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Enhancing research publication choices: A comparative study of journal recommender systems and their effectiveness

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ABSTRACT

In recent years, there has been a rapid increase in the number of research papers being published, leading to what many feel is an overload of information. This makes it difficult for researchers to choose the right journal for their work. To help with this, journal recommender systems have been suggested as useful tools to help researchers find the most appropriate journals for their research. With so many journals, publishers, and recommender systems to choose from, deciding on the best one can be complicated. This decision depends on several factors, including the publisher, the scientific database, and the specific needs and preferences of the user. In this paper, we offer a detailed comparison of popular journal recommender systems, both theoretically and through experiments, to see how effective they are at making recommendations. We focus on how relevant and helpful these recommendations are. We also provide advice for researchers on how to make the most of these recommender systems to aid in their publishing process.

1. Introduction

Scientific publications represent valuable studies and novel ideas that play a crucial role in disseminating new research findings to the scientific community (Liu et al., 2015). These publications undergo a thorough examination by qualified publishers and reviewers to evaluate their originality and eligibility for specific journals (Bai et al., 2019). Usually, the publication process involves two distinct phases: Peer Review and Production. During the peer review process, the manuscript is subjected to a rigorous evaluation by experts in the field who provide feedback and recommendations for improvement (Jana, 2019). The author incorporates these comments, making necessary modifications to the manuscript until it meets the standards for acceptance. This iterative process ensures that the published work maintains high quality and scientific rigor. Once the peer review phase is completed, the accepted manuscript moves to the production phase. In this phase, copy editing is conducted to refine the language, grammar, and formatting, ensuring adherence to the journal's guidelines (Jana, 2019). Typesetting is then performed to enhance the visual presentation of the document, aligning it with the journal's style and layout. Finally, the manuscript is prepared for online publishing, making it accessible to the scientific community (Jana, 2019). These rigorous processes of peer review and production uphold the originality, integrity, and credibility of scientific publications. They serve as important mechanisms for quality control, ensuring that research findings are accurately and effectively communicated to researchers, academics, and professionals. This facilitates the advancement of knowledge and fosters scientific progress in various fields.

However, the rapid increase in research paper production over the last decades has led to information overload in the scientific research domain. Consequently, selecting a suitable journal for publication and minimizing the risk of rejection has become a challenging task. Authors often struggle to identify the most appropriate journal for their research due to the multitude of available journals spanning diverse topics (Jain et al., 2019). Inadequate journal selection can lead to manuscript rejection even if the quality of the work is high. Novice researchers, in particular, face challenges in decision-making regarding submission venues and often rely on guidance from experienced colleagues

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or journal rankings. Making an incorrect journal choice can result in wasted time and effort for both authors and editors, potentially affecting authors' career trajectories (Forrester et al., 2017).

To address this issue, journal recommender systems have been developed to assist researchers in identifying relevant journals based on a simple configuration of inputs (Aymen and Imène, 2022; Kreutz and Schenkel, 2022). By adhering to these recommendations, users can successfully integrate journal recommender systems into their publication process: the user begins by entering pertinent data, such as keywords, abstracts, or the complete manuscript. The recommender system can better comprehend the context and topic of the research with the use of this information. Depending on their unique requirements and objectives, users can alter their preferences and criteria. This could involve elements like the publication scope, the intended audience, the impact factor (IF), or the release schedule. After the algorithm provides a list of suggested journals, users ought to carefully consider and assess each suggestion. They may consider elements like the journal's reputation, acceptance rates, and the journal's standing in their area of study. According to these recommendations, users can make the most of journal recommender systems to help them choose the best journals for their study, increasing the likelihood that their work will be published successfully and have the most possible impact.

Notable publishers such as Elsevier and IEEE (Kang et al., 2015; Curry, 2019; Mudrak, 2015; Rollins et al., 2017) have introduced their journal recommender systems, while other organizations offer both free and commercial alternatives (Small, 1973). This paper aims to present a comprehensive comparison of journal recommender systems while providing researchers insights into the effective utilization of journal recommender systems and facilitating informed decisions regarding journal selection. To achieve this, we conducted an empirical and experimental comparison of prominent journal recommender systems, evaluating them based on five criteria: Service quality, Publication cost and policy, Consistency, and Sensitivity. By examining these aspects, researchers can navigate the available recommender systems and select the most suitable journal for their research, considering their individual preferences and long-term career goals. By offering a robust evaluation framework and comparative analysis, this study seeks to empower the scientific research community to utilize journal recommender systems effectively, ultimately enhancing the publication process and the impact of their research.

The structure of the rest of the paper is as follows: Section 2 provides an overview of recommender systems and mentions well-known systems for recommending scientific journals. Section 3 details the empirical and experimental study we conducted to compare the effectiveness of current recommender systems in suggesting suitable journals. Lastly, Section 4 presents the conclusions and future research directions.

2. Background on recommender systems

2.1. Recommender systems: Definitions, approaches, and application domains

Recommender systems have become increasingly prevalent in our daily lives, allowing us to address the challenge of information overload by selecting relevant information fragments from vast amounts of generated content based on user preferences, choices, or observed behavior (Pan and Li, 2010). The objective of recommender systems is not only to minimize users' research time but also to recommend relevant items they might not have discovered otherwise, thereby increasing overall satisfaction (Konstan and Riedl, 2012). These systems can serve as information filtering tools, suggesting items to users that align with their interests and expectations. These items include articles to read, products to purchase, music to listen to, movies to watch, or web pages to explore. Recommender systems allow for the reduction of transaction costs associated with finding and selecting products in online purchasing environments (Isinkaye et al., 2015; Hu and Pu, 2009).

The outputs of recommender systems consist of three main objects, which are, respectively, "items," "users," and "preferences" (Jannach et al., 2010). Firstly, "items" represent the products or services that the system can recommend, such as the services available within a library or the content offered on Netflix. Secondly, "users" define the individuals who have access to the system and provide their socio-demographic information. Finally, "preferences" encompass personalized recommendations tailored to the user's needs and can be categorized into explicit and implicit data (Schafer et al., 2007; Mobasher et al., 2003). Explicit data refers to information expressed by users during their navigation activities, such as providing ratings on a predefined scale (e.g., rating products purchased online) or expressing opinions on objects (e.g., the "Like" button on Facebook). Implicit data, on the other hand, is collected by observing user behavior and activity, including web pages viewed, purchase history, click-stream data, and more. By leveraging explicit and implicit data, recommender systems generate personalized recommendations, enhancing the user experience and facilitating the discovery of new and relevant items.

The implementation of recommender systems can be based on different approaches (Xia et al., 2016; Song et al., 2017). These approaches are usually classified into content-based filtering (CBF), collaborative filtering (CF), and hybrid approaches (Bai et al., 2019; Thorat et al., 2015; Gupta and Dave, 2020). Content-based filtering (CBF) was one of the early successful recommendation techniques (Gedikli, 2024; Son and Kim, 2017). CBF primarily analyzes the characteristics of the items and then develops specific profiles for each item by running correlation matrices on the item information. CBF systems generate recommendations by comparing a user profile with the content of each item in the collection. Documents' content can be described using a set of terms obtained through parsing procedures involving the removal of stop words, HTML tags, prefixes, suffixes, and stems. The user profile is created by examining the content of documents that the user finds interesting and can be identified using explicit or implicit feedback (Van Meteren and Van Someren, 2000).

Other recommender systems are based on a collaborative filtering (CF) approach. CF systems are based on analyzing user behavior, assuming that predictions can be made by considering users' past decisions and comparing them to other users (Schafer et al., 2007; Vellino, 2015). CF operates by comparing user behaviors, purchases, ratings, and preferences to identify similarities and make recommendations. Users tend to favor items that other users with similar tastes have appreciated or preferred (Singh et al., 2020; Schafer et al., 2007). This approach requires significant data collection efforts and often involves categorizing users into groups based on demographics and behavioral tendencies to reduce the amount of information needed (Gedikli, 2024). CF systems typically utilize a user-item matrix representing users' ratings or feedback on items. Similarity between users is calculated based on this matrix to identify "neighbor users" who exhibit similar preferences, enabling personalized item recommendations (Schafer et al., 2007). Collaborative filtering systems encompass several variations, including User-User Collaborative Filtering, which identifies similar users and recommends items based on their preferences, and Item-Item Collaborative Filtering, which identifies similar items and suggests related products to a user who has already purchased an item from the store.

To address the potential limitations of both CBF and CF, hybrid recommender systems have been developed with the aim of creating comprehensive models that combine the strengths of both approaches (Tsolakidis et al., 2016). Based on the advantages of both strategies, hybrid systems aim to improve the accuracy of recommendations. By considering both user preferences and content similarities, these hybrid systems can provide more accurate and diverse recommendations. All these proposed recommender systems have been applied to a wide range of domains. For example, recommender systems are extensively used in e-commerce applications, both in business-to-consumer systems, where recommendations are personalized for individual customers, and in business-to-business systems, where recommendations focus on products and services for business users (Shambour and Lu, 2015; Wang and Chiu, 2008). Major e-commerce platforms like Amazon and eBay employ recommender systems to assist users in finding relevant products (Linden et al., 2003; Schafer et al., 2001). Many other domains can be cited including movie recommendations (e.g., MovieLens system), music recommendations, television program suggestions (e.g., Netflix recommendation system), e-tourism (Lu et al., 2015), e-learning (Tung and Soo, 2004; Martinez et al., 2009; Lucas et al., 2013), and book recommendations (e.g., TechLens) (Herlocker et al., 1999; McNee et al., 2002).

2.2. Journal recommender systems

A scientific journal recommender system is a tool or software designed to assist researchers in identifying relevant and appropriate journals for their research papers. These systems are based on different computer-based algorithms and techniques to analyze the characteristics of the manuscript and match them with the scope and focus of different journals (Entrup et al., 2023). These systems typically operate based on the input provided by the researcher, such as the title, abstract, keywords, or even the full manuscript. The system then processes this information and generates a list of recommended journals that align with the research topic, methodology, and field of study.

The recommendations provided by these systems are often based on several factors and user preferences, including the content similarity between the manuscript and the journals, the reputation and IF of the journals, the publication policies and guidelines, and sometimes even the availability and accessibility of the journals. Many scientific publishers and academic platforms have developed their journal recommender systems to support researchers in finding suitable scientific journals for their work. By using these systems, researchers can save time and effort in manually searching and analyzing numerous journals, increase the chances of successful publication, and ensure their work reaches the appropriate audience and scholarly community.

Journal recommender systems have been useful in saving researchers time and effort by offering a carefully selected list of journals that are pertinent to their field of study. Rather than exerting laborious effort to sift through a multitude of journals and publications, researchers can depend on these algorithms to recommend appropriate venues for their work. Recommender systems can improve the exposure and discoverability of researchers' work by recommending relevant articles. To suggest journals that complement the researchers' work, these algorithms frequently consider variables, including the research topic, keywords, and citation patterns. In addition to helping researchers reach their intended audience, this raises the likelihood that other experts in the field will read and credit their work. It might be difficult for researchers in specialized or niche fields to find journals that support their line of work. Journal recommender systems can help find these specialized journals that aren't well-known or difficult to find using conventional search techniques. This guarantees that their study reaches the relevant community and helps researchers choose the best venues for publishing their work. Researchers can obtain important details about different journals from recommender systems, such as citation metrics, IFs, publication prices, and policies. This enables researchers to select the journals to which they want to publish their work with knowledge. Researchers can improve their chances of acceptance and impact by matching their publication aims with the breadth and reputation of various journals by taking these criteria into account. These real-world examples show how journal recommender systems are practically applicable and can be very helpful to researchers by streamlining the journal selection procedure, increasing visibility, and offering insightful data for well-informed choices. We will give the following review of well-known journal recommender systems while describing the main interfaces and the recommendation algorithm.

2.2.1. Elsevier journal finder

The Elsevier Journal Finder† is a highly comprehensive journal recommender system that offers more than 2,900 peer-reviewed Elsevier publications across various scientific disciplines. It serves as a valuable resource for researchers looking for the most suitable journal to publish their work. The system utilizes the Scopus database as its source of journals and publications. Fig. 1 demonstrates how users can choose one or more scientific fields by just entering the paper's title, abstract, or keywords. Users can then select study areas from the Scopus database using a drop-down menu when searching.

To build the list of the most relevant journals to the user query, the Elsevier Journal Finder involves the following steps:

1. Annotation and Normalization: The system employs the Elsevier Fingerprint Engine (EFE) to annotate and normalize noun phrases from the text entered by the user, such as the paper's title, abstract, or keywords. EFE utilizes Natural Language Processing (NLP) techniques to identify key concepts across scientific disciplines and create a structured index of weighted terms known as a Fingerprint (Rollins et al., 2017).
2. Matching with BM25 Algorithm: The Okapi BM25 algorithm, a bag-of-words retrieval function, is used to match the user's query with existing papers in the database (Bavdekar and Save, 2015). The EFE generates normalized noun phrases as a query vector for the paper-matching algorithm. Optimization parameters are applied to ensure the highest accuracy in the ranking algorithm (Forrester et al., 2017).
3. Ranking and Journal Recommendation: The system provides a ranked list of papers with BM25 scores indicating their similarity to the input text. The top paper in the list is considered the most similar to the user's query. The journal recommendation ranking algorithm converts the paper scores into scores for journals. This process involves selecting the top 1 million papers based on BM25 scores and determining the journal and its scientific domains for each paper. Suppose the user has specified a domain; papers outside that domain are excluded. Finally, an average BM25 score per journal is computed by averaging the scores of all papers published in the same journal.

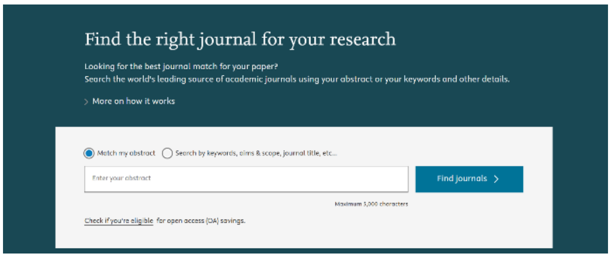

Fig. 1: The main interface of Elsevier journal finder

2.2.2. IEEE publication recommender

The IEEE Publication Recommender‡ is a tool that assists authors in selecting the most suitable publication for their research papers in the fields of electrical and electronics engineering and computer science. With the IEEE Xplore database, which holds over two million records, authors can submit their articles or enter keywords to receive personalized recommendations. The recommender provides valuable information about publications, such as their aims and scope, bibliometric ratings like the IF, open access availability, submission URLs, and more. This helps authors make informed decisions about where to submit their work. Fig. 2 shows the main interface of the IEEE Publication recommender.

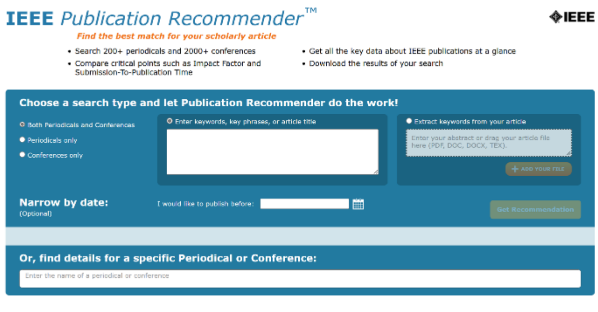

Fig. 2: The main interface of the IEEE Publication recommender system

2.2.3. JANE (Journal author name estimator)

JANE§ is a free online bibliographic journal selection tool developed as part of the Biorange project of the Netherlands Bioinformatics Centre (Curry, 2019). It utilizes the open-source Lucene search engine to find articles similar to the user's input query. By employing a weighted nearest-

† https://journalfinder.elsevier.com

‡ https://publication-recommender.ieee.org

§ https://jane.biosemantics.org

neighbor approach, JANE determines the most relevant journals or authors based on the ordered list of similar records. As described in Fig. 3, JANE offers a simple search interface with options to find journals, authors, or articles, providing researchers with an efficient way to identify potential publishing venues. The search results in JANE recommender include confidence scores and various identifiers indicating the journal's indexing status, open access availability, and presence in PubMed Central. JANE uses color-coded identifiers behind each journal name on the results page. The green "Medline-indexed" tab indicates that the journal is currently indexed for MEDLINE. The orange "High-quality open access" tab signifies that the journal is of high quality according to the Directory of Open Access Journals (DOAJ) and does not charge readers or institutions for access. The blue "PMC" tab denotes that some or all of the journal's articles are deposited, sometimes with a delay, in PubMed Central (PMC) (Reyna et al., 2018).

Fig. 3: The main Interface of JANE recommender system

2.2.4. Research square's journal guide

JournalGuide** is an online tool that helps authors find suitable journals for their manuscripts. As described in Fig. 4, JournalGuide allows authors to input keywords or text from their drafts and generates a ranked list of journals that have recently published articles related to the input terms. JournalGuide provides a comprehensive search platform with filters and sorting options that allow users to isolate the criteria that align with their publishing needs. Factors such as IF, open access availability (OA), and publication speed can be utilized to refine search results. To enhance the ranking of results, JournalGuide has developed a unique match "score" that robustly evaluates the relevance of journals to the user's query. Users can easily search for journals within specific categories or fields of study by utilizing the convenient drop-down list available in JournalGuide. This enables authors to focus their search on journals that are closely aligned with their research area. In assessing a journal's impact, JournalGuide employs the Source-Normalized Impact per Paper (SNIP) metric.

SNIP normalizes a journal's impact by considering the number of papers published in its field, allowing for direct comparisons across multiple disciplines. SNIP values are calculated by Scopus and are publicly available, further contributing to the transparency of the publication process. Journals listed as "Verified" on JournalGuide indicate their presence on the "White List" maintained by Research Square. These verified journals have undergone third-party index verification, ensuring their recognition and reputation within their respective fields. It should be noted that the absence of the "Verified" indicator does not imply that a journal is disreputable; it simply means that its status has not been independently confirmed.

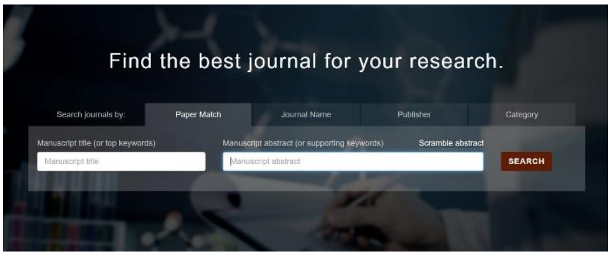

Fig. 4: The main interface of the JournalGuide recommender system

2.2.5. MDPI journal finder

The MDPI Journal Finder†† allows to assist authors in identifying suitable journals within the MDPI portfolio for publishing their manuscripts. The MDPI Journal Finder utilizes a comprehensive database of MDPI journals that cover a wide range of disciplines in the fields of science, technology, and engineering. As described in Fig. 5, MDPI Journal Finder provides a user-friendly interface to explore and identify the most suitable journals from MDPI's comprehensive collection of scientific, technological, and medical publications, facilitating the dissemination of their research to a wider audience. Authors can enter manuscript details, such as the title and abstract, and select the scientific databases in which the desired journals are indexed. Given that all MDPI journals operate under an open-access model and require article processing charges (APCs), authors have the flexibility to set a maximum APC limit for the journals identified in their search. When reporting a list of recommended journals, MDPI Journal Finder provides additional information about each recommended journal, such as its IF, citeScore, publication fees, and time to first decision. This allows researchers to evaluate the suitability of the journals based on their specific requirements and preferences.

2.2.6. EndNote match

EndNote Match‡‡ is a for-profit program that helps authors find the most relevant journals for their manuscripts. As depicted in Fig. 6, EndNote Match provides authors with a convenient way to

** https://www.journalguide.com

†† https://www.mdpi.com/about/journalselector

‡‡ https://www.myendnoteweb.com

identify suitable journals for their manuscript submissions. Upon entering the manuscript's title, abstract, and optional EndNote Group of references containing citations, the tool generates a results page with a list of 3 to 10 journal recommendations. Manuscript Matcher utilizes sophisticated algorithms and data from reputable sources like the Web of Science and Journal Citation Reports. By analyzing the content of the manuscript, the tool identifies the most relevant journals that align with the research.

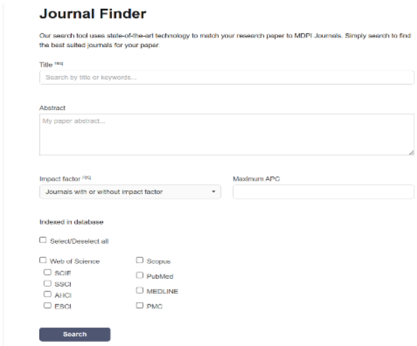

Fig. 5: The main interface of the MDPI journal finder system

The displayed results show crucial information about each recommended journal. This includes the Journal title, the Match Score (an index indicating how closely the article matches the published content in that journal), the ISSN (International Standard Serial Number), the eISSN (Electronic International Standard Serial Number), and Journal information (links to the journal's website). This detailed information empowers authors to make informed decisions during the journal submission process. By leveraging Manuscript Matcher, researchers can save time and effort and increase the chances of selecting the most appropriate journal for their manuscript (Jain et al., 2019).

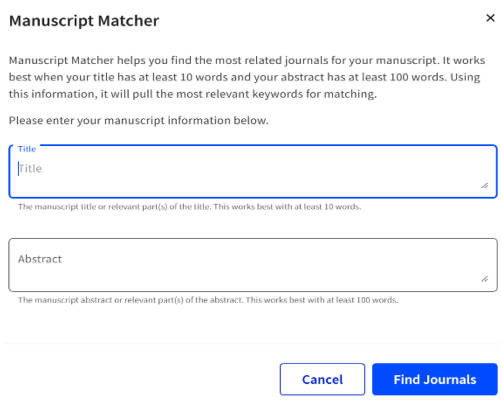

Fig. 6: The main interface of the EndNote recommender system

3. Experimental study

3.1. Methodology

A journal recommender system's selection is influenced by several variables, including the research area, database coverage, accessibility, and journal recommender system integration. Certain recommender systems are tailored to fields of science. For instance, if you are interested in computer science and electrical engineering, consider the IEEE Publication Recommender. While some solutions cover specific databases, others, like Elsevier Journal Finder, offer access to many systems that work well with reference management software like EndNote—like EndNote Match—can improve your efficiency. The distinctive qualities of every recommender system may also play a role in the selection of a journal recommender system. For example, Elsevier Journal Finder uses citation metrics from Scopus, and JANE suggests authors and collaborations. In the end, the optimal option is determined by various needs and tastes.

We decided to investigate six of the most well-known journal recommender systems: MDPI Journal Finder, IEEE Publication Recommender, JANE, JournalGuide, Elsevier Journal Finder, and EndNote Manuscript Matcher. Because of things like the standing of the publishers or organizations that developed these recommender systems, their extensive databases, their easy-to-use interfaces, and their capacity to offer tailored recommendations based on research interests or manuscript content, these journal recommender systems have become increasingly popular. Positive user experiences and comments have also helped these technologies become well-known. Scholars searching for choices for open-access publications frequently choose the MDPI Journal Finder because of its extensive database of MDPI journals. The popularity of MDPI's journal-finding tool has been aided by its standing as an open-access publisher. Because IEEE has a long history of publishing high-caliber research, scholars in these fields are familiar with and confident in the IEEE Publication Recommender. JANE became well-known because it could make suggestions for journals based on abstracts and titles of articles, which made it an easy-to-use tool for scholars looking for pertinent publications. The success of JournalGuide has been attributed to its broad coverage as well as features like subject area, IF, and open-access journal filtering. Utilizing Elsevier's vast library of scientific publications, the Elsevier Journal Finder is a well-known resource for researchers. Furthermore, Elsevier's affiliation with respectable databases such as Scopus amplifies the legitimacy and prominence of its journal-finding tool. One component of the popular reference management program EndNote is EndNote Manuscript Matcher. Researchers consider EndNote to be a reliable tool for managing their references, and the Manuscript Matcher feature enhances its usefulness by recommending appropriate journals based on the user's manuscript content.

Choosing the right journal for manuscript submission involves considering various factors and criteria. Authors consider factors such as time from submission to publication, importance of the journal, acceptance/rejection rates, potential audience, fees, IF, perceptions of the journal's prestige, circulation, and publication delay. These criteria and motives can be organized in different ways, as discussed by Forrester et al. (2017). In this study, we conduct a comparative analysis of well-known journal recommender systems based on five criteria. The criteria we consider are as follows:

1. Journal ranking scientometrics: We evaluate the recommendation results provided by each system and compare the rankings they assign to journals based on the scientometrics that significantly influence users' journal selection.
2. Service quality: This criterion enables us to examine the differences among various recommendation systems in terms of the services they offer. Factors such as the quality of the peer review process, publication speed, acceptance rates, and other related aspects are considered.
3. Publication cost and policy: We assess the open access (OA) policy of the journals, including factors such as Article Processing Charges (APCs) and other fees. Additionally, we explore the availability of external APC funding and institutional reward schemes.
4. Consistency: This criterion focuses on the consistency of recommendations over time. We compare the results obtained by each journal recommender system for the years 2017 and 2023, building upon the summarized findings from the article (Forrester et al., 2017) for the year 2017.
5. Sensitivity: We examine the sensitivity of recommender systems when inputs are slightly changed. A higher sensitivity score indicates a system's proficiency in providing accurate recommendations even with minor modifications, while a lower sensitivity score indicates limitations in capturing the nuances and context of the inputs.

By examining journal recommender systems through these criteria, we aim to provide insights into their performance, highlight differences in service quality and cost, evaluate consistency over time, and explore the sensitivity of the systems to changes in given inputs.

3.2. Journal ranking and scientometrics

When authors decide which journal to submit their research to, the reputation and prestige of the journal are among the primary considerations. Journal rankings are commonly used in academia to evaluate the value and impact of academic journals. These rankings aim to reflect a journal's standing within its field, the difficulty of getting published, and its overall renown. Various journal ranking metrics have been proposed and used. In this section, we assess the results of recommendation systems based on well-known ranking metrics. We describe the most prominent scientometrics used for journal ranking:

- IF: The journal IF is the most widely used measure of journal distinction and importance. It often plays a significant role in authors' decisions on where to publish. The IF reflects the average number of citations received by recent articles published in a journal. It serves as a proxy for a journal's relative importance within its field, with higher IFs indicating greater significance (Kim and Chung, 2018). The IF is calculated by dividing the number of citations in the current year by the number of articles published by the journal in the previous two years (Eq. 1).

$$IF_y = \frac{Citations_y}{Publications_{y-1} + Publications_{y-2}} \tag{1}$$

- CiteScore (CS): Introduced by Elsevier as an alternative to the IF, CiteScore is based on citations recorded in the Scopus database. It differs from the IF in that it considers citations for articles published in the previous four years instead of two. CiteScore for a given year is calculated by dividing the number of citations received in the previous four years (including the current year) by the number of articles published and indexed in the Scopus Database as described in Eq. 2.

$$CS_y = \frac{Citations_{y-3} + +Citations_{y-2} + Citations_{y-1} + +Citations_y}{Publications_{y-3} + Publications_{y-2} + Publications_{y-1} + Publications_y} \tag{2}$$

- Eigenfactor: Developed by Bergstrom et al. (2008) at the University of Washington. It measures the number of readers who consider a journal's contents to be significant. It is determined by counting the total number of citations a journal receives over a five-year period. It's worth noting that Eigenfactor counts all citations, and the volume of articles published by a journal can impact its Eigenfactor score (Elsevier, 2022). Eq. 3 gives the mathematical formula for computing the Eigenfactor.

$$E_y = \frac{Citations_y}{Publications_y} \tag{3}$$

- SCImago journal rank (SJR): SJR is an average measure of the weighted citations received by articles published in a journal over the previous three years. Higher SJR values indicate greater journal prestige (Kim and Chung, 2018; Elsevier, 2022). Eq. 4 gives the mathematical formula for computing SJR.

$$SJR_y = \frac{Citations_y}{Publications_{y-3} + Publications_{y-2} + Publications_{y-1}} \tag{4}$$

- SNIP: SNIP is a complex statistic that takes into account citation patterns specific to a particular field. It compares the number of citations per publication for each journal with the field-wide potential for citations, determined by the number of articles citing each journal. Eq. 5 describes the mathematical formula for computing SNIP. The

SNIP allows for the contextual assessment of citation impact and facilitates direct comparisons of journals across different subject fields (Elsevier, 2022; Kim and Chung, 2018).

$$SNIP_y = \frac{Citations_{y-3} + Citations_{y-2} + Citations_{y-1} + + Citations_y}{Publications_{y-3} + Publications_{y-2} + Publications_{y-1}} \quad (5)$$

In Table 1, we present an evaluation based on these journal ranking metrics for various journal recommender systems. The evaluation shows the presence of at least one metric when reporting the recommendation results. The IF is the most commonly used metric to assess journal prestige. Four out of six recommendation systems include the IF in their results. Elsevier Journal Finder stands out by providing the most comprehensive results, incorporating both IF and CiteScore in its recommendations.

Table 1: Comparison of journal recommender systems based on scientometric metrics

System	IF	CiteScore	Eigenfactor	SJR	SNIP
Elsevier journal finder	✓	✓	-	-	-
EndNote manuscript matcher	✓	-	-	-	-
JANE	-	-	✓	-	-
JournalGuide	-	-	-	-	✓
IEEE publication recommender	✓	-	-	-	-
MDPI journal finder	✓	✓	-	-	-

3.3. Service quality

When choosing a suitable journal for publication, it is essential to gather information about various journal services to make an informed decision. The peer review process, acceptance rate, and publication speed are crucial variables to consider when comparing the quality of services provided by journal recommender systems. Published research's credibility and dependability are directly impacted by the caliber and rigor of the peer review process. Strong and comprehensive peer review processes should be given priority when recommending journals via a good journal recommender system. The percentage of submitted papers that are approved for publication in a journal is indicated by the acceptance rate. It might serve as a gauge for a journal's selectivity and competition. A journal with a low acceptance rate can have strict guidelines and only publish a small number of excellent manuscripts. An extremely low acceptance rate, nonetheless, can also point to possible difficulties authors may have in having their work approved (Bavdekar and Save, 2015). Achieving a balance between selectivity and accessibility is crucial when considering the desired goals of the research. Researchers should consider the amount of time that elapses between submission and publication. Researchers can distribute their discoveries more swiftly with faster publication speeds, which can result in timely information diffusion and even career progress (Jana, 2019). Researchers can locate journals that promote rapid publishing without sacrificing quality with the use of a journal recommender system that identifies journals with effective publication processes. The total service quality of journal recommender systems can be assessed by researchers by considering the peer review process, acceptance rate, and publication speed. However, because it frequently requires gathering information from different sources and considering a variety of parameters, assessing or quantifying the service quality of journal recommender systems in terms of the peer review process, acceptance rate, and publication speed can be difficult. Factors like journal IF, indexing in reliable databases, and editorial board membership can be used to gauge the effectiveness of the peer review process. Surveys and interviews can be used to get input from researchers about how satisfied they are with the peer-review procedure for the journals that the system recommends. Direct access to acceptance rates from journals is possible via journal metrics databases. Scholars can do bibliometric analyses, which compare the number of accepted or rejected submissions to the number of published papers, to estimate acceptance rates. A few publishers or journal metrics databases offer average turnaround times or publication dates. These metrics can show how quickly journals that the system recommends publish new articles.

Table 2 presents an evaluation of different journal recommender systems based on service quality criteria. The systems are compared in terms of their peer review process, acceptance rates, and publication speed. Elsevier Journal Finder offers a comprehensive service covering all three criteria. EndNote Manuscript Matcher focuses primarily on publication speed, while JANE does not provide any of the mentioned journal quality services. Table 2 shows that publication speed is an essential factor for users seeking journal recommendations, as it is present in the results of most systems.

Table 2: Comparison of journal recommender systems based on service quality

System	Peer review process	Acceptance rate	Publication speed
Elsevier journal finder	✓	✓	✓
EndNote manuscript matcher	-	-	✓
JANE	-	-	-
JournalGuide	✓	-	✓
IEEE publication recommender	-	-	✓
MDPI journal finder	✓	-	-

3.4. Publication cost and policy

The distribution model of a journal plays a significant role in determining reader access to its content. Three main categories of journals can be identified: subscription, open-access, and hybrid. For the first category, subscription, journals require readers to pay a subscription fee to access the journal content. These fees are typically paid by individuals or institutions and grant access to a specific set of issues or a subscription period. The second category, open-access journals, makes research articles freely available to readers without any subscription or paywall barriers. Authors may be required to pay article processing charges (APCs) to cover publication costs, allowing the articles to be freely accessible to anyone interested. Concerning the third category, hybrid combines elements of both subscription and open-access models. Hybrid journals typically offer subscription-based access to their content but also provide an option for authors to pay APCs to make individual articles open-access.

When authors choose a journal for publication, it is important to consider the associated publication fees. While some journals may advertise themselves as free, they may still impose fees if certain criteria are exceeded, such as word count, number of printed pages, or number of figures. It is crucial for authors to thoroughly examine these fee conditions and take them into account when making their journal selection. Journal recommender systems can also incorporate this cost factor into their results, providing authors with valuable information to make informed decisions (Bavdekar and Save, 2015).

Table 3 presents an evaluation of journal recommender systems based on publication cost and policy. Table 3 compares the systems in terms of the publication model, publication charges, and license. Elsevier Journal Finder provides comprehensive information on the publication model, charges, and license. EndNote Manuscript Matcher indicates the publication model but does not provide information on charges or licenses. Jane and IEEE Publication Recommender also show the publication model but do not provide details on charges or licenses. JournalGuide, on the other hand, explicitly indicates publication charges and licenses but does not specify the publication model. Overall, Elsevier Journal Finder stands out by offering the most extensive information about the journal, including the publication model, charges, and license. JournalGuide also provides valuable information on publication charges and licenses.

Table 3: Comparison of journal recommender systems based on the existence of publication cost and policy

System	Publication model	Publication charges	License
Elsevier journal finder	✓	✓	✓
EndNote manuscript matcher	✓	-	-
JANE	✓	-	-
JournalGuide	-	✓	✓
IEEE publication recommender	✓	-	-
MDPI journal finder	-	✓	-

3.5. Consistency

In this section, we aim to examine the consistency of recommendations provided by journal recommender systems over a certain period. To compare the results, we refer to an article titled "New web services that help authors choose journals," published in Learned Publishing, Wiley Online Library. This article was previously used in a study (Forrester et al., 2017) to evaluate several journal recommender systems in 2017. In this analysis, we utilize the same article as a reference point and compare the results obtained in 2017 with those obtained in 2023.

Table 4 presents the comparative results of journal recommender systems for the years 2017 and 2023. Table 4 displays the top three journals recommended by each service and indicates the similarity between the recommendations from the two time periods. To quantify the similarity between the 2017 and 2023 results, we define a similarity function denoted as S(2017, 2023). This function calculates the ratio of the intersection of the recommendations in 2017 and 2023 to the union of the recommendations:

$$S(2017, 2023) = \frac{Recommendations_{2017} \cap Recommendations_{2023}}{Recommendations_{2017} \cup Recommendations_{2023}} \quad (6)$$

Table 4: Comparison of system recommendations for the same paper for the periods 2017-2023

System	Year	Top three recommended journals	Similarity
Elsevier journal finder	2017	Policy and Society; Journal of Informetrics; Energy Research and Social Science	0%
	2023	Decision Support Systems; International Journal of Information Management; International Journal of Information Management	
Endnote manuscript	2017	IEEE Internet Computing; International Journal of Web Services Research; Learned Publishing	33%
	2023	International Journal of Web and Grid Services; International Journal of Web Services Research; Administration and Policy in Mental Health and Mental Health Services Research	
JANE	2017	PLOS ONE; Prilozi; Indian Journal of Anesthesia	33%
	2023	PLOS ONE; Peerj Computer Science; Early Human Development	
JournalGuide	2017	PLOS ONE; International Neurology Journal; Scientometrics	0%
	2023	Learned Publishing; Care Management; Journals Science	
IEEE publication recommender	2017	Computer; IEEE Transactions on Professional Communication; IEEE Transactions on Big Data	0%
	2023	Oceanic Engineering; Systems Engineering and Electronics; Internet of Things Journal	

By analyzing Table 4, we observe that the recommendations provided by Elsevier Journal Finder, JournalGuide, and IEEE Publication Recommender have completely changed from 2017 to 2023, resulting in a 100 % change. Table 4 also highlights significant variations in the top three recommended journals across all systems. These differences can be attributed to the utilization of distinct databases by the recommended systems, as well as a tendency to prioritize journals from the publisher's system in the recommendations.

3.6. Sensitivity

In this section, our main objective is to compare different journal recommender systems based on their sensitivity to a given input. To conduct the comparison, we utilize a set of 10 titles of published articles. For each title, we systematically remove a single keyword and observe how the recommendations provided by the system change. This process is repeated for all 10 titles, resulting in two sets of recommendations for each title: one with the original title and one with a keyword missing from the title. We apply this methodology to all the compared journal recommender systems.

To calculate the sensitivity score, we define the following formula:

$$Sensitivity = \sum_{i=1}^{i=10} \frac{diff(r_i)}{total(r_i)} \quad (7)$$

where, $diff(r_i)$ represents the number of changes in the recommended journals when a key-word is removed from the ith title, and $total(r_i)$ represents the total number of considered recommendations that is fixed at the first five recommended journals. A higher sensitivity score indicates that the system is more responsive to changes in the inputs, implying its ability to accurately recommend journals even with minor modifications to the article title. Conversely, a lower sensitivity score suggests limitations in capturing the nuances and context of inputs.

Table 5 presents the obtained sensitivity scores for all the compared systems. We show that both Elsevier Journal Finder and JournalGuide have the highest sensitivity scores. For instance, the Elsevier Journal Finder system has a sensitivity score of 35% which indicates that when a keyword is removed from the title of an article, the system can adapt its recommendations with a sensitivity of 35%. The other systems listed in Table 5 including EndNote Manuscript Matcher, JANE and IEEE Publication Recommender have a lower sensity compared to Elsevier Journal Finder and JournalGuide.

Table 5: Comparison of the sensitivity of recommendations

System	Sensitivity
Elsevier journal finder	35%
EndNote manuscript matcher	27%
JANE	23%
JournalGuide	37%
IEEE publication recommender	21%

3.7. Strengths, weaknesses, and distinctive features

To give a more nuanced comparison of the studied journal recommender systems. Table 6 highlights the strengths, weaknesses, and distinctive features of each journal recommender system, providing a brief overview. It's crucial to remember that the advantages, disadvantages, and distinctive qualities listed above are approximations based on the facts at hand. As these systems develop and advance, their real capabilities and performances may change over time.

Table 6: Comparison based on strengths, weaknesses, and distinctive features

System	Strengths	Weaknesses	Unique features
EndNote Match	Uses advanced algorithms to match users' research interests with relevant journals	Limited to users of the EndNote software May not provide as extensive coverage as other independent journal recommender systems.	Offers personalized recommendations based on the user's existing library and research interests
MDPI Journal Finder	Covers a wide range of scientific disciplines	Limited to journals published by MDPI May not consider a broader range of journals outside the MDPI portfolio	Offers a user-friendly interface for browsing and searching MDPI journals. Allows users to filter journals based on specific criteria such as subject area and IF
Research Square Journal Guide	Provides recommendations based on a user's research abstract or keywords. Offers a simple and intuitive interface	Limited to journals indexed by the Research Square database.	Integrates with the Research Square platform, which offers additional services like preprint hosting and manuscript editing
JANE	Allows users to find relevant journals based on a scientific article's title and/or abstract. Covers a broad range of scientific fields	Relies on the user's input rather than analyzing the full text of the article May not provide as precise recommendations as systems that analyze the full article content	Provides suggestions for potential authors or collaborators based on article similarity
IEEE Publication Recommender	Specifically tailored for researchers in the field of electrical engineering and computer science	Limited to IEEE publications and related disciplines May not be suitable for researchers from other scientific fields	Considers the user's membership status and publication history within the IEEE community
Elsevier Journal Finder	Uses advanced analytics and semantic search techniques	Restricted to Elsevier's journal portfolio May not cover journals from other publishers comprehensively	Incorporates Elsevier's Scopus database to provide comprehensive bibliographic information and citation metrics

4. Conclusion and discussions

In this study, we conducted a comprehensive comparison of journal recommender systems to provide researchers with valuable insights on effectively utilizing these systems for identifying suitable journals to publish their work. Through our experimental comparison, we have demonstrated the effectiveness of our evaluation in assessing various widely recognized journal recommender systems. Our comparison was based on five key evaluation criteria: service quality, publication cost and policy, consistency, and sensitivity. By considering these criteria, we discovered that no single system outperforms all others across all criteria. This implies that researchers should use more than one system to effectively find a suitable journal. Furthermore, we have shown that the performance and results of these systems may vary based on several factors, such as time, indexed databases, and publisher preferences. Therefore, researchers must carefully review and revise the list of recommended journals to ensure they maximize their potential in identifying the most suitable journal for their research.

While this study provides valuable insights into journal recommender systems, it is important to consider its limitations. These limitations include:

- Restricted scope: The study may focus on a specific subset of journal recommender systems, potentially excluding other existing systems. Consequently, the conclusions and findings may not apply to all current systems.
- Evaluation criteria: The chosen evaluation criteria—such as service quality, publication cost, policy, consistency, and sensitivity—might overlook certain important aspects of journal recommender systems. Other factors, such as user interface, system accuracy, and recommendation diversity, may also be significant.
- Data quality: The effectiveness of recommender systems largely depends on the availability and quality of data. The study assumes that the provided data—such as abstracts or keywords—accurately reflects the researchers' needs. However, issues with data quality or missing information could affect the system's performance.
- Evolving systems: The field of journal recommender systems is dynamic, with new methods and systems continually being developed. As new systems emerge or significant improvements are made to existing ones, the study's conclusions may become outdated.

As the field of journal recommendation continues to evolve, further research and advancements are needed to enhance the accuracy and efficiency of these systems to better assist researchers in finding suitable journals.

One crucial area of improvement is incorporating contextual-aware recommendations based on user experience. Contextual-aware recommendations consider various factors such as the researcher's expertise, research stage, and publication history. By incorporating user information, recommender systems can provide more tailored and personalized recommendations that align with the unique needs and preferences of individual researchers. For instance, a researcher who is relatively new to a field may benefit from recommendations that prioritize journals with a lower barrier. On the other hand, an experienced researcher may require recommendations that align with his expertise and target higher-impact journals. To implement such recommendations, existing systems can leverage data such as a researcher's publication history, citation patterns, research interests, and collaboration networks. Machine learning techniques and algorithms can then analyze this data to identify relevant contexts and generate personalized recommendations. Another important area of improvement in journal recommender systems is the integration of researcher feedback and Alternative Metrics (Altmetrics) in the recommendation results. Future studies should focus on incorporating researcher feedback and preferences to enhance the evaluation process of these systems. By analyzing feedback from other colleagues, researchers can gain valuable insights into the relevance and effectiveness of a recommended journal, enabling a more effective evaluation. Additionally, the integration of Altmetrics into journal recommender systems is a promising avenue for exploration. Altmetrics can provide a broader perspective on the impact of an article by considering factors such as social media mentions, downloads, and citations. By integrating Altmetrics data into recommender systems, researchers can make more informed decisions by considering the popularity and visibility of journals within the scholarly community. This enables a more comprehensive assessment of journal impact beyond traditional citation-based metrics.

Future directions for scientific journal recommender system research may open the door to even more developments and enhancements. This can involve combining information from user profiles on sites like ORCID, citation databases, research funding information, and academic social network data. Using a variety of data sources, recommender systems can offer thorough and trustworthy recommendations. To ensure fair and relevant comparisons, common assessment metrics and benchmark datasets for journal recommender systems must be developed. Subsequent investigations may concentrate on generating benchmark datasets that encompass the intricacies of actual situations and formulating assessment criteria that surpass conventional measures of correctness. These metrics may consider elements such as diversity, novelty, and the long-term effects of the publications that are suggested. Subsequent studies ought to investigate methods for offering clear and comprehensible justifications for the suggestions produced by journal recommender systems. This may entail creating hybrid models that preserve interpretability and transparency while combining the best features of several recommendation systems.

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Compliance with ethical standards

Conflict of interest

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