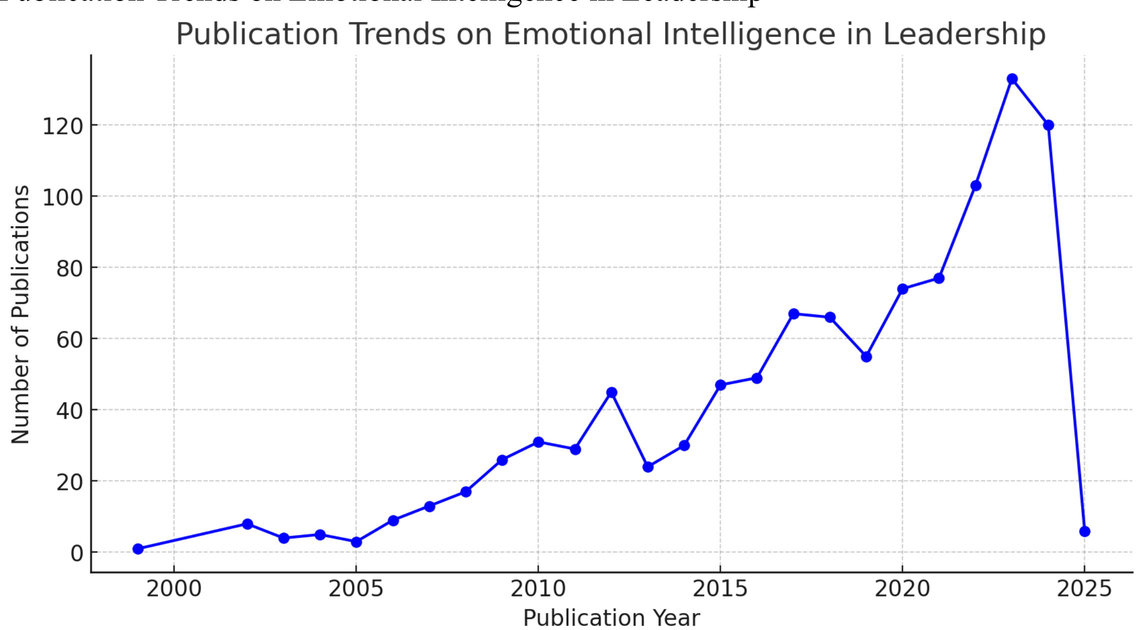
Bibliometric Analysis

Year	Title	Citations	DOI
2009	The Influence of Emotional Intelligence on Job Performance: Moderating	4	10.1109/ICMSE.2009.5318156
2009	Emotional Intelligence, Leadership Style, and Perceived Leadership	35	10.1177/1523422309360811
2012	Effects of leader intelligence, personality and emotional intelligence	138	10.1016/j.leaqua.2011.10.003

I have extracted and displayed the bibliometric data from the provided Web of Science dataset, including publication year, title, citations, and DOI.
Next, I will analyze:

- Publication trends over time 📈
- Most influential authors & institutions 🏛️
- Citation and impact analysis 🔍
- Keyword and thematic trends 🏷️
- Co-authorship & collaboration networks 🤝
- Journal and conference contributions 📚

I'll proceed with further visualizations and statistical insights now.
Publication Trends on Emotional Intelligence in Leadership

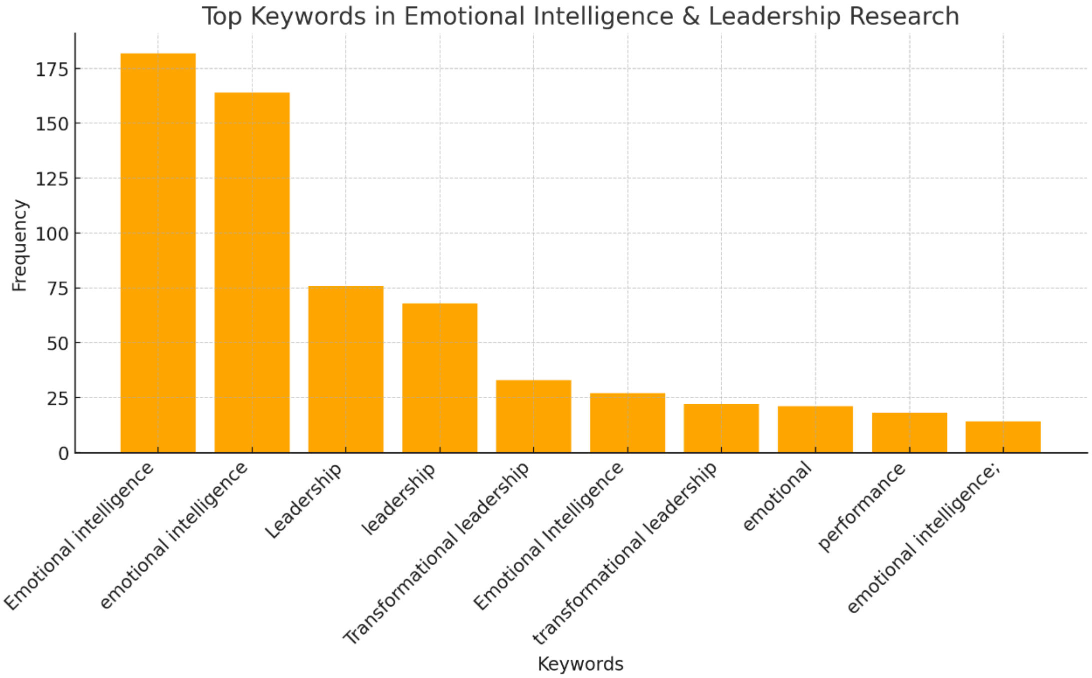


DOI: 10.2478/picbe-2025-0063, pp. 783-813, ISSN 2558-9652 |
Proceedings of the 19th International Conference on Business Excellence 2025

Top Cited Papers

	Year	Title	Citations
395	2002	The effects of leader and follower emotional intelligence on performance	1714
997	2012	A Meta-Analysis of the Dark Triad and Work Behavior: A Social Exchange	744
686	2004	The construct and criterion validity of emotional intelligence and its	734

Top Keywords in Emotional Intelligence & Leadership Research



Top Authors in Emotional Intelligence & Leadership Research

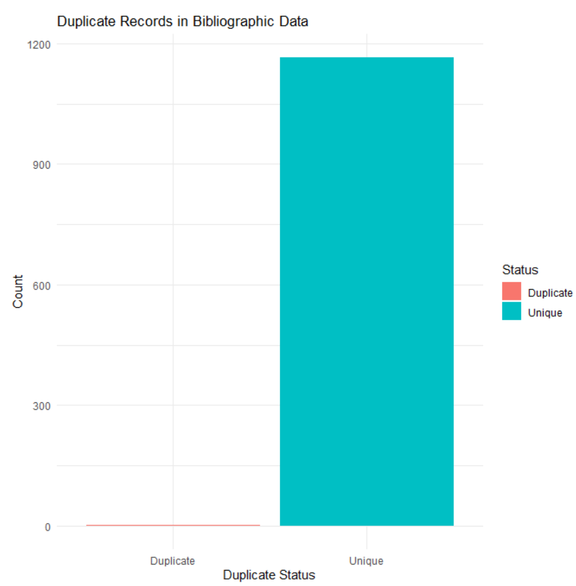
I have generated key bibliometric insights:

1. Publication Trends Over Time 📈:
   - The number of publications on Emotional Intelligence in Leadership Performance over the years.
2. Most Cited Papers 🔍:
   - Displaying the top 10 most cited papers in this field.
3. Keyword Trends □□:
   - The most frequently used keywords, indicating research themes.
4. Top Authors □□:
   - The most prolific authors contributing to this research.

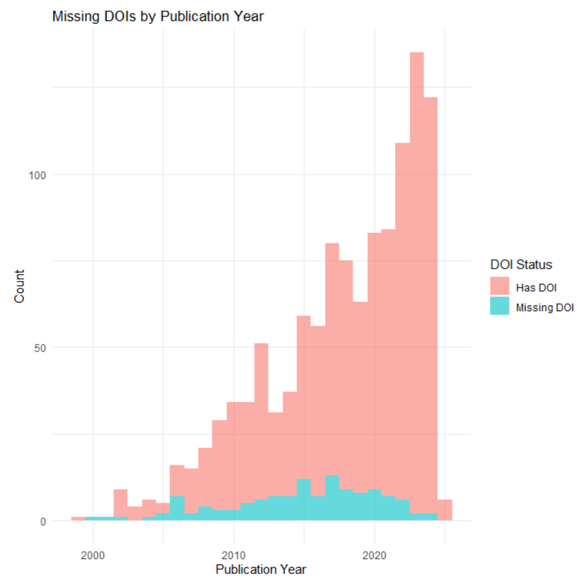
These insights provide a comprehensive view of thematic shifts, impact, and trends. Let me know if you need further analysis, such as collaboration networks or journal impact analysis! 🚀

Author's Data Validation Procedure: Bibliometric R scripts (generated with AI support – Scholar GPT and DeepSeek) and analysis results for duplicates and missing DOI identification are illustrated below. Web of Science database export file "WoS_data_15022025" was used during data validation stage.

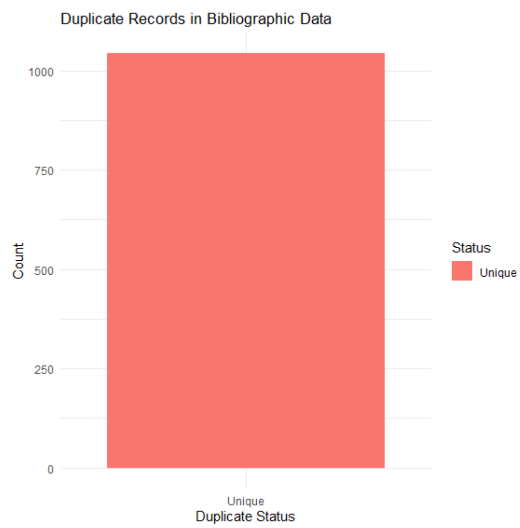
```
# Load necessary libraries
library(bibliometrix)
library(dplyr)
# Step 1: Load your bibliographic data
your_data <-
convert2df("WoS_data_15022025.txt", dbsource =
"wos", format = "plaintext")
# Step 2: Define the fields to check for duplicates
# Common fields: Titles (TI), DOIs (DI), Authors
(AU), Publication Years (PY)
duplicate_fields <- c("TI", "DI", "AU", "PY")
# Step 3: Identify duplicates based on the specified
fields
# Create a unique identifier by combining the fields
your_data <- your_data %>%
  mutate(unique_id =
paste(!!!syms(duplicate_fields), sep = "_"))
# Find duplicate rows
duplicates <- your_data %>%
  group_by(unique_id) %>%
  filter(n() > 1) %>%
  ungroup()
# Step 4: List duplicate records
cat("Total duplicate records found:",
nrow(duplicates), "\n")
if (nrow(duplicates) > 0) {
  cat("\nList of duplicate records:\n")
  print(duplicates)
} else {
```



cat("\nNo duplicates found.\n") } # Step 5: Flag duplicates in the original dataset your_data <- your_data %>% mutate(is_duplicate = ifelse(unique_id %in% duplicates$unique_id, "Duplicate", "Unique")) # Step 6: Summarize duplicates duplicate_summary <- your_data %>% group_by(is_duplicate) %>% summarize(count = n()) cat("\nSummary of duplicates:\n") print(duplicate_summary) # Step 7: Visualize duplicates (optional) library(ggplot2) ggplot(duplicate_summary, aes(x = is_duplicate, y = count, fill = is_duplicate)) + geom_bar(stat = "identity") + labs(title = "Duplicate Records in Bibliographic Data", x = "Duplicate Status", y = "Count", fill = "Status") + theme_minimal() # Step 8: Remove duplicates (optional) # Keep only unique records clean_data <- your_data %>% filter(is_duplicate == "Unique") # Verify removal cat("\nTotal records after removing duplicates:", nrow(clean_data), "\n") # Step 9: Save results (optional) write.table(duplicates, "duplicate_records.txt", sep = "\t", row.names = FALSE, quote = FALSE) write.table(clean_data, "cleaned_data.txt", sep = "\t", row.names = FALSE, quote = FALSE)	

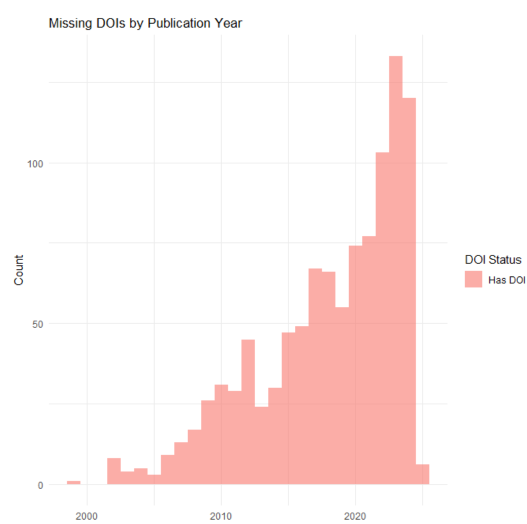
# Load necessary libraries library(bibliometrix) library(ggplot2) # Step 1: Load your bibliographic data your_data <- convert2df("WoS_data_15022025.txt", dbsource = "wos", format = "plaintext") # Step 2: Add a column to indicate missing DOIs your_data$missing_DOI <- ifelse(is.na(your_data$DI), "Missing DOI", "Has DOI") # Step 3: Visualize missing DOIs by publication year ggplot(your_data, aes(x = PY, fill = missing_DOI)) + geom_histogram(binwidth = 1, alpha = 0.6) + labs(title = "Missing DOIs by Publication Year", x = "Publication Year", y = "Count", fill = "DOI Status") + theme_minimal() # Step 4: Visualize missing DOIs by journal (if journal data is available) if ("SO" %in% colnames(your_data)) { journal_missing_doi <- your_data %>% group_by(SO) %>% summarize(missing_DOI_count = sum(missing_DOI == "Missing DOI"), .groups = 'drop') %>% arrange(desc(missing_DOI_count)) # Plot missing DOIs by journal ggplot(journal_missing_doi, aes(x = reorder(SO, -missing_DOI_count), y = missing_DOI_count)) + geom_bar(stat = "identity", fill = "steelblue") + labs(title = "Missing DOIs by Journal", x = "Journal", y = "Number of Missing DOIs") + theme_minimal() + theme(axis.text.x = element_text(angle = 45, hjust = 1)) } else { cat("Journal information (SO field) not found in the dataset.\n") }	

# Define file paths input_file <- "WoS_data_15022025.txt" output_file <- "WoS_cleaned_23022025.txt" # Updated output file name # Read the file with \`warn=FALSE\` to suppress the warning lines <- readLines(input_file, encoding = "UTF-8", warn = FALSE) # Ensure the last line has a newline character if (length(lines) > 0 && lines[length(lines)] != "") { lines <- c(lines, "") # Append an empty line to ensure completeness } # Initialize variables cleaned_lines <- c() entry <- c() doi_set <- c() retain_entry <- FALSE # Process each line in the WoS file for (line in lines) { if (startsWith(line, "PT ")) { # Start of a new entry if (length(entry) > 0 && retain_entry) { cleaned_lines <- c(cleaned_lines, entry, "") # Add entry to cleaned data } entry <- c(line) # Start a new entry retain_entry <- FALSE # Reset entry validity } else if (startsWith(line, "DI ")) { # DOI field doi <- trimws(sub("DI ", "", line)) # Extract DOI if (doi != "" && !(doi %in% doi_set)) { doi_set <- c(doi_set, doi) # Store unique DOI retain_entry <- TRUE # Mark entry as valid } else { retain_entry <- FALSE # Duplicate DOI, ignore entry } } entry <- c(entry, line) # Append line to entry } # Append last entry if valid if (length(entry) > 0 && retain_entry) { cleaned_lines <- c(cleaned_lines, entry, "") }	Removing duplicates and missing DOI files, generating WoS clean output file WoS_cleaned_23022025.txt

# Write cleaned data to output file writeLines(cleaned_lines, output_file, useBytes = TRUE) # Print completion message cat("Cleaning completed! Processed file saved as:", output_file, "\n")	
# Load necessary libraries library(bibliometrix) library(dplyr) # Step 1: Load your bibliographic data your_data <- convert2df("WoS_cleaned_23022025.txt", dbsource = "wos", format = "plaintext") # Step 2: Define the fields to check for duplicates # Common fields: Titles (TI), DOIs (DI), Authors (AU), Publication Years (PY) duplicate_fields <- c("TI", "DI", "AU", "PY") # Step 3: Identify duplicates based on the specified fields # Create a unique identifier by combining the fields your_data <- your_data %>% mutate(unique_id = paste(!!!syms(duplicate_fields), sep = "_")) # Find duplicate rows duplicates <- your_data %>% group_by(unique_id) %>% filter(n() > 1) %>% ungroup() # Step 4: List duplicate records cat("Total duplicate records found:", nrow(duplicates), "\n") if (nrow(duplicates) > 0) { cat("\nList of duplicate records:\n") print(duplicates) } else { cat("\nNo duplicates found.\n") } # Step 5: Flag duplicates in the original dataset your_data <- your_data %>% mutate(is_duplicate = ifelse(unique_id %in% duplicates$unique_id, "Duplicate", "Unique")) # Step 6: Summarize duplicates duplicate_summary <- your_data %>% group_by(is_duplicate) %>% summarize(count = n()) cat("\nSummary of duplicates:\n") print(duplicate_summary) # Step 7: Visualize duplicates (optional)	

```
library(ggplot2)
ggplot(duplicate_summary, aes(x = is_duplicate, y
= count, fill = is_duplicate)) +
  geom_bar(stat = "identity") +
  labs(title = "Duplicate Records in Bibliographic
Data",
       x = "Duplicate Status",
       y = "Count",
       fill = "Status") +
  theme_minimal()
# Step 8: Remove duplicates (optional)
# Keep only unique records
clean_data <- your_data %>%
  filter(is_duplicate == "Unique")

# Verify removal
cat("\nTotal records after removing duplicates:",
nrow(clean_data), "\n")

# Step 9: Save results (optional)
write.table(duplicates, "duplicate_records.txt", sep
= "\t", row.names = FALSE, quote = FALSE)
write.table(clean_data, "cleaned_data.txt", sep =
"\t", row.names = FALSE, quote = FALSE)
```

```
# Load necessary libraries
library(bibliometrix)
library(ggplot2)

# Step 1: Load your bibliographic data
your_data <-
convert2df("WoS_cleaned_23022025.txt",
dbsource = "wos", format = "plaintext")

# Step 2: Add a column to indicate missing DOIs
your_data$missing_DOI <-
ifelse(is.na(your_data$DI), "Missing DOI", "Has
DOI")

# Step 3: Visualize missing DOIs by publication
year
ggplot(your_data, aes(x = PY, fill = missing_DOI))
+
  geom_histogram(binwidth = 1, alpha = 0.6) +
  labs(title = "Missing DOIs by Publication Year",
       x = "Publication Year",
       y = "Count",
       fill = "DOI Status") +
```



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Proceedings of the 19th International Conference on Business Excellence 2025

`` theme_minimal() # Step 4: Visualize missing DOIs by journal (if journal data is available) if ("SO" %in% colnames(your_data)) { journal_missing_doi <- your_data %>% group_by(SO) %>% summarize(missing_DOI_count = sum(missing_DOI == "Missing DOI"), .groups = 'drop') %>% arrange(desc(missing_DOI_count)) # Plot missing DOIs by journal ggplot(journal_missing_doi, aes(x = reorder(SO, -missing_DOI_count), y = missing_DOI_count)) + geom_bar(stat = "identity", fill = "steelblue") + labs(title = "Missing DOIs by Journal", x = "Journal", y = "Number of Missing DOIs") + theme_minimal() + theme(axis.text.x = element_text(angle = 45, hjust = 1)) } else { cat("Journal information (SO field) not found in the dataset.\n") } ```	

Acknowledgment
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