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Prescriptive Analytics: A Bibliometric Analysis of Current Trends in Data - Driven Decision - Making

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Abstract: This study presents a bibliometric synthesis of prescriptive analytics with the aim of charting its intellectual structure, historical trajectory, and emerging frontiers in data-driven decision making. We delineated the review scope, implemented systematic searches in Scopus and Web of Science (WoS), extracted and harmonized records, and undertook descriptive trend analysis alongside thematic mapping. The corpus evidence marked growth in the field: Scopus records increased from a single item in 1970 to 39 in 2024 (reported as 19.4% of the total), while WoS expanded from one publication in 1976 to 107 in 2024 (reported as 10.7%). More than 83% of the outputs have appeared since 2013, accompanied by substantial citation accumulation. The analysis identified leading authors, institutions, and recurrent topics spanning "prescriptive analytics," "decision science" and "decision intelligence." It also surfaces conceptual inconsistencies and underexplored areas, motivating the development of adaptive, context-aware frameworks that reconcile competing objectives and enable practical, interdisciplinary AI solutions.

Given the rapid technological change and database coverage effects, the observed trends should be interpreted as time- and source-dependent. Overall, the bibliometric perspective clarifies temporal patterns, disciplinary distribution, and high-frequency keywords and delineates a research agenda to address the most salient gaps.

Keywords: Scopus; Web of Science (WoS); Prescriptive Analytics; Decision Intelligence; Decision Science.

规定性分析：数据驱动决策中的当前趋势之书目计量学分析

摘要：
本研究对规定性分析进行书目计量学综合，旨在梳理其知识结构、历史演进轨迹及在数据驱动决策领域中的新兴前沿。我们明确评述范围，基于 Scopus 与 Web of Science（WoS）实施系统检索，随后完成记录的提取与规范化处理，并开展描述性趋势分析与主题图谱构建。结果显示，该领域呈现显著增长：Scopus 收录文献由 1970 年的 1 篇增长至 2024 年的 39 篇（占总量的 19.4%）；WoS 由 1976 年的 1 篇增长至 2024 年的 107 篇（占总量的 10.7%）。自 2013 年以来，发表量超过 83%，并累计获得大量引文。分析进一步识别出核心作者、机构及“规定性分析”“决策科学”“决策智能”等反复出现的主题，同时揭示若干概念分歧与研究空白，因而主张发展兼具自适应性与情境感知能力的框架，以在竞争性目标之间取得平衡，并推动可落地的跨学科人工智能解决方案。鉴于技术的快速迭代与数据库收录范围效应，上述趋势应被解读为与时间与数据源相关的观察。总体而言，书目计量视角有助于澄清时间演化模式、学科分布与高频关键词，并据此勾勒需要优先推进的研究议程与问题清单。

关键词： Scopus；Web of Science（WoS）；规定性分析；决策智能；决策科学。

1. Introduction

In the increasingly Data-Driven World, new technologies have emerged and evolved with the ability to analyze vast amounts of data effectively to allow advancement in the digital landscape [1][2][3][4]. Prescriptive analytics, a sophisticated branch of data analytics, provides advanced tools for analyzing complex data. By utilizing prescriptive analytics tools, such as statistical algorithms, optimization techniques, and machine learning, decision making is provided to evaluate various cases to maximize the potential impact [5].

Compared to descriptive analytics, which summarize historical data, or predictive analytics, which project future patterns, prescriptive analytics provide actionable insights that promote informed decision-making [6]. This analytical technique uses data modeling and simulation to examine numerous elements, helping firms negotiate complexity, ambiguity, and dynamic market situations. For instance, in supply chain management, prescriptive analytics can identify the best inventory levels, distribution strategies, and supplier selections, ensuring that operations function smoothly and efficiently [7].

As the digital landscape continues to evolve, prescriptive analytics has garnered significant attention across various sectors, including finance, healthcare, marketing, and supply chain management [3][8][9]. Organizations are progressively acknowledging their capacity to augment operational efficiency, optimize resource allocation, and enhance consumer experience. Nonetheless, the incorporation of prescriptive analytics presents several challenges, including issues related to data quality, interpretability of models, and ethical considerations regarding automated decision-making [10].

This study provides a comprehensive review of contemporary insights and prospective developments in prescriptive analytics, investigating the manner in which this potent instrument is revolutionizing data-driven decision-making across diverse industries. Through an analysis of technological advancements, methodological innovations, and emergent applications, we present a thorough overview of the evolving role of prescriptive analytics and its implications for both practitioners and researchers. As we progress, comprehending and utilizing prescriptive analytics is imperative for organizations aiming to excel in an increasingly intricate and data-saturated landscape [11][12].

2. Literature Review

There are various studies related to the field of analytics. Based on the screening of publications from

Scopus and WoS, descriptive analytics are often used for big data reports or visualization, which provides a comprehensive understanding of the current case scenario. Descriptive and diagnostic tools are more efficient in assessing a firm's current and future needs, which are linked to better decision-making and returns [3]. In normative decision theory, emphasis is placed on the processes by which individuals arrive at decisions, and the subsequent evaluation of those decisions through established theoretical frameworks. In descriptive decision theory, assessment is grounded in empirical validity and emphasizes the mechanisms and rationale underlying individuals' thought processes and decision-making behaviors [13]. According to (W. Raghupathi), descriptive analytics are more data-driven. Most companies employ descriptive analytics to create fact-based judgments using data to comprehend previous and present business decisions ("IS"). Descriptive analytics transforms data into information that can be used to analyze business decisions and results by classifying, aggregating, characterizing, and categorizing data [9].

Predictive analytics constitutes a specialized domain within data analytics that employs an array of statistical methodologies, machine learning algorithms, and data mining techniques to examine both historical and contemporary data [14]. The objective of this analysis is to generate forecasts of prospective events or outcomes. This type of analytics is essential for assisting organizations in forecasting trends, identifying potential hazards, and making informed decisions based on expected future scenarios [15][16]. Wissuchek stated that the complete potential of predictive analytics can only be utilized when integrated with prescriptive analytics, which facilitates proactive decision-making processes. Minimizing the temporal gap between event prediction and proactive decision making is essential for optimizing business value [17]. Thakre utilized predictive analytics together with machine learning algorithms and natural language processing to analyze diverse data sources and generate actionable recommendations to optimize HR decision-making processes [18]. The method used was employed to develop a prescriptive decision-making model specifically designed to augment contextual intelligence in human resource analytics [19][20].

There are various differences between the application of prescriptive analytics in various fields of study. According to (S. Ieva et al) which focus on integrating prescriptive analytics with energy management frameworks, the availability of prescriptive analytics optimizes energy distribution, consumption, and predictive maintenance, and focuses on the establishment of a data-driven and knowledge-based digital twin framework for energy systems, which incorporates a range of advanced methodologies to improve the administration of energy infrastructures, with particular emphasis on high-voltage energy systems [1]. There have been various applications of prescriptive analytics, as they can be utilized in many fields. The article titled "Knowledge Visualization of Internet Usage Pattern to Improve Students' Academic Performance Using Prescriptive Analytics" uses several approaches for prescriptive analytics such as regression techniques, R-squared evolution, proactive recommendation, and data visualization using Microsoft Power BI [21]. The work on prescriptive analytics by Kumari utilized the use of simulation model development, prediction mechanisms, intervention schemes, and prescriptive generation in the process of developing a prescriptive decision support system for shop floor control [22]. The publication from M, Strand states that the prescriptive analytics provided in this case study enhance decision-making processes, resulting in optimized operations and improved efficiency in waste management activities, the method used is involving Optimized Route Planning, Fleet Utilization Optimization, Fuel Optimization, Predictive Features for Operations, and Decision Support in Changing Conditions [23]. This was also a prescriptive analytics study on drug evaluation and usage in China, which is related to Regulatory Decision Support, Optimized Drug Evaluation, Pilot Studies and Real-World Studies (RWS), Recommendations for Drug Use and Patient Management, and Development of Technical Guidelines and Frameworks [24]. The purpose of this study is to provide a bibliometric analysis of data-driven decision-making in Prescriptive Analytics. The major contributions of this study are as follows.

1) This paper provides an overview of the overall publication trend in prescriptive analytics in recent years, compared with previous descriptive and predictive analytics. This comparison includes trend projection and the identification of relevance in the field of study.

2) Provide a synopsis of the technological software employed in the field. Technological Software includes optimization software, simulation software, data analysis and business intelligence tools, supply chain management systems, manufacturing execution systems, and decision support systems (DSS).

3) Provide a summary of the leading entities in the domain of prescriptive analytics, focusing on the following aspects: authors (both productive and influential), academic disciplines, sources (productive and influential), countries, institutions (productive and influential), and works of significant influence. This will offer a comprehensive overview of current trends for future projections.

3. Methods

The procedure for selecting articles pertinent to prescriptive analytics, decision science, and decision intelligence involves a methodological approach. At the outset, subject matter, parameters, and eligibility criteria were delineated to concentrate on prescriptive analytics within the realms of decision science and intelligence. The Scopus and WoS databases were utilized, with a focused search conducted explicitly within the titles of the articles. The scope encompassed all temporal frameworks and stipulated that the articles must be in English, derived from journals, books, book series, or trade publications, and formally recorded.

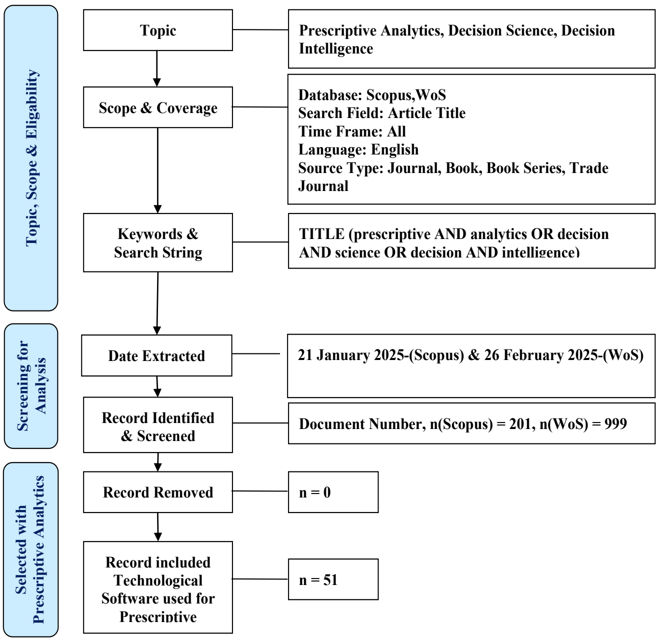

Figure 1. Overview of Scopus and WoS data-extraction workflow [25]. Source: K. Burhanudin, M. H. Jusoh, Z. I. A. Latiff, M. H. Hashim, and N. D. K. Ashar, "The Estimation of the Geomagnetically Induced Current Based on Simulation and Measurement at the Power Network: A Bibliometric Analysis of 42 Years (1979–2021)," *IEEE Access*, 10, 56525–56549 (2022), doi: 10.1109/ACCESS.2022.3175882

To guarantee thorough coverage, a particular search string was employed: prescriptive AND analytics OR decision AND science OR decision AND intelligence (TITLE). Analysis filtering was conducted using the data extracted on January 21, 2025. During this phase, 201 Scopus and 999 WoS recordings were identified and evaluated in accordance with the established criteria. After conducting a thorough analysis, 150 documents were eliminated. The final corpus comprised 51 records with a pronounced emphasis on software-enabled implementations of prescriptive analytics. This systematic protocol spanning database harmonization, deduplication, and multi-stage screening yielded a rigorously delimited body of literature for comprehensive analysis. Figure 1 provides an overview of the Scopus and WoS data extraction workflow.

We queried Scopus and WoS using field-restricted Boolean strings to assemble the datasets (Figure 2). In Scopus, the illustrative query was: TITLE-ABS-KEY(("prescriptive analytics") OR ("decision science") OR ("decision intelligence")) AND (LIMIT-TO(LANGUAGE,"English")) AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-TO(DOCTYPE,"ch") OR LIMIT-TO(DOCTYPE,"re") OR LIMIT-TO(DOCTYPE,"bk")) with a timespan of 1970–2025. (Equivalently expressed without phrase quotes, explicit parentheses are required to preserve operator precedence). According to Scopus, the comprehensive search returned 201 publications. The earliest item matching the query was published on March 15, 1970, titled *Control Theory and Decision Making in Organisations: A Reconnaissance* [26].

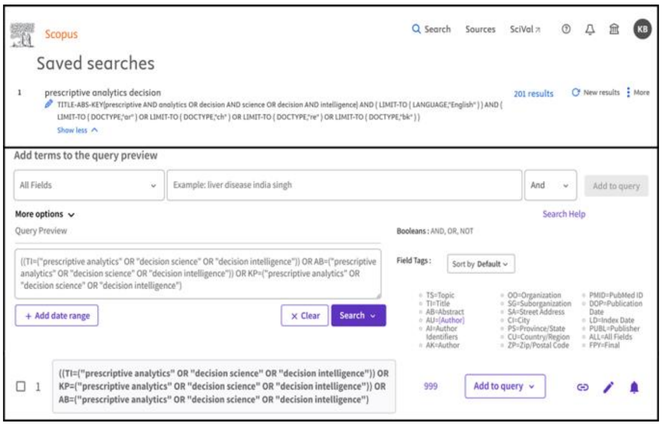

Figure 2. Scopus and WoS Search Keywords.

For the WOS search query, the keywords included are as follows: ((TI=("prescriptive analytics" OR "decision science" OR "decision intelligence")) OR AB=("prescriptive analytics" OR "decision science" OR "decision intelligence")) OR KP=("prescriptive analytics" OR "decision science" OR "decision intelligence")) where TI indicating the title of the research paper, AB indicates the abstract and KP indicates the keyword plus. The search keywords for SCOPUS and WoS are shown in (Figure 2). The search keywords used for SCOPUS and WoS were similar, and this approach was executed to collect similar fields of study from both databases.

4. Publication Analysis

In the field of Prescriptive Analytics, comprehensive Publication Analysis has revealed several key insights. Research Growth and Productive Authors highlight the dynamic expansion of research output, pinpointing the pivotal contributors who drive innovation and inquiry in the domain. Simultaneously, the examination of Technological Software Related to Prescriptive Analytics underscores the increasing reliance on advanced tools that enhance decision-making capabilities, showcasing how emerging technologies shape analytical practices.

Delving into Discipline Wise and Top Journal Sources, the analysis identifies the primary disciplines contributing to this field, alongside leading journals that disseminate influential research, thereby establishing a scholarly foundation. Moreover, a detailed account of Country and Institution Wise publications highlights the geographic and organizational hubs of research activity, reflecting the global collaboration and competition landscape.

Finally, identifying the Most Influential Publications offers valuable insights into groundbreaking studies that have significantly impacted the evolution of prescriptive analytics and guided future research trajectories and methodologies. This multidimensional analysis provides a holistic view of the current landscape and future directions for prescriptive analytics research.

4.1. Research Growth and Productive Author

The presented chart in Figure 3 shows the trends in total publications (TP) across four different categories (descriptive, predictive, and prescriptive) from Scopus, and WoS shows a clear picture of the dynamic environment of research over the course of 17 years. From the Scopus perspective, the landscape has changed significantly from a modest start of only 18 publications in 2012 to a spectacular spike to 162 publications by 2024. This expansion reflects a more active research community driven by creativity and investigation. While the diagnostic category has remained a dominant force, reaching 73 in 2021, descriptive publications have been progressively increasing, reaching a peak of 61 in 2023.

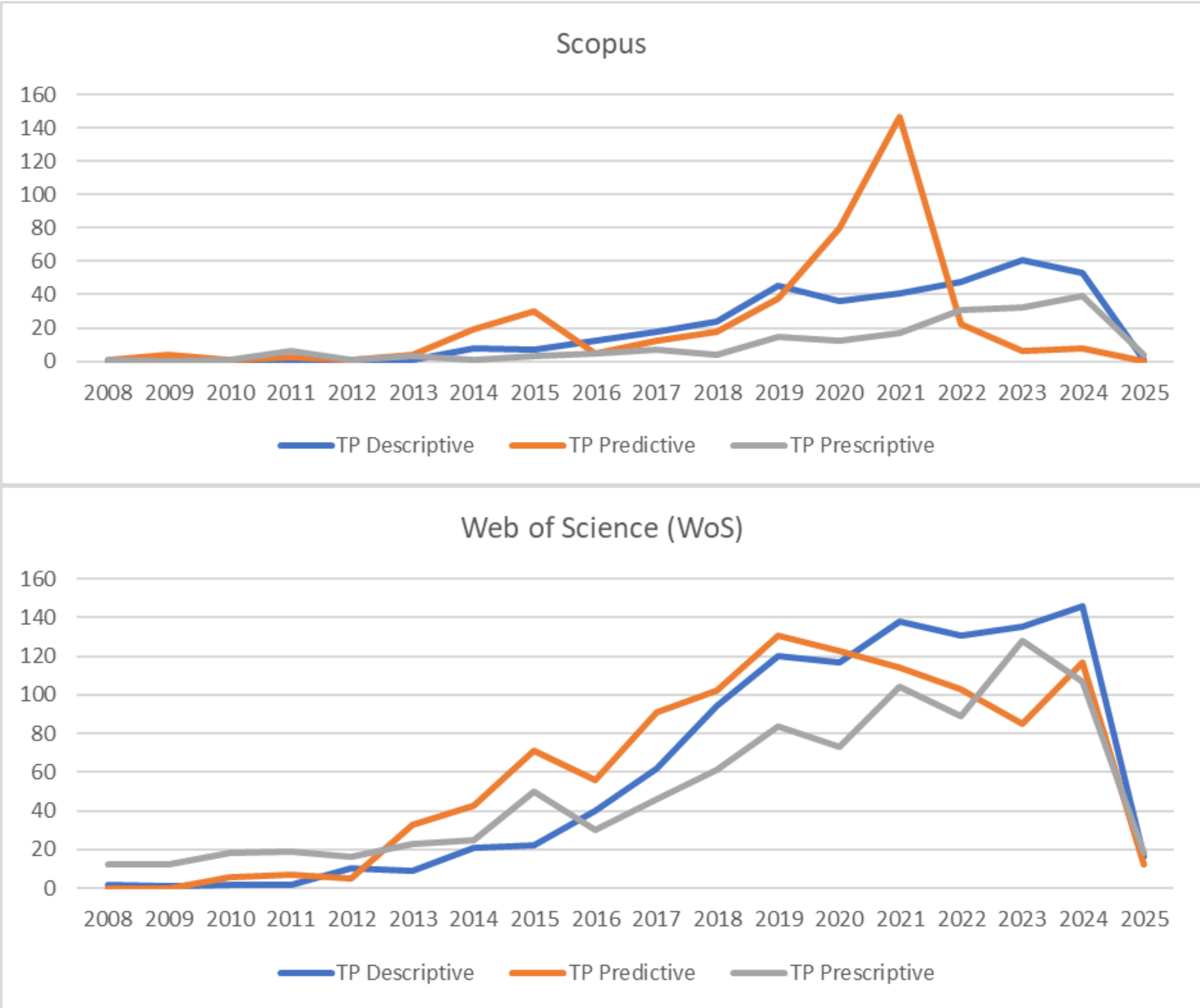

Figure 3. Total Publications by Year (2012-2024) for Descriptive, Diagnostic, Predictive and Prescriptive Analytics from Scopus and WoS.

A more complex story is revealed by the predicted papers, which, after reaching an incredible peak of 147 in 2021, has fallen to just eight in 2024, suggesting that research priorities may have changed or that there may be obstacles in the field of predictive modeling. With a peak of 39 articles in 2024 from Scopus, the prescriptive category has resurfaced with newfound energy, indicating a rising dedication to converting research findings into useful insights. A disruptive and revolutionary surge of interest, which may be sparked by new approaches and technological developments, emerged from 2017 to 2021 following a nascent research phase marked by decreased participation in the early years of 2012 to 2016. The Web of Science (WoS) analysis of Total Publications (TP) in

Descriptive, Predictive, and Prescriptive Analytics from 2008 to 2025 demonstrated substantial trends in research activity within these domains. Descriptive Analytics has experienced a consistent increase in the number of publications, from 2 in 2008 to 146 in 2024. This rise is indicative of the foundational role of descriptive analytics in data exploration and visualization, which inform decision-making processes. Predictive Analytics, which was initially underrepresented, experienced a significant increase in publications after 2013, reaching a peak of 131 in 2019. However, a notable decrease to 85 publications by 2023 indicates a potential plateau in research activity, which may be influenced by market saturation or a transition to prescriptive approaches. Prescriptive Analytics, on the other hand, demonstrates a more volatile trend, with record-breaking 128 publications in 2023.

This suggests a growing interest in the generation of actionable insights, although fluctuations may be indicative of the difficulties associated with effective integration into practical applications. The data as a whole reveal a changing landscape in which Descriptive Analytics are still essential, Predictive Analytics has gained significant traction but may be approaching maturity, and the emergence of Prescriptive Analytics represents an exciting trend toward the development of comprehensive analytical models that guide decision-making. Consequently, the data underscores opportunities for interdisciplinary collaboration to improve data-driven strategies across a variety of sectors. Descriptive and prescriptive outputs have stabilized in recent years, highlighting their continued importance in addressing difficult problems. All things considered, this data not only shows changing research goals, but also acts as a call to action for the community to look into the causes of the drop in predictive publications. This will open the door for future research to adjust to the opportunities and challenges that lie ahead. Essentially, the trajectory shown in this chart captures a rich story of development, adaptability, and an unrelenting quest for knowledge in the field of study.

(Figure 4) shows the overall publication and citation trends of Scopus and WoS from 1970 to 2025. From 1970 to 2025, the analysis of Total Publications (TP) and citations (TC) for Prescriptive Analytics, as documented in Scopus and the Web of Science (WoS), demonstrates a remarkable growth trajectory in this field. The growth of the field was gradual, with sporadic publications until the early 2000s, when engagement began to pick up slightly. This begins with minimal output in the early years, with only one publication recorded in 1970-1976 in Scopus and no citations. The impact of emerging research during this period is reflected in the notable peak in 2011, when Scopus recorded six publications and staggered 2,559 citations. In 2018, Scopus reported four publications and 125 citations, while WoS recorded 61 publications and 726 citations, indicating the pervasive recognition and application of prescriptive analytics. This indicated a significant turning point. TP increased to 128 publications and TC to 2,706 by 2023, indicating robust interest and development in prescriptive analytics methodologies. Additionally, a high citation count reinforces the relevance and quality of the research being produced. The years 2019 to 2022 were characterized by exponential growth, particularly in WoS, where TP surged to 128 publications and TC to 2,706 by 2023. It is important to note that the data indicate that despite the fact that both databases are experiencing growth, WoS tends to capture a greater number of publications and citations in general, suggesting that it places greater emphasis on high-impact research in this field. The rise in publications and citations is not only indicative of the increasing academic interest in prescriptive analytics but also suggests that its applications are expanding across a variety of sectors. This expansion is likely driven by technological advancements and the demand for data-

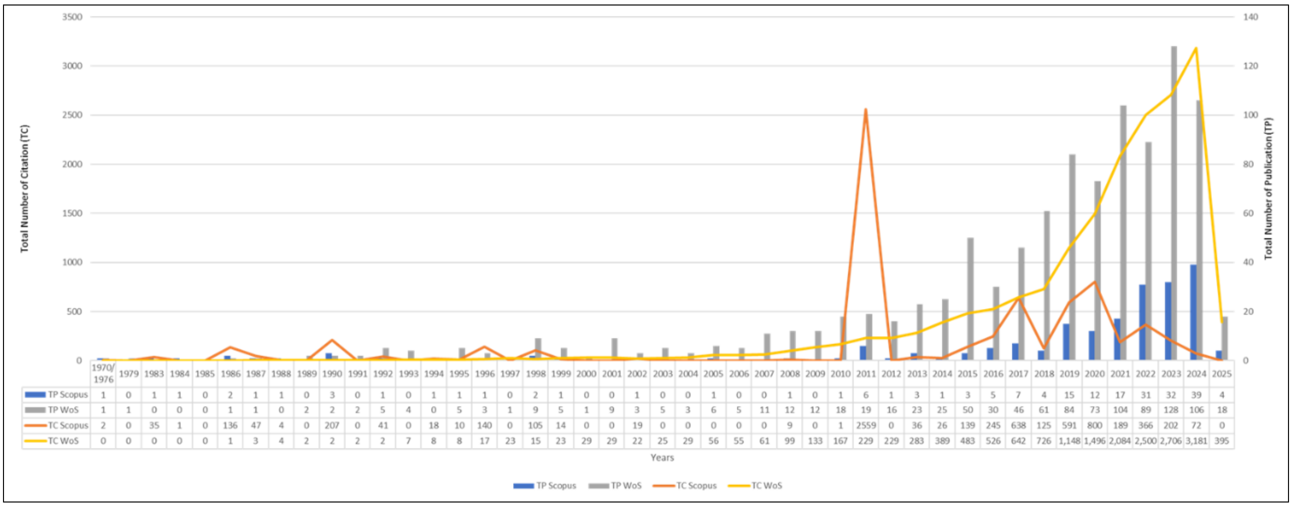

Figure 4. Total Publications and Citations by Year (1970-2025).

driven decision-making frameworks. It is anticipated that researchers will continue to make substantial contributions to the development of methodologies and applications in prescriptive analytics, thereby advancing the evolution of the discipline and its integration into practical solutions across various fields. As of 2025, the trajectory remains positive, with an estimated 4 publications in Scopus and 18 in WoS. Based on (Table 1), the analysis of the most productive authors in Prescriptive Analytics from Scopus and Web of Science (WoS) reveals a diverse ensemble of literature is enriched by the diversity of research approaches, as evidenced by variations in publication categories. Some authors prioritize theoretical frameworks, whereas others concentrate on application-oriented research. This landscape emphasizes the significance of collaboration, institutional support, and the quality of contributions over quantity, as impactful research has the potential to significantly influence the domain, guide future research directions, and foster innovative practices in the application of Prescriptive Analytics across various sectors.

Table 1. Most Productive Authors

	Scopus					WoS			
Author's Name	**TP**	**TC**	**C/CP**	***h***	**Author's Name**	**TP**	**TC**	**C/CP**	***h***
Liu, L.	42	326	8.81	10	**Pirjola R**	34	916	28.63	18
Pirjola, R.	36	1210	34.57	20	**Viljanen A**	25	663	28.83	15
Overbye, T.J.	29	458	20.82	10	**Liu LG**	23	236	16.86	7
Viljanen, A.	27	826	31.77	16	**Boteler DH**	18	309	19.31	10
Liu, C.	26	179	7.78	8	**Overbye TJ**	18	173	21.63	3
Liu, L.G.	26	410	19.52	8	**Liu CM**	16	248	19.08	7
Boteler, D.H.	22	503	22.86	14	**Cilliers PJ**	14	132	12.00	5
Gaunt, C.T.	17	233	16.64	6	**Pulkkinen A**	14	495	38.08	11
Rezaei-Zare, A.	16	232	17.85	6	**Rezaei-zare A**	14	157	15.70	5
Beggan, C.D.	13	271	22.58	9	**Thomson AWP**	14	363	25.93	10
Dalzell, M.	13	267	22.25	8	**Beggan CD**	13	262	21.83	9
Pirjola, R.J.	13	297	22.85	9	**Gaunt CT**	13	146	16.22	4
Pulkkinen, A.	13	638	49.08	13	**Rodger CJ**	13	179	14.92	8
Thomson, A.W.P.	13	268	20.62	9	**Dalzell M**	12	171	15.55	7
Marti, L.	12	250	20.83	7	**Pirjola RJ**	11	203	18.45	7
Rodger, C.J.	12	180	16.36	7	**Marti L**	10	149	24.83	5
Cilliers, P.J.	10	125	12.5	5	**Divett T**	8	110	15.71	6
Pilipenko, V.A.	11	42	5.25	4	**Pilipenko VA**	8	48	6.86	4
Liu, C.M.	10	325	36.11	6	**Richardson GS**	8	76	9.50	5
Shetye, K.S.	10	148	18.5	4	**Boteler D**	7	229	32.71	6

contributors, each of whom is distinguished by its unique academic influence, citation impacts, and publication outputs. In Scopus, Wang, F.Y. is the lead author, with three publications and 64 citations (C/CP of 21.33), indicating significant recognition. Appelbaum and Kogan, each with two publications and exceptionally high citation counts of 515, demonstrate a profound impact relative to their output, resulting in extraordinary C/CP values of 257.5.

In contrast, WoS emphasizes Fischhoff, B., who has 11 publications and 255 citations (C/CP of 25.5 and h-index of 7), demonstrating a significant impact in conjunction with authors such as Wang SA and Possingham, H.P., who produced similarly productive outputs. The auspicious potential of new leaders in the field is indicated by the presence of emerging talent, such as Ahmed, M.U., who has only one publication but 61 citations (C/CP of 61). Furthermore, the

4.2. Technological Software Related to Prescriptive Analytics

The examination of software and technologies identified in numerous research publications reveals the substantial utilization of a variety of analytical and technological instruments within domains such as prescriptive analytics and decision science. For example, machine learning frameworks, such as TensorFlow, PyTorch, and Scikit-learn, are commonly employed, underscoring their significance in the development of predictive and prescriptive models. In the healthcare sector, systems such as Electronic Medical Records (EMR) and Picture Archiving and Communication Systems (PACS) have been incorporated with artificial intelligence tools to augment decision-making processes and improve

Table 2. Technology used for Prescriptive Analytics

Scopus		
Year	**Title**	**Software/Technology**
2011	Non-Deterministic Policies in Markovian Decision Processes	TensorFlow/PyTorch/OpenAI Gym/Matlab/Simulink [36].
2013	The effect of market orientation dimensions on multinational SBU's strategic performance: An empirical study	SPSS (Statistical Package for the Social Sciences) and SAS (Statistical Analysis System) [37].
2015	Potential of Cognitive Computing and Cognitive Systems	IBM Watson, Microsoft Azure Cognitive Services, TensorFlow and PyTorch, Open AI GPT model [38].
2016	Are Randomized Controlled Trials the (G)old Standard? From Clinical Intelligence to Prescriptive Analytics	RapidMiner,Various predictive modeling and machine learning algorithms (Support Vector Machines (SVM), Neural Networks and Deep Learning methods, Random Forests, Ensemble Methods), CRISP-DM Model (Data Mining Software), Data visualization tools [39].
2021	Optimizing integrated imaging service delivery by tier in low-resource health systems	UTD Anonymization Toolbox, Cornell Anonymization Toolkit, TIAMAT, SECRETA, Open Anonymizer, AnonTool, PARAT, µArgus [40].
2021	Decision Intelligence for Nationwide Ventilator Allocation During the COVID-19 Pandemic	Pyomo, CPLEX, C programming language, NEOS Server, GitHub, Statistical software [41].
2022	Achieving Competitive Sustainable Advantages (CSAs) by Applying a Heuristic-Collaborative Risk Model	Microsoft Power BI, SQL Server Integration Services (SSIS), ORA, UCINET, Graph algorithms [42].
2024	A data-driven prioritisation framework to mitigate maintenance impact on passengers during metro line operation	Stan, Markov Chain Monte Carlo (MCMC), One-Class Support Vector Machine (OCSVM) [2].
2024	A Descriptive-Predictive–Prescriptive Framework for the Social-Media–Cryptocurrencies Relationship	Python, NLP, Logistic Regression Classifier, LSTM (Long Short-Term Memory), Glassnode [43].
2024	AI implementation in big data: Shaping data analysis for business decisions	NVIVO, Tableau, Python, Natural Language Processing libraries, ARIMA and Prophet [3].
2024	A Prescriptive Simulation Framework with Realistic Behavioural Modelling for Emergency Evacuations	Unity 3D, Python, C#, POMDP (Partially Observable Markov Decision Process) Framework, Monte Carlo Simulation Tools, Statistical Analysis Software, Visualization Tools [44].
2016	Are Randomized Controlled Trials the (G)old Standard? From Clinical Intelligence to Prescriptive Analytics	Statistical Analysis Software, Machine Learning Libraries, Natural Language Processing (NLP) Software, Predictive Analytics Tools, Secure Multiparty Computation Software (not mentioning the name of the software) [39].
2024	A Retrieval-Augmented Generation Approach for Data-Driven Energy Infrastructure Digital Twins	Keycloak, PostgreSQL, Neo4j, Apache Kafka and RabbitMQ, Python Libraries (Pandas, NumPy, Scikit-learn), Llama 2, GIS (Geographic Information Systems) [1].
2024	Artificial intelligence and prescriptive analytics for supply chain resilience: a systematic literature review and research agenda	Machine Learning Tools, Optimization Software, Autonomous Robotics Software, Natural Language Processing (NLP) Tools (not mentioning the name of the software) [6].
2024	Assessing ChatGPT's theoretical knowledge and prescriptive accuracy in bacterial infections: a comparative study with infectious diseases residents and specialists	Microsoft, SAP, Amazon (AWS), Oracle, Dassault Systèmes, Synopsys [8].
2022	A Survey onArtificial Intelligence (AI) and eXplainable AI in Air Traffic Management: Current Trends and Development with Future Research Trajectory	Machine Learning Frameworks (TensorFlow, Keras), data analysis (Scikit-learn and R), Simulation Software (Any Logic and MATLAB), Agent-Based Modeling Platforms (NetLogo & Repast), Optimization (IBM ILOG CPLEX and Gurobi) [45].
2024	Beyond Predictive Learning Analytics Modelling andontoExplainable Artificial Intelligence with Prescriptive Analytics and ChatGPT	Scikit-learn, SHAP, Anchors, ChatGPT, CatBoost [14].
2024	Challenges of the Biopharmaceutical Industry in the Application of Prescriptive Maintenance in the Industry 4.0 Context: AComprehensive Literature Review	Computerized Maintenance Management Systems (CMMS), Predictive Maintenance Software, Data Analysis and Visualization Software, Condition Monitoring Systems, Enterprise Resource Planning (ERP) Systems [15].

service delivery [4]. This integration is evidenced by research focused on the optimization of imaging services and allocation of ventilators. Moreover, sophisticated business analytics are facilitated by platforms such as IBM Watson and Microsoft Azure, signifying a shift towards cognitive computing to tackle intricate data challenges. Prescriptive maintenance models within the manufacturing sector utilize predictive maintenance software and SCADA systems, highlighting the transition towards Industry 4.0. Furthermore, natural language processing and artificial intelligence-driven platforms significantly enhance research across diverse fields such as social media analysis and education [27][28]. This

Table 2. Technology used for Prescriptive Analytics (Continue)

2021	Contemporary Business Analytics: An Overview	Business Intelligence (Tableau, Tibco Spotfire, QlikSense), Statistical and Data Analysis (SAS, R, SPSS), Data Warehousing and Processing Tools (Cognos, Business Objects, Hyperion) [9].
2018	Automatically Identifying Fake News in Popular Twitter Threads	Data Analysis and machine learning (Stochastic Gradient Descent, Random Forest Classifier), Programming (R and Python), Amazon Mechanical Turk (AMT), NLP (NLTK) [46].
2021	Decision Intelligence for Nationwide Ventilator Allocation During the COVID-19 Pandemic	CPLEX, Pyomo, Stochastic Decomposition (SD) [41].
2024	Design principles for artificial intelligence augmented decision making: An action design research study	Google Analytics, Shopify Analytics, Scikit-learn, TensorFlow, PyTorch, LIME, SHAP and Statistical Tools [5].
2022	Developing a prescriptive decision support system for shop floor control	Arena Simulation, AnyLogic, Microsoft Azure Machine Learning, IBM SPSS, Tableau, Microsoft Power BI [22].
2021	Digital Transformation and Artificial Intelligence Applied to Business: Legal Regulations, Economic Impact and Perspective	Scikit-learn, TensorFlow, Keras, Tableau, Power BI, NLTK (Natural Language Toolkit), AWS (Amazon Web Services) [47].
2024	European Nephrologists' Attitudes toward the Application of Artificial Intelligence in Clinical Practice: A Comprehensive Survey	EuCliD AI Solutions, STATA [48].
2023	Explaining and predicting human behavior and social dynamics in simulated virtual worlds: reproducibility, generalizability, and robustness of causal discovery methods	R pcalg, Bayesian Network Repositor, Random Forest (RF), k-Nearest Neighbors (KNN), Logistic Regression (LR), Deep Neural Networks (DNN) [49].
2024	Exploring trends and autonomy levels of adaptive business intelligence in healthcare: A systematic review	Electronic Health Records (EHR), Medical Health Records (MHR), Predictive Analytics Software, Prescriptive Analytics Tools, Deep Learning Frameworks [16].
2022	Forecasting of in situ electron energy loss spectroscopy	Hyperspy, Python, Keras, TensorFlow, Hyperopt, NumPy, Pandas, Scikit-learn [50].
2023	From process mining to augmented process execution	Apromore, Business Activity Monitoring (BAM) Tools, Machine Learning Libraries, Simulation Software, Natural Language Processing (NLP) Systems [11].
2024	Fully Individualized Curriculum with Decaying Knowledge, a NewHardProblem:Investigation andRecommendations	Prolog, Paradiseo, Scikit-learn, Machine Learning Libraries (not specified) [51].
2022	Is trust in artificial intelligence systems related to user personality? Review of empirical evidence and future research directions	Chatbots and Virtual Assistants, Autonomous Vehicles, AI-Driven Healthcare Systems, Automated Decision-Support Systems, Security Robots [52].
2025	Knowledge Visualization of Internet Usage Pattern to Improve Students' Academic Performance Using Prescriptive Analytic	Microsoft Power BI, SQL Server, Advanced Data Analytics Tools, Learning Management Systems (LMS) [21].
2021	MenGO: A Novel Cloud-based Digital Healthcare Platform for Andrology Powered by Artificial Intelligence, Data Science & Analytics, Bioinformatics and Blockchain	Cloud Computing Platforms, Artificial Intelligence (AI) Frameworks, Natural Language Processing (NLP), Blockchain Technology, Data Analytics Tools, Database Management Systems [53].
2022	Mitigating the impact of biased artificial intelligence in emergency decision-making	Machine Learning Frameworks, Natural Language Processing (NLP) Libraries, Statistical Analysis Software, Web-based Survey Platforms, AI Deployment Platforms, Decision Support Systems, Risk Assessment and Management Software (Does not specify specific name) [54].
2011	Non-Deterministic Policies in Markovian Decision Processes	Clinical Decision Support Systems (CDSS), Cloud Computing Platforms, Data Visualization Tools, Simulation and Modeling Tools, Statistical Analysis Software, Optimization Software, Machine Learning Frameworks [36].
2019	On measuring agreement with numerically bounded linguistic probability schemes: Are analysis of data from Wintle, Fraser, Wills, Nicholson, and Fidler (2019)	Statistical Analysis Software, Data Visualization Tools, Text Analysis Software (Not Specify specific name) [55].
2021	Optimizing integrated imaging service delivery by tier in low-resource health systems	Picture Archiving and Communication Systems (PACS), Digital Imaging and Communications in Medicine (DICOM) Software, Radiology Information Systems (RIS), Electronic Medical Records (EMR) Systems, Artificial Intelligence (AI) Tools for Imaging, Health Informatics Software, Quality Management Systems (QMS) [40].

underscores the adaptability and growing influence of AI technologies in improving strategic decision making and operational efficiency across various industries.

The examination of the software and technologies delineated in the data highlights notable diversity in the tools employed across different domains for prescriptive analytics and decision-making.

1) **Machine Learning Frameworks**: Noteworthy among these are Machine learning frameworks such as TensorFlow and PyTorch are extensively utilized owing to their adaptability in the development and training of models for predictive analytics. These frameworks support intricate algorithms, thereby empowering researchers to address a multitude of challenges ranging from forecasting patient outcomes to enhancing supply chain processes. For example, the application of Long Short-Term Memory (LSTM) networks in the investigation of the relationship between social media and cryptocurrency serves as a prime illustration of how deep learning methodologies can reveal intricate patterns within data.

2) **Data Analysis Tools**: Statistical analysis software, particularly SPSS and SAS, are integral to empirical research, facilitating comprehensive data manipulation, rigorous statistical testing, and insightful interpretation [29]. These instruments are indispensable in research investigating the effects of market orientation on multinational corporations, thereby underscoring their significance in the realm of business intelligence.

3) **Business Intelligence Platforms**: Solutions such as Microsoft Power BI and Tableau are distinguished by their capabilities in

Table 2. Technology used for Prescriptive Analytics (Continue)

2022	Parallel cognition: hybridintelligenceforhuman-machine interaction andmanagement	Machine Learning Frameworks, Data Analysis and Statistical Software, Simulation Software, Neural Network Libraries, Cognitive Modeling Tools, Virtual Environment Development Tools, Statistical Process Control (SPC) Software [56].
2021	PI Prob: A risk prediction and clinical guidancesystem for evaluating patients with recurrent infections	GeNIe Modeler, Epic Clarity Database, scikit-learn, Prism GraphPad [57].
2015	Potential of Cognitive Computing and Cognitive Systems	PILOTS, Neural Network Visualization Tools, Cognitive Interfaces, Cognitive Personal Assistants [38].
2024	Prescriptive analytics systems revised: a systematic literature review from an information systems perspective	Machine Learning Algorithms, Mathematical Programming Software, Reinforcement Learning Frameworks, Prescriptive Analytics Software (Does not mention specific name) [17].
2024	Prescriptive Decision-Making Model for Contextual Intelligence in Human Resource Analytics	Machine Learning Algorithms, Natural Language Processing (NLP), Bidirectional Recommender Systems, Optimization Software, Data Mining and Visualization Tools (Does not mention specific name) [19].
2019	PriMa: a prescriptive maintenance model for cyber-physical production systems	Predictive Maintenance Software, Data Management Tools, Condition Monitoring Systems, Supervisory Control and Data Acquisition (SCADA) Systems, Computerized Maintenance Management Systems (CMMS), Enterprise Resource Planning (ERP) Systems (Does not specify specific name) [33].
2022	Reducing the Total Product Cost at the Product Design Stage	Enterprise Resource Planning (ERP) Software, Computer-Aided Design (CAD) Software, Computer-Aided Engineering (CAE) Software, Computerized Maintenance Management Systems (CMMS), Predictive Analytics and Business Intelligence Tools [58].
2022	Review of Decision Support Systems and Allocation Models for Integrated Water Resources Management Focusing on Joint Water Quantity-Quality	AQUATOOL, WEAP21 (Water Evaluation and Planning), QUAL2K, Mike ECOLab, MITSIM, GIBSI (Integrated Modelling System), SWAT (Soil and Water Assessment Tool), MODSIM [59].
2024	Revisiting a Teaching Sequence on the Topic of Electrolysis: A Comparative Study with the Use of Artificial Intelligence	Electrolysis Computer Simulation, GPT-4, GPT-3.5 [60].
2013	The effect of market orientation dimensions on multinational SBU's strategic performance an empirical study	Customer Relationship Management (CRM) software, Business Intelligence (BI) tools (like Tableau or Power BI), Market research and analytics platforms [37].
2023	The Impact of Artificial Intelligence and Digital Economy on Vietnam's Legal System	Virtual Personal Assistants (VPAs), Chatbots, Machine Learning, AI Technologies for Business Applications, Cloud Technologies, Big Data Technologies [61].
2019	The potential beyond IC 4.0: the evolution of business intelligence towards advanced business analytics	Business Intelligence Tools, Analytics Platforms, Big Data Technologies, Data Management Tools, Predictive Analytics Software, Machine Learning Frameworks (Does not specify specific name) [62].
2023	Trust in Artificial Intelligence: Modeling the Decision Making of Human Operators in Highly Dangerous Situations	Simulation Software, Predictive Analytics Tools, AI Algorithms, Decision Support Systems (DSS), Human–Machine Interface (HMI) Software, Computer-Based Operator Training Systems [63].
2023	Use of Real-World Evidence for Drug Regulatory Decisions in China: Current Status and Future Directions	Data Management Systems, Statistical Analysis Software, Database Systems, Clinical Trial Management Systems (CTMS), Data Integration Tools, Artificial Intelligence/Machine Learning Tools [24].
2024	Volve Oil Field S-Wave Log Data Prediction Using GBR and MLPR	Machine Learning Libraries, Statistical Analysis Software, Data Processing Tools, Geospatial Analysis Software, Visualization Software, Integrated Development Environments (IDEs), Data Management Systems (Does not specify specific name) [64].

visualizing and interpreting data. These tools assist organizations in presenting intricate datasets in a comprehensible format, thereby facilitating the extraction of actionable insights [20][30]. The amalgamation of Business Intelligence with data management systems significantly augments decision-making capabilities, enabling enterprises to make informed strategic decisions.

4) **Healthcare Applications**: Within the healthcare sector, instruments such as Electronic Medical Records (EMR) systems, Picture Archiving and Communication Systems (PACS), and an array of clinical trial management systems are essential for effective administration of extensive volumes of patient data [31]. The incorporation of artificial intelligence technologies into these systems not only facilitates data administration but also enhances the analysis of treatment outcomes, thereby augmenting patient care and operational efficiency [32].

5) **Predictive and Prescriptive Maintenance**: Software solutions designed for predictive maintenance, including Computerized Maintenance Management Systems (CMMS) and Supervisory Control and Data Acquisition (SCADA) systems, facilitate operations within manufacturing and industrial sectors [33]. By utilizing real-time data and machine learning algorithms, these systems can predict equipment failures and optimize maintenance schedules, thereby reducing downtime and cost [27].

6) **Natural Language Processing (NLP)** encompasses the utilization of tools such as the Natural Language Toolkit (NLTK) along with sophisticated artificial intelligence algorithms. This trend reflects increasing interest in deriving insights from unstructured data, thereby augmenting organizations' abilities to analyze customer sentiment, automate responses, and enhance decision-making processes [34].

7) **Collaboration Tools**: Technologies such as GitHub, utilized for code management and collaborative efforts, underscore the significance of Version Control Systems in research and development, especially within software-centric initiatives [35].

The extensive variety of software tools reflects a comprehensive strategy for integrating data analysis, machine learning, and business intelligence across multiple sectors. This multifaceted application of technologies promotes the establishment of resilient prescriptive analytics frameworks that improve decision making, operational efficiency, and, ultimately, innovation in the development of products and services. (Table 2) listed the technological software used in the application of prescriptive analytics.

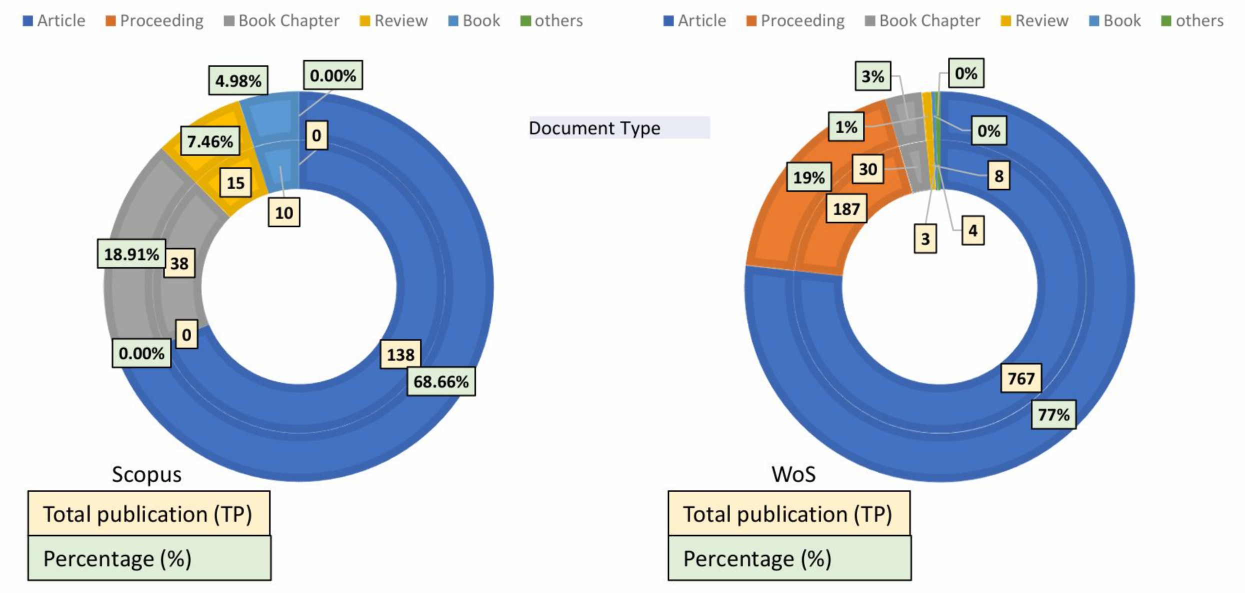

Figure 5. Total Publications and Citations

4.3. Discipline Wise and Top Journal Sources

Scopus and Web of Science (WoS) have provided data on document types for Prescriptive Analytics. These databases exhibit significant differences in their publication patterns and preferences. A total of 201 publications were recorded in Scopus, with Articles comprising 138, accounting for 68.66% of the total output. This prevalence of articles is indicative of a trend in academic publishing that emphasizes empirical studies and original research, suggesting that researchers are actively contributing new insights and discoveries to the field of Prescriptive Analytics. Book Chapters, which account for 18.91% of the total in Scopus, also indicate a preference for comprehensive discussions regarding the specific aspects of prescriptive methodologies. Conversely, the absence of Proceedings underscores the dearth of conference-focused research in this field, which suggests that the community is favoring more formalized and peer-reviewed publications. In contrast, WoS displays a total of 999 publications, with articles comprising the largest proportion at 767 (76.78%). This figure is slightly higher than that of Scopus, further emphasizing their preference for peer-reviewed research. Nevertheless, the substantial presence of Proceedings (187 publications, or 18.72%) in WoS suggests that researchers are actively engaging with conference proceedings, which suggests that they may be using these platforms to disseminate preliminary findings and innovations in Prescriptive Analytics. This highlights the vibrant exchange of ideas within academic and industrial circles. Moreover, although Book Chapters and Reviews are included in both databases, their percentage contributions in WoS are significantly lower.

This may indicate that the editorial strategies or publication patterns of these platforms differ. In addition, the limited number of publications in categories such as Book Chapters and Reviews in WoS suggests a more focused approach in that database, where researchers may be more focused on the production of original articles rather than on comprehensive syntheses or discussions.

In general, the disparities in publication categories between Scopus and WoS suggest that the Prescriptive

The Table 3. Most Popular Subject Area

Scopus			WoS		
Subject Area	TP	% of 601	Research Areas	TP	% of 357
Computer Science	104	51.74%	Computer Science Artificial Intelligence	159	15.92%
Business, Management and Accounting	60	29.85%	Computer Science Information Systems	144	14.41%
Engineering	56	27.86%	Operations Research Management Science	133	13.31%
Social Sciences	35	17.41%	Management	111	11.11%
Decision Sciences	33	16.42%	Computer Science Interdisciplinary Applications	82	8.21%
Economics, Econometrics and Finance	23	11.44%	Computer Science Theory Methods	82	8.21%
Medicine	23	11.44%	Engineering Electrical Electronic	63	6.31%
Mathematics	19	9.45%	Engineering Industrial	52	5.21%
Materials Science	14	6.97%	Business	49	4.91%
Psychology	12	5.97%	Environmental Sciences	48	4.81%
Arts and Humanities	9	4.48%	Health Care Sciences Services	43	4.30%
Biochemistry, Genetics and Molecular Biology	7	3.48%	Health Policy Services	36	3.60%
Environmental Science	5	2.49%	Engineering Manufacturing	31	3.10%
Multidisciplinary	5	2.49%	Ecology	29	2.90%
Nursing	5	2.49%	Medical Informatics	28	2.80%
Physics and Astronomy	5	2.49%	Computer Science Software Engineering	27	2.70%
Chemistry	4	1.99%	Psychology Multidisciplinary	26	2.60%
Energy	4	1.99%	Automation Control Systems	25	2.50%
Agricultural and Biological Sciences	3	1.49%	Telecommunications	24	2.40%
Chemical Engineering	3	1.49%	Economics	23	2.30%
Earth and Planetary Sciences	3	1.49%	Engineering Multidisciplinary	23	2.30%
Health Professions	3	1.49%	Education Educational Research	22	2.20%
Neuroscience	1	0.50%	Environmental Studies	21	2.10%
Pharmacology, Toxicology and Pharmaceutics	1	0.50%	Public Environmental Occupational Health	21	2.10%

*Subject Area Trends

Analytics community employs distinct methodologies to disseminate research. The emphasis on original research was underscored by the predominance of articles in both databases. However, the presence of Proceedings in WoS suggests the potential for the rapid sharing of insights and developments that may not yet be completely represented in peer-reviewed formats. This discrepancy emphasizes the necessity for researchers to evaluate publication formats that are most compatible with their research objectives and the audience they aim to reach, as well as factors such as publication timelines and the potential for collaborative engagements within the academic community. (Figure 5) summarizes the document types obtained from the search sources. The interdisciplinary nature of Prescriptive Analytics is revealed through an analysis of subject areas from Scopus and Web of Science (WoS). Computer Science was the leading field in Scopus, accounting for 104 publications (51.74%).

This underscores the critical role of algorithms and data processing techniques in optimizing decision-making. The integration of AI and information systems in the development of prescriptive models is further emphasized by WoS, particularly in the areas of Artificial Intelligence (159 publications, 15.92%) and Information Systems (144 publications, 14.41%). The practical implementation of prescriptive analytics to improve organizational decision-making and resource allocation is emphasized by the prominence of Business, Management, and Accounting (60 publications, 29.85% in Scopus) and Management (111 publications, 11.11% in WoS). Moreover, Engineering is a significant contributor to both databases, demonstrating its use in optimizing operations and design efficiency. Decision Sciences, on the other hand, emphasizes the method's significance in structured decision-making (33 publications, 16.42%). The versatility of analytics is also evident in WoS areas such as Operations Research Management Science (133 publications, 13.31%) and Health Care Sciences Services (43 publications, 4.30%), as evidenced by the increasing interest in applying prescriptive analytics to address healthcare outcomes and social issues. Social Sciences (35 publications, 17.41% in Scopus) and Medicine (23 publications, 11.44%) are among the emerging contributions. In general, the data demonstrates the critical role that Prescriptive Analytics plays in addressing complex problems across a variety of disciplines, revealing opportunities for future interdisciplinary collaboration that is designed to

Table 4. Most Active Source

Scopus				WoS			
Source Title	TP	TC	% of 601	Source Title	TP	TC	% of 357
IEEE Access	4	66	1.99%	Elsevier	198	5415	19.82%
Decision Support Systems	3	214	1.49%	Springer Nature	157	2093	15.72%
Expert Systems With Applications	3	164	1.49%	IEEE	86	1267	8.61%
Information Systems Research	3	153	1.49%	Wiley	76	2277	7.61%
Plos One	3	29	1.49%	Mdpi	42	581	4.20%
Studies In Computational Intelligence	3	16	1.49%	Taylor & Francis	38	602	3.80%
ACM Computing Surveys	2	64	1.00%	Sage	37	1104	3.70%
Applied Sciences Switzerland	2	75	1.00%	Emerald Group Publishing	26	479	2.60%
Computers And Industrial Engineering	2	38	1.00%	Informs	24	856	2.40%
Eai Springer Innovations In Communication And Computing	2	10	1.00%	Assoc Computing Machinery	18	102	1.80%
Electronic Markets	2	95	1.00%	Lippincott Williams & Wilkins	14	152	1.40%
European Journal Of Operational Research	2	85	1.00%	Oxford Univ Press	14	168	1.40%
International Journal Of Artificial Intelligence In Education	2	16	1.00%	Frontiers Media Sa	10	50	1.00%
International Journal Of Information Management	2	37	1.00%	Ios Press	9	29	0.90%
International Journal Of Production Research	2	9	1.00%	Asce-Amer Soc Civil Engineers	8	221	0.80%
Journal Of Business Analytics	2	16	1.00%	Amer Inst Mathematical Sciences-Aims	6	36	0.60%
Journal Of Business Research	2	1	1.00%	Cambridge Univ Press	6	49	0.60%
Journal Of Medical Internet Research	2	68	1.00%	NATURE PORTFOLIO	6	102	0.60%
Practical Data Analytics For Innovation In Medicine Building Real Predictive And Prescriptive Models In Personalized Healthcare And Medical Research Using AI Ml And Related Technologies Second Edition	2	1	1.00%	HICSS	5	0	0.50%
Risk Analysis	2	14	1.00%	INST OPERATIONS RESEARCH MANAGEMENT SCIENCES	5	0	0.50%

Research Trends

accelerate the adoption of effective decision-making practices. (Table 3) shows the most popular subject area from the analysis.

The importance of several academic journals in the dissemination of research in this field is underscored by the examination of the most active sources of Prescriptive Analytics from Scopus and Web of Science (WoS). Based on (Table 4), IEEE Access is the leading publication in Scopus, with four publications and 66 citations, which account for 1.99% of the total output. This underscores the importance of IEEE Access in the advancement of engineering and technology, which are the foundations of prescriptive analytics. Journals, such as Decision Support Systems and Expert Systems with Applications, each with three publications, exhibit high citation impacts of 214 and 164, respectively, indicating their critical contributions to analytical frameworks and decision-making. In contrast, the World Scientific Database (WoS) indicates that Elsevier is the most active publisher, with 198 publications and 5,415 citations (19.82%). This indicates that research conducted under this umbrella is both prolific and influential. Springer Nature followed 157 publications (15.72%). The significance of journal reputation is emphasized by the variation in citation impacts, with Decision Support Systems exhibiting a C/CP of 71.33, indicating a particularly high level of visibility. The diversity of these sources is indicative of the extensive application of prescriptive analytics in decision-making frameworks, operational research, and emerging areas, such as healthcare. Journals such as the Journal of Business Analytics underscore the growing relevance of this research in new sectors. In general, these results underscore the active involvement of significant publishers in the development of high-quality research that tackles intricate challenges by employing prescriptive analytical methodologies.

4.4. Country and Institution Wise

The international research landscape is significantly illuminated by an analysis of the top 20 countries contributing to publications in Prescriptive Analytics from Scopus and Web of Science (WoS). Based on (Table 5), the United States is the dominant player, with 69 publications and 2,202 citations in Scopus, and 97 publications with 1,352 citations in WoS. This underscores its leadership role in research and innovation in the field. India's visibility in WoS is less prominent, suggesting potential variations in research concentration across platforms, despite its second-place ranking in Scopus with 35 publications and 122 citations, which reflects a growing interest in analytical research. Their substantial contributions to the advancement of high-impact analytics research are underscored by the United Kingdom's 18 publications (323 citations) in Scopus and 31 publications (261 citations) in WoS as well as Germany's impressive 2,694 citations from 14 publications in Scopus and 57 publications (1,416 citations) in WoS. Australia also exhibits significant engagement with nine publications (242 citations in Scopus) and 61 publications (490 citations in WoS), whereas China is swiftly emerging with seven publications in Scopus, 64 in WoS, and

Table 5. Top 20 Countries contributed to the publications

	Scopus			WoS	
Country	TP	TC	Country	TP	TC
United States	69	2202	United States	97	1352
India	35	122	China	64	1187
United Kingdom	18	323	Australia	61	490
Canada	14	292	Germany	57	1416
Germany	14	2694	England	31	261
Australia	9	242	India	25	474
Italy	9	167	Canada	21	503
Spain	8	110	Italy	17	145
China	7	135	France	15	214
Brazil	6	217	Netherlands	12	173
France	5	70	Spain	11	161
Poland	5	45	Taiwan	10	70
Singapore	5	142	Austria	8	48
Turkey	5	15	Brazil	7	160
Colombia	4	80	Singapore	6	66
Finland	4	105	Greece	5	110
New Zealand	4	82	Portugal	5	85
Portugal	4	19	Belgium	5	34
Switzerland	4	77	South Korea	5	123
Austria	3	170	Malaysia	4	109

Notes: TP=total number of publications; NCP=number of cited publications; TC=total citations; C/P=average citations per publication; C/CP=average citations per cited publication; h=h-index; and g=g-index.

1,187 citations. Furthermore, the presence of Brazil and Poland indicates a developing regional interest in utilizing analytics for decision-making, whereas countries such as Canada and Italy contribute to niche research in area. The correlation between publication and citation counts, particularly in Germany and the U.S., suggests a focus on the quality and impact on research outputs. The dynamics represent a diverse global landscape in which both established research hubs and emerging contributors are influential, suggesting opportunities for collaboration that can further enhance the development and application of prescriptive analytics across various sectors and improve decision-making processes.

The analysis of the most influential institutions in the field of Prescriptive Analytics in (Table 6), as indicated by Total Publications (TP) and Total Citations (TC) from both Scopus and Web of Science (WoS), underscores the substantial contributions of numerous world-renowned universities and research organizations.

Table 6. Most influential institutions

Scopus					WoS				
Institution	TP	TC	% of 201	Country	Affiliations	TP	TC	% of 999	Country
Massachusetts Institute of Technology	4	241	1.99%	United States	Pennsylvania Commonwealth System of Higher Education Pcshe	28	909	2.80%	Finland
Université McGill	3	26	1.49%	Canada	Harvard University	26	362	2.60%	China
SRM Institute of Science and Technology	3	8	1.49%	India	University of California System	22	699	2.20%	Canada
University of Washington	3	35	1.49%	United States	Carnegie Mellon University	18	483	1.80%	United Kingdom
National University of Singapore	3	101	1.49%	Singapore	Hong Kong Polytechnic University	18	80	1.80%	United Kingdom
Institute of Automation Chinese Academy of Sciences	3	66	1.49%	China	Harvard University Medical Affiliates	17	176	1.70%	United Kingdom
Chinese Academy of Sciences	3	66	1.49%	China	Massachusetts Institute of Technology Mit	16	619	1.60%	Sount Africa
Amity University	3	2	1.49%	India	National Institutes of Health Nih Usa	14	750	1.40%	United Kingdom
Rutgers University-Newark	2	518	1.00%	United States	Pennsylvania State University	14	634	1.40%	United States
University of Pennsylvania	2	11	1.00%	United States	State University System of Florida	14	162	1.40%	United States
The City University of New York	2	13	1.00%	United States	University System of Ohio	14	166	1.40%	United States
Università degli Studi di Messina	2	29	1.00%	Italy	United States Department of the Interior	13	287	1.30%	New Zealand
Montclair State University	2	245	1.00%	United States	United States Geological Survey	13	287	1.30%	Canada
Università degli Studi di Messina, Facoltà di Medicina e Chirurgia	2	29	1.00%	Italy	University of Pittsburgh	13	266	1.30%	Russian
Aston University	2	11	1.00%	United Kingdom	University of Queensland	13	553	1.30%	New Zealand
University of Maryland, College Park	2	338	1.00%	United States	University of Texas System	13	467	1.30%	United States
Indiana University Bloomington	2	149	1.00%	United States	Commonwealth Scientific Industrial Research Organisation Csiro	12	497	1.20%	United States
İstanbul Teknik Üniversitesi	2	11	1.00%	Turkey	Indiana University System	12	336	1.20%	United Kingdom
Aalborg University	2	49	1.00%	Denmark	University System of Georgia	12	607	1.20%	Russian
University College London	2	73	1.00%	United Kingdom	University System of Maryland	12	190	1.20%	Russian

Notes: TP=total number of publications; NCP=number of cited publications; TC=total citations; C/P=average citations per publication; C/CP=average citations per cited publication; h=h-index; and g=g-index.

The Massachusetts Institute of Technology (MIT) is the leading institution in Scopus, with four publications and 241 citations, which is indicative of its exceptional research and innovative analytical methodologies. The Université McGill and SRM Institute of Science and Technology both make significant contributions, with three publications each. Relevant activities in this discipline were also demonstrated by the University of Washington and the National University of Singapore.

Table 7. Most Influential Publications (Scopus)

Scopus					
No.	**Authors**	**Title**	**Year**	**Cites**	**Cites per Year**
1	G. Gigerenzer, W. Gaissmaier	Heuristic decision making	2011	2445	174.64
2	L. Ma, B. Sun	Machine learning and AI in marketing – Connecting computing power to human insights	2020	322	64.4
3	D. Appelbaum, A. Kogan, M. Vasarhelyi, Z. Yan	Impact of business analytics and enterprise systems on managerial accounting	2017	286	35.75
4	D. Appelbaum, A. Kogan, M.A. Vasarhelyi	Big data and analytics in the modern audit engagement: Research needs	2017	232	29
5	K.P. Sycara	Persuasive argumentation in negotiation	1990	174	4.97
6	D. Pessach, G. Singer, D. Avrahami, H. Chalutz Ben-Gal, E. Shmueli, I. Ben-Gal	Employees recruitment: A prescriptive analytics approach via machine learning and mathematical programming	2020	147	29.4
7	F. Ansari, R. Glawar, T. Nemeth	PriMa: a prescriptive maintenance model for cyber-physical production systems	2019	141	23.5
8	B.C. Wheeler, J.S. Valacich	Facilitation, GSS, and Training as Sources of Process Restrictiveness and Guidance for Structured Group Decision Making: An Empirical Assessment	1996	140	4.83
9	Carl Hewitt	OFFICES ARE OPEN SYSTEMS.	1986	128	3.28
10	M.T. Lash, K. Zhao	Early Predictions of Movie Success: The Who, What, and When of Profitability	2016	120	13.33
11	V. Bader, S. Kaiser	Algorithmic decision-making? The user interface and its role for human involvement in decisions supported by artificial intelligence	2019	101	16.83
12	K.-K. Phoon	The story of statistics in geotechnical engineering	2020	98	19.6
13	Z. Sedighi Maman, Y.-J. Chen, A. Baghdadi, S. Lombardo, L.A. Cavuoto, F.M. Megahed	A data analytic framework for physical fatigue management using wearable sensors	2020	81	16.2
14	W.R. Mendes, F.M.U. Araújo, R. Dutta, D.M. Heeren	Fuzzy control system for variable rate irrigation using remote sensing	2019	74	12.33
15	M. Lombardi, M. Milano, A. Bartolini	Empirical decision model learning	2017	73	9.13
16	T. Pape	Prioritising data items for business analytics: Framework and application to human resources	2016	72	8
17	A.W. Labib, G.B. Williams, R.O. Connor	An intelligent maintenance model (System): An application of the analytic hierarchy process and a fuzzy logic rule-based controller	1998	72	2.67
18	A.K. Noor	Potential of cognitive computing and cognitive systems	2015	68	6.8
19	D. Dellermann, N. Lipusch, P. Ebel, J.M. Leimeister	Design principles for a hybrid intelligence decision support system for business model validation	2019	66	11
20	E.D.R.S. Gonzalez, J. Sarkis, D. Huisingh, L.H. Huatuco, N. Maculan, J.R. Montoya-Torres, C.M.V.B. De Almeida	Making real progress toward more sustainable societies using decision support models and tools: Introduction to the special volume	2015	63	6.3

Notes: TP=total number of publications; NCP=number of cited publications; TC=total citations; C/P=average citations per publication; C/CP=average citations per cited publication; h=h-index; and g=g-index.

The Pennsylvania Commonwealth System of Higher Education stands out in the WoS sector, with 28 publications and 909 citations, suggesting a robust output in prescriptive analytics research. Other notable contributors include Harvard University and Carnegie Mellon University, which underscore the strong presence of North American institutions in the research area. Harvard University Medical Affiliates and the University of California System, both of which exhibit substantial affiliations and impactful research output, further echo this trend. Global analytics research is also being increasingly influenced by Chinese institutions,

Table 8. Most Influential Publications (WoS)

WoS					
No.	**Authors**	**Title**	**Year**	**Cites**	**Cites per Year**
1	Wang. Y, Chen. QX, Hong. T, Kang. CQ	Review of Smart Meter Data Analytics: Applications, Methodologies, and Challenges	2019	706	100.86
2	Han. PKJ, Klein. WMP, Arora. NK	Varieties of Uncertainty in Health Care: A Conceptual Taxonomy	2011	551	36.73
3	DYER. JS, FISHBURN. PC, STEUER. RE, WALLENIUS. J, ZIONTS. S	MULTIPLE CRITERIA DECISION-MAKING, MULTIATTRIBUTE UTILITY-THEORY - THE NEXT 10 YEARS	1992	370	10.88
4	Boudreau. JW, Ramstad, PM	Talentship, talent segmentation, and sustainability: A new HR decision science paradigm for a new strategy definition	2005	324	15.43
5	Bertsimas. D, Kallus. N	From Predictive to Prescriptive Analytics	2020	265	44.17
6	Game. ET, Kareiva. P and Possingham. HP	Six Common Mistakes in Conservation Priority Setting	2013	260	20
7	Andrienko. G, Andrienko. N, Jankowski. P, Keim. D, Kraak. MJ, Maceachren. A, Wrobel. S	Geovisual analytics for spatial decision support: Setting the research agenda	2007	235	12.37
8	Sengupta. S, Basak. S, Saikia. P, Paul. S, Tsalavoutis. V, Atiah. F, Ravi. V, Peters. A	A review of deep learning with special emphasis on architectures, applications and recent trends	2020	225	37.5
9	Marcot, BG and Penman, TD	Advances in Bayesian network modelling: Integration of modelling technologies	2019	215	30.71
10	Lepenioti. K, Bousdekis. A, Apostolou. D, Mentzas. G	Prescriptive analytics: Literature review and research challenges	2020	214	35.67
11	ROY. B	DECISION SCIENCE OR DECISION-AID SCIENCE	1993	198	6
12	Haddud. A, DeSouza. A, Khare. A, Lee. H	Examining potential benefits and challenges associated with the Internet of Things integration in supply chains	2017	197	21.89
13	Tang. M and Liao. HC	From conventional group decision making to large-scale group decision making: What are the challenges and how to meet them in big data era? A state-of-the-art survey	2021	195	39
14	Davenport. TH	Analytics 3.0	2013	194	14.92
15	Appelbaum. D, Kogan. A, Vasarhelyi. M, Yan. ZK	Impact of business analytics and enterprise systems on managerial accounting	2017	191	21.22
16	Xu. XH, Du. ZJ, Chen. XH, Cai. CG	Confidence consensus-based model for large-scale group decision making: A novel approach to managing non-cooperative behaviors	2019	165	23.57
17	Sheng. J, Amankwah-Amoah. J, Khan. Z, Wang. XJ	COVID-19 Pandemic in the New Era of Big Data Analytics: Methodological Innovations and Future Research Directions	2021	151	25.17
18	Sony. M, Antony. J and Douglas. JA	Essential ingredients for the implementation of Quality 4.0 A narrative review of literature and future directions for research	2020	145	24.17
19	Nelson. JA	ARE WOMEN REALLY MORE RISK-AVERSE THAN MEN? A RE-ANALYSIS OF THE LITERATURE USING EXPANDED METHODS	2015	144	13.09
20	Hochman. Z, Van Rees. H, Carberry. PS, Hunt. JR, McCown. RL, Gartmann. A, Holzworth. D, Van Rees. S, Dalgliesh. NP, Long. W, Peake. AS, Poulton. PL, McClelland. T	Re-inventing model-based decision support with Australian dryland farmers. 4. Yield Prophet® helps farmers monitor and manage crops in a variable climate	2009	140	8.24

Notes: TP=total number of publications; NCP=number of cited publications; TC=total citations; C/P=average citations per publication; C/CP=average citations per cited publication; h=h-index; and g=g-index.

particularly the Institute of Automation at the Chinese Academy of Sciences and Chinese Academy of Sciences. In this discipline, the interdisciplinary and collaborative nature of research is emphasized by the diversity of institutions that contribute to prescriptive analytics, which spans countries such as Canada, the United States, China, India, and the United Kingdom. The varying citation counts also suggest that certain institutions not only produce numerous publications, but also contribute significantly to high-impact research that shapes the future of prescriptive analytics. This demonstrates the field's dynamic evolution and the importance of these institutions in advancing knowledge and methodologies across diverse sectors.

4.5. Most Influential Publication

The analysis of the most influential publications in the field of Prescriptive Analytics, as reported in Scopus, reveals a diverse set of contributions that emphasize both foundational and emergent research themes within the discipline. G. Gigerenzer and W. Gaissmaier's seminal work on "Heuristic decision making," published in 2011, is at the top of the list. This work received an impressive 2,445 citations and an average of 174.64 citations per year, underscoring the importance of heuristic approaches in decision-making processes.

Ma and Sun are closely following, as their 2020 paper has garnered significant traction, accruing 322 citations and demonstrating the growing importance of analytics in comprehending consumer behavior. This study connects machine learning and AI to marketing insights. Appelbaum and collaborators are other notable contributors. Their research on the impact of business analytics on managerial accounting and audit engagements has had a significant impact, with citation counts of 286 and 232, respectively. The enduring influence of foundational research in negotiation and open systems is illustrated by the presence of researchers such as Sycara and Hewitt, whose earlier publications remain pertinent.

Furthermore, contemporary themes have been introduced in papers such as Pessach et al.'s prescriptive approach to employee recruitment using machine learning, which illustrates the integration of advanced analytics into HR practices. The interdisciplinary character of prescriptive analytics is reflected in the extensive range of topics addressed by authors, such as Ansari, Lash, and Bader. These authors addressed a variety of sectors, including algorithmic decision-making interfaces in AI and maintenance models in cyber-physical systems. This diversity demonstrates the extent to which prescriptive analytics influences a diverse array of disciplines, indicating its increasing significance in the development of data-driven methodologies that improve decision-making processes in both traditional and emerging domains. (Table 7), and **8** summarizes the most influential publications based on the analysis.

The significant contributions from various researchers are highlighted in (Table 8)**.** The analysis of the most influential publications in the field of Prescriptive Analytics, as documented in Web of Science (WoS). This reflects the diversity and impacts of their work. Wang et al.'s 2019 review on smart meter data analytics, which has garnered an astounding 706 citations, is at the top of the list. This review, which has an average of 100.86 citations per year, underscores its relevance in the intersection of technology and energy management. This is followed by Han et al., who published a conceptual taxonomy of uncertainty in healthcare that has garnered 551 citations since its publication in 2011. This underscores the significance of comprehending variability in healthcare decision making. Dyer et al. 's(1992) foundational paper on multiple criteria decision-making, which has amassed 370 citations, continues to be influential, illustrating the enduring influence of foundational research in analytics. Boudreau and Ramstad's (2005) work on HR decision science is also noteworthy, as it demonstrates the implementation of analytics in talent management with 324 citations.

The transition from predictive to prescriptive analytics is the subject of recent contributions by Bertsimas and Kallus (265 citations), while Lepenioti et al. (214 citations) addressed the literature gaps in prescriptive analytics. These contributions reflect current research challenges. Davenport, who has 194 citations for his insights into the evolution of analytics, and Sheng et al., who emphasize the impact of COVID-19 on big data analytics (151 citations), is another noteworthy author who suggests that prescriptive analytics are becoming more relevant in modern contexts. This collection of influential studies illustrates the expanding nature and increasing significance of prescriptive analytics in a variety of domains, including healthcare, environmental management, and organizational decision-making, through a combination of theoretical frameworks and practical applications. The authors' contributions to the advancement of knowledge in prescriptive analytics are not the only thing that the overall citation counts reflect; they also indicate the growing recognition and application of analytics as a critical instrument for informed decision making in complex environments.

5. Result and Discussion

The Results and Discussion section provides a thorough analysis of the research landscape using several network visualizations. The network visualization map of the authors' keywords (5.1) highlights the prominent themes and evolving topics within the field. This illustrates how various keywords are interconnected, and identifies emerging areas of interest. Similarly, the network visualization of citations by country (5.2) reveals the geographical distribution of influential research, emphasizing the leading nations contributing to prescriptive analytics and potential collaborative clusters. The visualization of author coupling (5.3) sheds light on collaborative networks, indicating the key researchers and institutions that drive the discourse. Finally, the discussion on future trends (5.4) offers insights into anticipated directions for prescriptive analytics, suggesting growth areas, such as advanced machine learning integrations, real-time decision-making, and cross-disciplinary applications. Together, these visualizations and analyses provide a nuanced understanding of the current research dynamics and forecast future developments in prescriptive analytics.

5.1. Network Visualisation Map of the Authors Keyword

In this section, we visualize the bibliographic connection cluster between the top authors in the research field and the field of study that the authors are involved in. The literature analysis was simulated using the VOS viewer platform [65][66]. This is a tool capable of visualizing a network of publications, authors, institutions, subject areas, and countries. Bibliographic coupling is used to describe the frequency with which two entities (e.g., writers or countries) reference the same entity [67]. This delineates the disciplinary connections between nodes [68]. (Figures 6) and (Figure 7) illustrate the bibliometric clusters in accordance with Scopus and WoS. The diagrams contain nodes (represented as authors) and connections between nodes. The breadth of these connections represents the overlap between the common references in the papers indexed by the respective repository. Nodes are distinguished by their color in the Network Visualization (NW) modes [25].

The author keyword network visualization map shows prescriptive analytics research key terms with a minimum occurrence threshold of 812 instances over 21 items and five clusters for Scopus, and a minimum occurrence threshold of 158 instances over 26 items and six clusters. (Figure 6) shows how these terms are related, exposing the field's main themes and focal points and stressing the role of AI and data analytics in determining research trajectories. The network visualization map shows the interconnectedness of prescriptive analytics research topics.

The graphic prominently features "Artificial Intelligence," indicating its centrality in prescriptive analytics. Keyword clustering shows a rich tapestry of related concepts, and how field elements interact and overlap. The terms "Prescriptive Analytics" and "Business Intelligence" cluster around "Artificial Intelligence," indicating their close association. This picture shows how AI improves prescriptive analytics and enables more advanced decision-making frameworks. The clusters "Data Analytics," "Predictive Analytics," and "Analytics" highlight the breadth of analytics. These terms show how predictive and prescriptive models increasingly use massive datasets, making data-driven insights crucial for informed decision making. Prescriptive analytics is used in current industrial settings and affects organizational strategy, as demonstrated by Decision Making and "Decision Making" and "Industry 4.0". This image shows how these terms relate to and emphasize the multidimensionality of prescriptive analytics research. This interconnection means that advances in one sector, such as artificial intelligence, can cascade into others and improve decision making across domains. The network visualization map helps explain prescriptive analytics research ideas and collaborations.

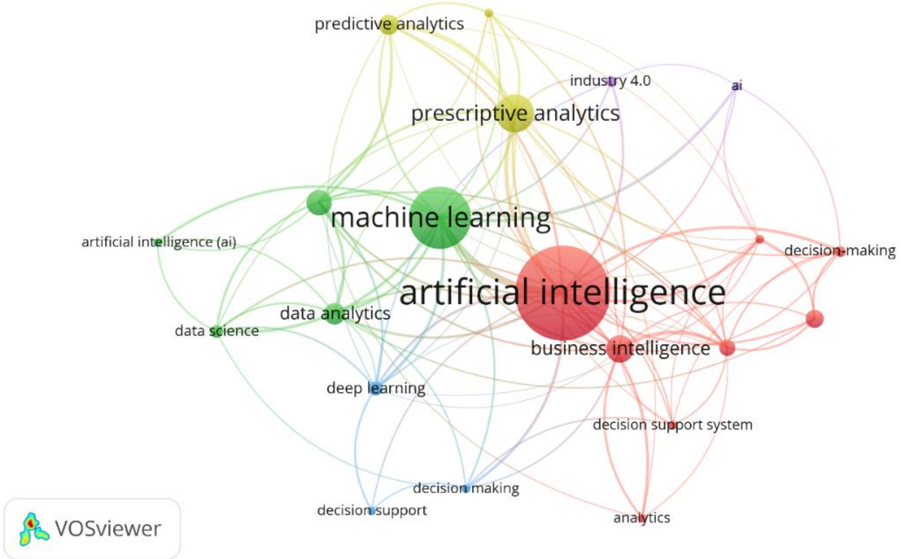

Figure 6. Network visualization map of the author keywords (Minimum number of occurrences of keyword = 812, items = 21, cluster = 5) (Scopus).

Keyword summary on Artificial Intelligence frequently existed in Prescriptive Analytics publications. The use of statistical models, data mining and machine learning, and artificial intelligence has existed for decades, and recently, more advanced and sophisticated information technologies and tools have been available to support decision-making in an integrated fashion [9]. Based on the study on "AI implementation in big data: Shaping data analysis for business decisions" states that Diagnostic analysis demands proper attention for gaining an understanding of the situation in depth therefore artificial intelligence promotes diagnostic skills [3]. Studies have shown that when modeling is executed correctly, precise predictive models can evolve and enhance over time, and the resultant artificial intelligence may have the capacity to quantify and optimize therapeutic effects and adherence [39]. Another study utilized artificial intelligence (AI) within a data-driven energy digital twin framework to enhance energy infrastructure including machine learning (ML), expert systems, and autonomous automation, into supply chain components, including demand forecasting, inventory management, process optimization, and supplier selection [6]. Prescriptive Analytics typically leverages the Artificial Intelligence in various situations. AI is also utilized to simulate different scenarios and their potential outcomes, enabling organizations to assess the impacts of various decisions prior to implementation. From a prescriptive analytics perspective

It was a component of the artificial intelligence process from the perspective of machine learning; however, it is frequently referenced in publications, which has made it a popular keyword among the enumerated keywords. Studies have used machine learning techniques to improve various ATM tasks. It categorizes ML applications into four primary areas: prediction, which involves forecasting future behaviors of aircraft and traffic; optimisation/automation, which

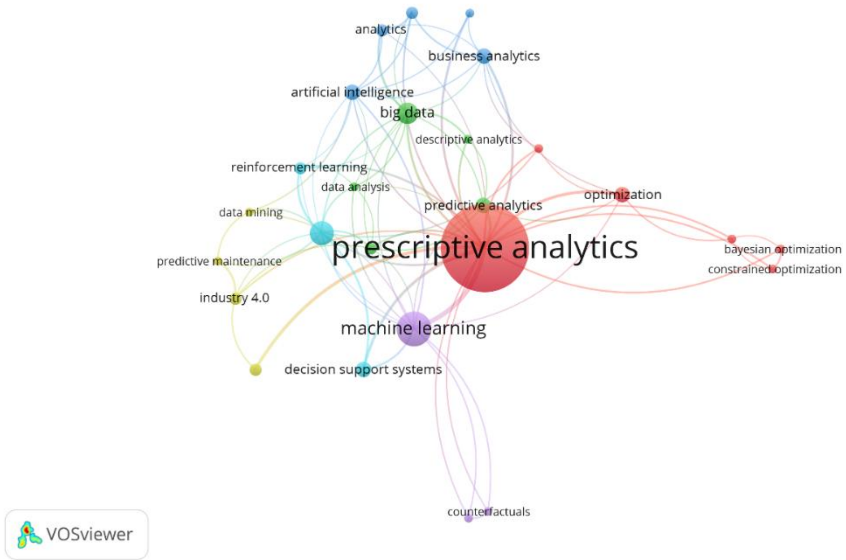

Figure 7. Network visualization map of the author keywords (Minimum number of occurrences of keyword = 158, items = 26, cluster = 6) (WoS).

management [1]. It employs machine learning (ML) to predict maintenance needs, enabling data analysis to anticipate failures and optimize operations. Large-scale language models (LLMs) facilitate decision-making by producing relevant content regarding energy systems [69].

LLMs are combined with knowledge graphs (KGs) in the retrieval-augmented generation (RAG) method to enhance the context and accuracy of responses, whereas conversational virtual assistants simplify user interactions [1]. There was also a study on the systematic literature review "Artificial Intelligence and Prescriptive Analytics for Supply Chain Resilience, " which examines the transformative impact of artificial intelligence (AI) on supply chain resilience. It emphasizes the integration of a variety of AI functions, enhances traffic flow and conflict resolution; analysis, aimed at understanding and interpreting traffic patterns and the actions of air traffic controllers; and Modelling/Simulation, where realistic models of air traffic scenarios are created [45]. This review highlights the increasing interest in ML techniques, including neural networks and reinforcement learning, and underscores the necessity for additional research on XAI to ensure that these ML applications in ATM are transparent and user-friendly, ultimately contributing to enhanced safety and efficiency in air traffic operations [45][70]. was also used for machine learning in Learning Analytics (LA) to predict at-risk children and improve educational outcomes, according to the journal.

This underlines the need for predictive and prescriptive analytics to provide model interpretability and transparency [14]. The proposed methodology uses cutting-edge technologies such as eXplainable AI (XAI) and massive language models such as ChatGPT to transform complex data analysis into practical evidence-based feedback for at-risk learners [14]. Using a large dataset of 7,000 students, this study emphasizes the need for models that categorize students by risk and explain their academic performance. This dual approach builds stakeholder confidence and enables rapid and effective interventions to improve student retention and completion. A biopharmaceutical sector prescriptive maintenance (PsM) study integrated machine learning (ML) and deep learning (DL), demonstrating its importance in sector 4.0. Predictive maintenance (PdM) is common, but an AI-powered PsM can boost efficiency by delivering actionable insights to reduce downtime and boost productivity.

A literature study showed that convolutional and recurrent neural networks are increasingly used to anticipate equipment breakdowns. However, the biopharmaceutical PsM implementation gap highlights the need for more ML tool investments to improve data integration and decision-making [15]. Prescriptive Analytics is part of the most popular author keywords, and since the search keyword is prescriptive analytics, it is reasonable to be part of the most influential searched authors keyword. Business analytics and industry 4.0 is also part of the most popular keyword search authors. An overview of business analytics studies related to prescriptive analytics, a research study examined 43 studies from 2006 to 2022 to evaluate the trends and autonomy levels of Adaptive Business Intelligence (ABI) systems in healthcare [16]. This emphasizes the role of ABI in the transformation of healthcare data into actionable insights, with predictive analytics being the predominant method in 88.4% of the studies and prescriptive analytics at 11.6%. The majority of ABI systems are classified as having low-to-moderate autonomy, particularly at levels 4 and 5. This classification is based on Sheridan's classification.

This study underscores the necessity of enhancing the incorporation of ABI into clinical workflows and encourages additional research into the ethical implications and implementation of ABI in healthcare [16]. This was a business analytics study that examined the evolution of Business Process Management (BPM) toward "(AI-)augmented process execution," which automates and improves business processes using process mining and AI. BPM is used to make inefficient decisions owing to manual data analysis, but data-driven solutions now allow proactive business process monitoring and optimization [11]. Descriptive Process Analytics, Predictive Process Analytics, Prescriptive Process Optimization, and Augmented Process Execution form a pyramid of capabilities that aims to autonomously manage processes with less human oversight [11]. Hyperautomation can alter commercial operations; however, system composability and effectiveness are issues. Research has also shown that digital transformation and AI increase consumer engagement, operational efficiency, and data-driven decision-making in business analytics [47]. AI technologies, especially predictive analytics and machine learning, enable businesses to use large datasets for actionable insights, process improvements, and tailored consumer experiences. AI is expected to boost global GDP and productivity across sectors [71]. To balance innovation and fundamental rights, the authors stress the need for a strong legislative framework to ensure ethical AI use and compliance with data protection [47]. The industry 4.0 transforms manufacturing by merging IoT, big data, and digital simulation to create smart, data-driven environments. This evolution uses resilient factories and data analytics for predictive and prescriptive insights to improve real-time decision making and operational efficiency [22]. Moving from descriptive analytics to predictive and prescriptive approaches helps firms foresee hazards, optimize processes, and apply dynamic control mechanisms.

The framework emphasizes simulation models and decision support tools for shop floor management, improving performance and adaptability in current production contexts [22]. A publication discussed Prescriptive Analytics Systems (PAS) in Industry 4.0, which combines cutting-edge technologies including IoT, AI, and big data analytics [17]. These advances enable companies to build intelligent networked manufacturing environments that optimize operations. The PAS uses these technologies to improve resource allocation, process efficiency, and operational efficiency across sectors. The research emphasizes the importance of data-driven decision-making in manufacturing, where PAS optimizes maintenance and production scheduling and supports innovation and competitiveness in a complex business environment [17]. Cyber-Physical Production Systems (CPPS) use cutting-edge sensing, computational technologies, and data analytics to improve production efficiency and decision making, marking a major shift in manufacturing in Industry 4.0 [33]. This new paradigm shifts from conventional maintenance to predictive and prescriptive maintenance, which uses real-time data analyses to detect breakdowns and optimize procedures. Knowledge-based maintenance (KBM) models, such as the PriMa framework, help organizations improve maintenance procedures, reduce downtime, and strengthen system resilience by collecting and analyzing varied data sources [33]. Industry 4.0 aims to create smart factories with improved responsiveness, operational efficiency, and continuous improvement through a data-driven culture that integrates maintenance with production planning and control systems.

5.2. Network Visualization of Citation by Countries

(Figure 8) depicts a network visualization map that highlights citations by country, emphasizing the relationships and interactions between various national contributions to the field of prescriptive analytics research. The map indicates that the minimum requirement for the number of documents authored by a researcher was five, whereas the minimum citation threshold per author was set at one. In this visualization, the United States is prominently positioned as a central locus, signifying its preeminent role in the generation and dissemination of research within the discipline. India has emerged as a notable contributor, demonstrating its growing influence in prescriptive analytics. The relationships among countries, including the United Kingdom, underscore collaborative research initiatives, emphasizing the global character of the discipline and the interdependence of research communities across various nations [72]. This map effectively highlights the collaborative and competitive dynamics inherent in prescriptive analytics and illustrates the contributions of various countries to the ongoing development of this field.

The network visualization map of citation relationships by country for Scopus is detailed in the (Figure 8), which reflects the academic influence of various nations based on their research outputs. The intensity of citations within the network is indicated by the total link strength, citations received, number of documents published, and country of each entry. The United States is a dominant player, as evidenced by the considerable total link strength of 1,754 and the publication of 69 documents, which have accumulated 2,200 citations. This implies not only a substantial amount of research, but also substantial recognition within the global academic community.

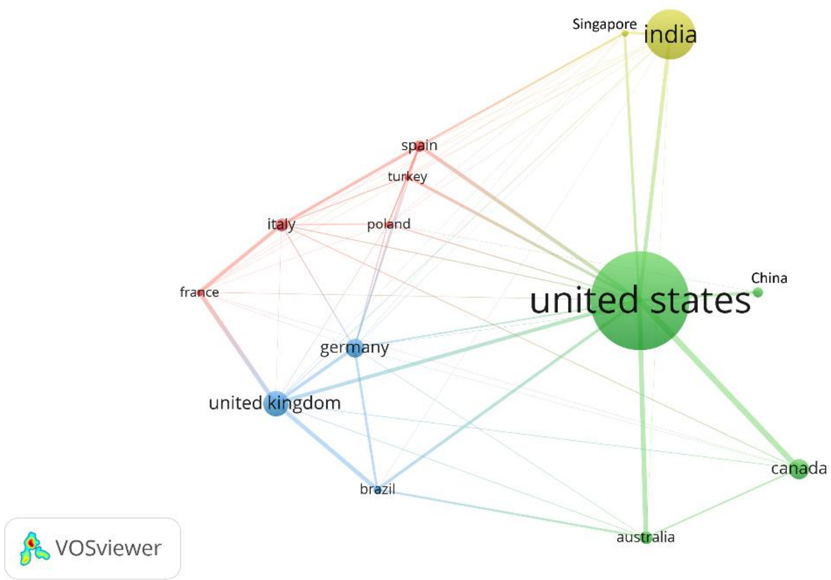

Figure 8. Network visualization map of the citation by countries coupling
Note: Minimum number of documents of an author = 5; Minimum number of citations of an author = 1. (Minimum number of occurrences of country = 56, items = 14, cluster = 4).

Germany is closely followed by 13 documents that have amassed an impressive 2,686 citations and link strength of 297, underscoring its significant role in research. This influence is particularly evident in disciplines likely to be associated with advanced technologies or influential studies.

Australia, with 9 documents and 242 citations, as well as a link strength of 395, is a significant contributor, demonstrating the active exchange of scholastic works. Canada and the United Kingdom are examples of countries that have made significant academic contributions. Canada has produced 14 documents, resulting in 291 citations (494 link strength). The United Kingdom, on the other hand, has 18 documents, which have a notable citation count of 323 and an impressive link strength of 810. These findings suggest that the research community engaged in substantial collaborative efforts. Conversely, countries such as India and Turkey exhibit lower total citations of 122 and 15, respectively, but they make substantial contributions to the academic landscape, indicating the emergence of new perspectives in a variety of disciplines. Interestingly, the global dissemination of research is further exemplified by countries, such as Brazil and Singapore. Brazil has 217 citations from six documents and a link strength of 475, whereas Singapore's five documents refer to 141 citations, indicating its specialized but impactful contributions. The citation landscapes of other nations in the figure, including China, France, Italy, Poland, and Turkey, are diverse and may indicate their developmental stages in academia or specific research interests. In general, the data demonstrate the intricate interplay of scholarly output across countries, emphasizing the citation dynamics and collaboration that enrich global academic discourse. It also illustrates how varying research focuses can affect citation impact and total link strength within the international scholarly network.

Based on (Figure 9), the network visualization map of citations by country for documents indexed in the WoS illustrates the academic contributions and impact of various nations in the field of scholarly publishing. Australia was a notable contributor, with five documents and 41 citations, indicating substantial engagement and a total link strength of 241. This suggests an active collaboration within an academic network. Austria, despite possessing only three documents, achieved a total link strength of 275, indicating strong integration into the scholastic discourse, as evidenced by its impressive 85 citations. Germany is distinguished by its substantial volume of documents, which totals 12 and 144 citations, respectively, and a robust total link strength of 672. This reflects its status as a research center. Greece and India exhibited distinct profiles. Greece has published six documents, resulting in 269 citations (with a total link strength of 307).

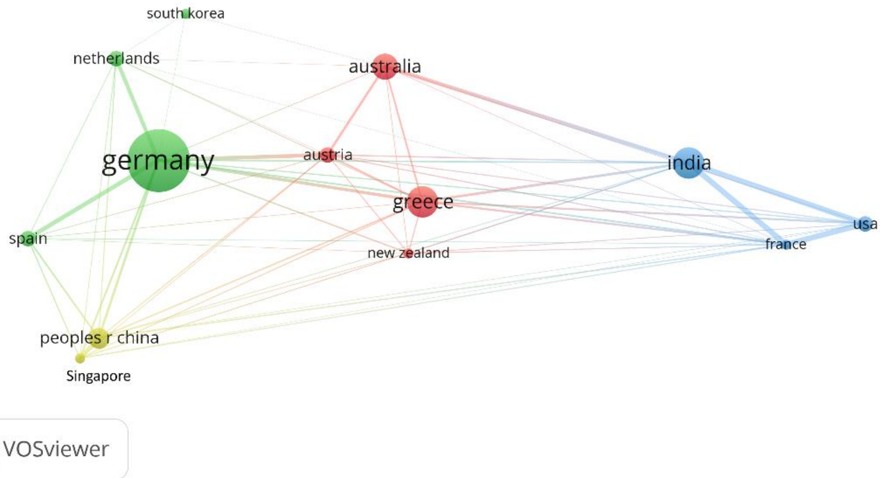

Figure 9. Network visualization map of the citation by countries
Note: Minimum number of documents of an author = 2; Minimum number of citations of an author = 1 (Minimum number of occurrences of country = 28, items = 13, cluster = 6).

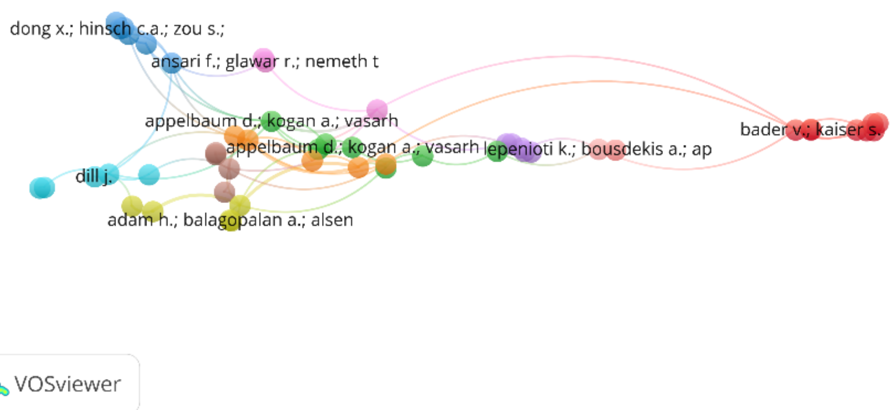

Figure 10. Network visualization map of the author coupling (min document 1, min citation 1) (items= 51, cluster = 10). (Scopus).

India, on the other hand, has 25 citations despite having the same number of documents, but it has a remarkable total link strength of 809. This suggests that India has a highly impactful network of collaborations, which enhances its academic visibility. The

Netherlands, New Zealand, and Singapore exhibit a spectrum of participation, with total link strengths of 163, 68, and 213, respectively, underscoring their varying degrees of influence on the global research community. In contrast, the USA and South Korea demonstrated intriguing patterns. The USA has 22 citations with a significant total link strength of 623, despite having only three documents, whereas South Korea's minimal contributions yield a total link strength of only 3. This suggests that the influence of citation dynamics is distinct from that of the document volume. In general, these data capture the complex landscape of international academic contributions, demonstrating how interconnectedness and collaboration influence the scholastic communication framework among nations.

5.3. Network Visualisation of the Author Coupling

drives the development of predictive analytics tools. In conclusion, this map sheds light on the patterns of co-authorship among countries, drawing attention to the collaborative dynamics vital for encouraging innovation in this emerging field. The network visualization map of author coupling is shown in the (Figure 10), which depicts the Scopus interconnections among various authors based on their collaborative publications. The group comprising Appelbaum, Kogan, and Vasarhelyi was one of the most notable entries. They amassed a remarkable citation tally of 232 and a total link strength of 11, which suggests their strong influence and collaborative synergy in the academic community. However, the authors Lepenoti, Bousdekis, Apostolou, and Mentzas exhibit a relatively moderate level of interconnectedness, with a total link strength of 5 and 10 citations. Similarly, Ansari, Glawar, and Nemeth are distinguished by their 141

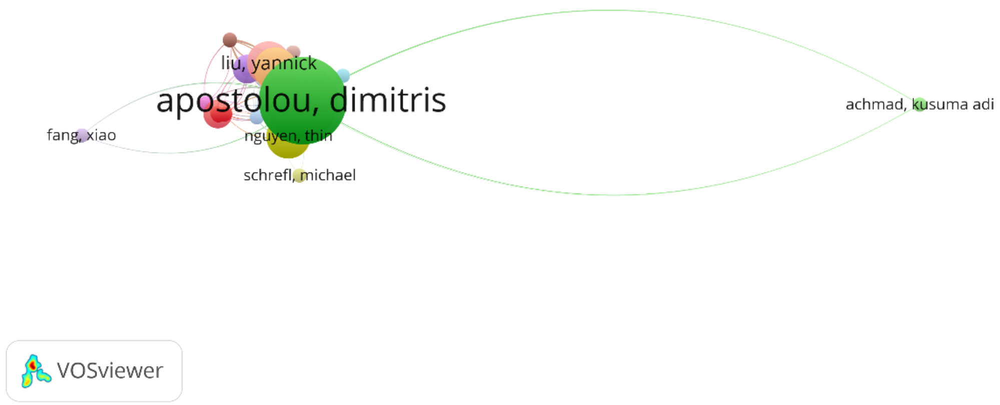

Figure 11. Network visualization map of the author coupling (min document 1, min citation 1) (items= 96, cluster = 18). (WoS).

An analysis of co-authorship by nation using the full counting approach is shown in (Figure 10), which is a network visualization map. A prominent node in this picture represents the United States, indicating its heavy involvement in prescriptive analytic-related joint research projects. The study included nations with three papers and five or more citations, for a total of forty-three items divided into 10 groups. Knowledge development in the field of prescriptive analytics is global, and this compilation highlights the interconnectedness of many nations through joint research. The bare minimum of the country documents available in VOSviewer is zero. The participation of the network in many nations highlights the value of international cooperation in advancing research. The visualization shows how research collaborations cross borders, allowing for a rich flow of information that

citations; however, their link strength of 3 implies a lower level of collaborative engagement. Adam, Balagopalan, Alsentzer, Christia, and Ghassemi exhibited modest contributions in their entry, with 28 citations but a link strength of only one, suggesting a more isolated presence within the network. Bader and Kaiser obtained 101 citations, while Dong, Hinsch, Zou, and Fu obtained a citation count of 21. These figures are consistent with a total link strength of one, indicating that they play significant yet solitary roles in their respective fields. Finally, Dill is the least collaborative, with only four citations and a link strength of one, indicating a lack of cooperation. In general, these data offer a comprehensive understanding of the diverse degrees of academic influence and collaborative interaction among authors.

(Figure 11) shows a network visualization map of author coupling for WoS documents, which illuminates the interrelationships among authors by examining their published documents and the citations they have received. Dimitris Apostolou is a prominent figure in this network, with a maximum document count of six and an impressive number of 269 citations. This translates to a substantial total link strength of 2,501, suggesting strong connections and considerable influence within the academic community. In contrast, Kusuma Adi Achmad and Thin Nguyen contributed only one document with limited citation counts of 3. However, they possess varying total link strengths. Nguyen achieved a total link strength of 561, demonstrating a distinctive impact despite the limited number of published studies. Similarly, Fang Xiao published a single document, but he has amassed 15 citations and a total link strength of 270, which is indicative of his influence within the research landscape in relation to his output. The diverse scholarly contributions in this figure are also underscored by Liu Yannick, who has 23 citations and two documents, as evidenced by his link strength of 480. Collectively, these data emphasize the varied levels of scholarly impact and collaboration among authors, as evidenced by their total link strengths and citation counts. It also demonstrates how certain researchers accomplish substantial recognition, with fewer publications, through influential work.

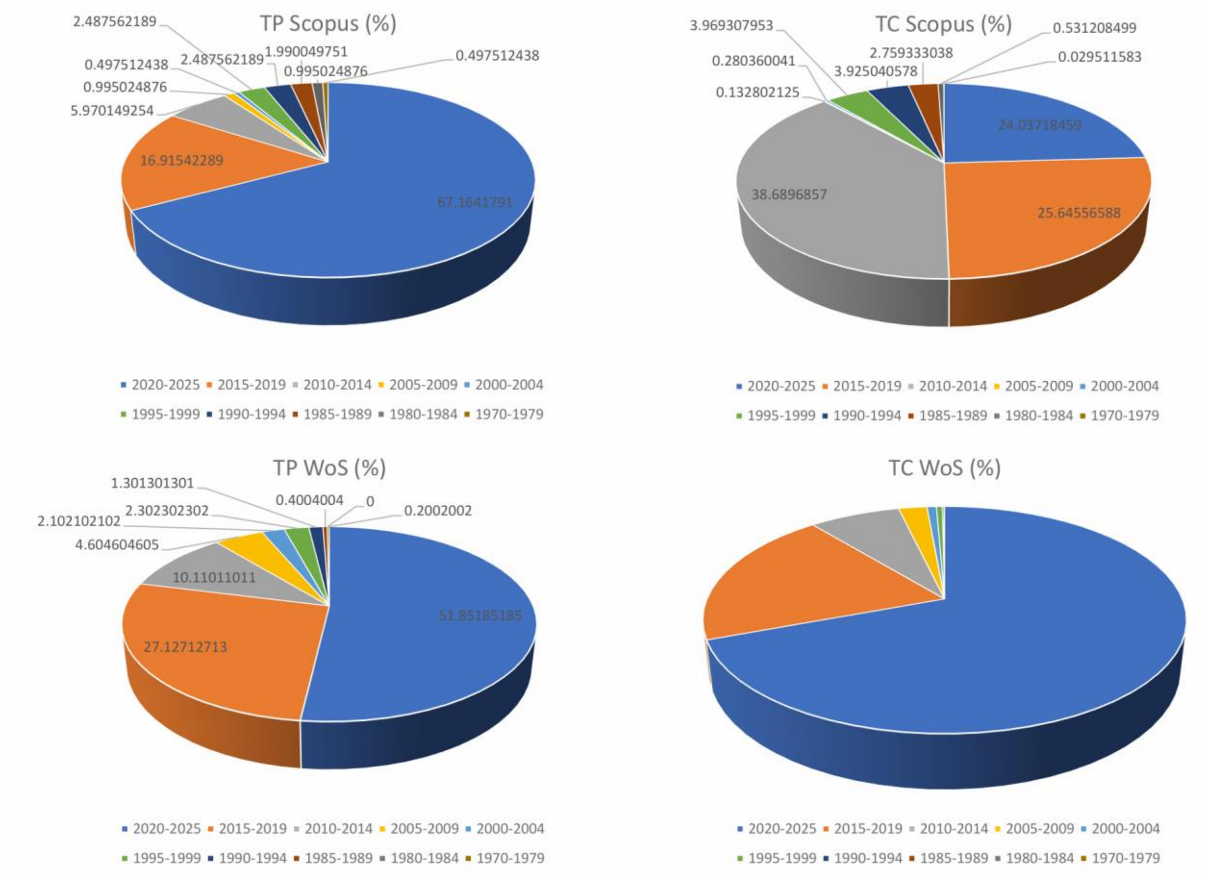

Figure 12. Prescriptive Analytics Publication Trends.

5.4. Future Trends of Prescriptive Analytics

The integration of AI and machine learning is expected to significantly advance the field of prescriptive analytics, enabling the analysis of large datasets and generation of more precise recommendations [73]. The development of advanced algorithms will enhance the precision and efficacy of prescriptive models, whereas real-time analytics will enable businesses to make instantaneous decisions based on the most recent information [74]. In addition, the automation of data analysis will optimize the processes and mitigate human error. Ultimately, prescriptive analytics will be positioned as a critical component in strategic decision-making across industries, fostering innovation and efficiency, as ethical considerations regarding transparency and fairness become more significant as AI's role of AI in prescriptive analytics expands [75]. (Figure 12) provides a valuable perspective on the changing academic publishing landscape, as measured by Total Publications (TP) and Total Citations (TC) in Scopus and Web of Science (WoS) from 1970 to 2025. Notably, the most recent period, which spans from 2020 to 2025, represents the zenith in activity. Scopus has documented 135 publications and has accumulated an impressive 1,629 citations, while WoS has a larger number of 518 publications, resulting in 12,362 citations.

A significant portion of research output is not only increasing but is also being widely recognized by peers in the field, as evidenced by the strikingly high percentages of Scopus and WoS 67.16% of total publications and 24.04% of total citations, and 51.85% of publications and a dominant 69.30% of citations. We observe a significant increase in research output when we examine the preceding periods. From 2015 to 2019, Scopus recorded 34 publications that generated 1,738 citations, whereas WoS contributed 271 publications that generated 3,525 citations. This era is indicative of a growing emphasis on prescriptive analytics in academic research, as evidenced by the burgeoning growth in scholarly activities. In fact, the landscape has undergone a transformation characterized by enhanced research output and visibility, in contrast to earlier years, such as 2005 to 2009, which documented only two publications with minimal citations. Longitudinal data, which extend back to the late 1970s, illustrate a consistent rise in both publications and citations.

For example, the 1990s saw the emergence of burgeoning academic interest, as evidenced by the 269 citations in Scopus that resulted from five publications. The research community's response to technological advancements and emerging topics is illustrated by the trend of increasing publication activity, which acquires momentum in the following decades, particularly in the 2010s and beyond. This dynamic is effectively captured through the use of pie charts, which illustrate an upward trajectory emphasizing the increasing proportion of both publications and citations over time. This upward trend is noteworthy because it emphasizes increasing involvement in prescriptive analytics, which indicates a larger dedication to the dissemination and generation of knowledge in the academic community. We can expect a perpetuation of this growth in publications and citations as we progress into the future of research, which is indicative of the ongoing evolution of academic inquiry and collaboration in areas of urgent relevance. These data not only indicate a prospering academic environment, but also indicate the potential for further innovation in research methodologies and dissemination strategies that are in accordance with global scientific and technological challenges.

Based on collective research, the integration of artificial intelligence in organizational decision making has evolved from simple descriptive models to sophisticated prescriptive analytics systems. This literature spans diverse domains including healthcare [8, 32, 48], supply chain management [6, 30], human resources [18, 19, 20], and infrastructure management [1, 27], representing a comprehensive view of AI's transformative impact on organizational intelligence. The evolution of AI decision-making paradigms initially focused on cognitive computing potential [38] and basic business intelligence frameworks [13]. Limited integration and theoretical foundations. The growth period of prescriptive analytics [39] and increased focus on big data integration [10]. Introduction of domain-specific applications in manufacturing [33] and waste management [23]. The work started to mature with sophisticated frameworks combining explainable AI [32], multifaceted approaches [30], and real-time decision-support systems [29]. Integration of ethical considerations and bias mitigation [54]. The domain is linked with healthcare, which emphasizes explainable AI [32] and bias mitigation [54] owing to life-critical decisions and businesses that focus on competitive advantage [42] and operational efficiency [22]. The key difference is that healthcare prioritizes interpretability over performance, whereas business applications often prioritize efficiency over transparency. Regarding the key trends and pattern involves methodological convergence with Hybrid Intelligence Models [56]: Integration of human cognitive capabilities with AI systems, Real-time Decision Frameworks [29, 44]: Shift from batch processing to continuous decision support, Explainable AI Integration [32, 14]: Growing emphasis on interpretable AI across all domains. Based on Sectoral Adoption Patterns, advanced adoption with regulatory compliance focuses on healthcare [48, 57], process optimization, and predictive maintenance in manufacturing [15, 33]. Emerging adoption with ethical considerations in human resources [18, 19, 20] and resilience and risk management focus in the supply chain [6,30]. Critical contradictions and tension. Studies emphasize both high-performance AI systems [69] and explainable AI requirements [32, 14]; however, limited research has addressed the inherent trade-off between model complexity and interpretability. The evidence can be obtained from healthcare studies prioritizing explainability [32] even at performance cost, and financial applications [69] prioritize performance over interpretability. There is a lack of frameworks for the context-dependent optimization of this trade-off. There has been a simultaneous push for full automation [44] and human-centered design [5]. This can be viewed from emergency systems favoring automation [44] for speed, and strategic decision systems emphasizing human oversight [5]. This limits guidance on determining the optimal automation levels by context. This review identifies several significant gaps across methodological, theoretical, and practical dimensions. Methodologically, there is a lack of longitudinal impact assessments to understand the sustained benefits of AI decision systems [61], limited cross-cultural validation to ensure generalizability across diverse environments [61], and insufficient failure mode analysis to develop robust risk-management frameworks [9]. Theoretically, current research is fragmented, with the absence of a unified theory for AI decision-making across different organizational contexts [56] and the need for more sophisticated models of human-AI collaboration to optimize decision processes. Practically, there is a lack of clear implementation roadmaps that offer step-by-step guidance and risk-mitigation strategies [9], as well as a lack of standardized frameworks for measuring the return on investment (ROI) of AI decision systems [9], making it challenging for organizations to justify AI investments and ensure successful deployment. Current research on AI decision systems reveals contradictions, such as the tension between large-scale, stable systems and the need for agile and adaptable systems [1], [44], the trade-off between data-driven performance and privacy preservation [3], [4], and the debate between general AI frameworks and domain-specific optimization [38], [29]). The literature also faces three main limitations: fragmentation in evaluation methods, lack of practical guidance for implementation, and insufficient attention to organizational and cultural contexts. To address these issues, future research should focus on developing standardized assessment frameworks that consider multiple performance metrics and long-term impacts, establishing evidence-based implementation strategies that include organizational readiness and risk management, and advancing models of human-AI collaboration that account for trust and decision context. Practitioners are encouraged to create context-specific deployment plans, prioritize change management, and implement continuous learning mechanisms for ongoing AI improvement.

5. Conclusion

This study is a comprehensive collection of recent developments in the fields of prescriptive analytics and bibliometric research. The hidden structures of publications in this field were identified by bibliometric analysis. This enhanced analysis reveals that while AI-driven decision making has achieved significant technological advances, the field faces critical challenges in integration, implementation, and evaluation. The identified contradictions and gaps represent opportunities for advancing both theoretical understanding and practical applications. The future of AI decision systems lies not in choosing between competing approaches (automation vs. human oversight, standardization vs. customization, performance vs. interpretability), but in developing sophisticated frameworks that optimize these trade-offs based on context. This requires interdisciplinary collaboration that combines computer science, organizational behavior, cognitive psychology, and domain expertise. Developments in prescriptive analytics have shown an increasing trend in popularity over time. Approximately 86.069% (TP 173) of the 201 papers in Scopus and 83.784% (TP 837) of the publications in WoS were published after 2013. The total number of citations since 1970 for Scopus and 1976 for WoS were 6777 and 17839, respectively. Fischhoff B. is the most productive author for WoS, and Wang F.Y. is the most productive author for Scopus. While WoS focuses on computer science, artificial intelligence, and computer science information systems, the majority of the work published in Scopus is in the fields of computer science, business, accounting, and management. The journal with the most publications on Scopus is IEEE Access, followed by Elsevier on WoS. According to a countrywise study, the United States continues to lead both Scopus and WoS in terms of the number of publications. According to institution-wise analysis, the Pennsylvania Commonwealth System of Higher Education (Pcshe) continues to lead in WoS, while the Massachusetts Institute of Technology leads in Scopus. Next, a comparative analysis of the prescriptive analytics domain is conducted using the most significant articles in the area as a framework. New researchers may gain a better and more lucid perspective from this investigation. As evidenced by indexing by WoS and Scopus, prescriptive analytics research has changed over time. The specifics of prescriptive analytics publication patterns are shown in Fig. 12. We can see that articles on the technological aspects of prescriptive analytics and general prescriptive analytics research are very different. Therefore, the number of papers available in prescriptive analytics is one of the main weaknesses of this study. However, it also draws attention to the vast amount of research needed in the field of prescriptive analytics. The scholarly contribution of this analysis lies in providing a structured framework for understanding the current state of AI decision-making research and identifying specific directions for future research. By moving beyond a simple literature compilation to critical analysis and synthesis, we advance the field's theoretical foundation while providing practical guidance for researchers and practitioners. The scope of this study might involve focusing on a few prescription-related technologies or conducting a deeper investigation using different indexing databases.

Declarations

Author Contributions

The following statements should be used:

Conceptualization, K.B. and Z.A.A.; methodology, K.B.; software, K.B. and M.F.M.E; validation, K.B., N.M.Y., and A.S.M.J.; formal analysis, K.B. and A.F.N.A.R; investigation, M.F.M.E.; resources, K.B.; data curation, K.B.; writing—original draft preparation, K.B.; writing—review and editing, K.B. and Z. A. A.; visualization, M.F.M.E.; supervision, N.M.Y.; project administration, A.S.M.J, A.F.N.A.R, and M.H.J. All authors have read and agreed to the published version of the manuscript.

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