ORIGINAL ARTICLE

Can generative AI improve academic journal selection decisions? Assessing traditional and algorithmic approaches in medical research

L'intelligence artificielle générative peut-elle améliorer le choix des revues scientifiques? Évaluation des approches traditionnelles et algorithmiques en recherche médicale

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Abstract

Introduction: Journal selection is a critical step in the scientific publishing process, influencing the visibility, impact, and credibility of the published work. This task has become increasingly complex due to the proliferation of journals, predatory practices, and the diversity of editorial criteria. This narrative review presented an overview of classical tools, artificial intelligence (AI)-driven platforms, and generative models (ChatGPT, Grok) used to recommend suitable journals for an unpublished manuscript.

Methods: Six tools were tested (Springer Journal Finder, Jane, Manuscript Matcher, Trinka Journal Finder, ChatGPT, and Grok) using either the abstract or full text of a clinical article on nonspecific low back pain. The results were compared based on thematic relevance, availability of bibliometric indicators, and transparency of the recommendations.

Results: Classical tools are limited by their narrow editorial scope and the absence of key indicators. AI platforms offer broader coverage but sometimes lack precision for targeted topics. Generative tools stand out for their ability to structure recommendations, although the data provided (impact factor, fees, timelines) are often inaccurate or unverifiable. Several technological biases and algorithmic limitations impact the overall reliability of these systems.

Conclusion: While AI tools expedite initial journal identification, they frequently suggest journals outside the manuscript's scope and provide incorrect journal metrics. These systems function best as exploratory instruments rather than authoritative advisors. The most successful approach positions the researcher as the primary decision-maker who employs computational assistance to survey options while exercising scholarly judgment for final determinations.

Keywords: Algorithmic Bias; Bibliometrics; Editorial Ethics; Impact Factor; Information Retrieval; Publication Standards; Research Dissemination; Scopus; Scimago; Software Validation; Web of Science

Résumé

Introduction: Le choix du journal constitue une étape déterminante du processus de publication scientifique, influençant la visibilité, l'impact et la crédibilité des travaux publiés. Cette tâche s'est complexifiée avec la multiplication des revues, l'émergence de pratiques prédatrices et la diversité des critères éditoriaux. Cette revue narrative propose un aperçu des outils classiques, des plateformes fondées sur l'intelligence artificielle (IA) et des modèles génératifs (Chat Generative Pre-trained Transformer (ChatGPT), Grok) utilisés pour recommander des revues adaptées à un manuscrit non publié.

Méthodes: Six outils ont été testés (Springer Journal Finder, Jane, Manuscript Matcher, Trinka Journal Finder, ChatGPT et Grok) à partir du résumé ou du texte intégral d'un article clinique sur les lombalgies non spécifiques. Les résultats ont été comparés selon la pertinence thématique, la disponibilité d'indicateurs bibliométriques et la transparence des recommandations.

Résultats: Les outils classiques sont limités par la restriction de leur couverture éditoriale et l'absence d'indicateurs clés. Les plateformes d'IA offrent une couverture plus large mais manquent parfois de précision sur des sujets ciblés. Les modèles génératifs se distinguent par leur capacité à structurer les recommandations, bien que les données fournies (facteur d'impact, frais, délais) soient souvent inexactes ou invérifiables. Plusieurs biais technologiques et limites algorithmiques affectent la fiabilité globale de ces systèmes.

Conclusion: Bien que les outils d'IA accélèrent l'identification initiale des revues, ils suggèrent fréquemment des titres hors champ et des métriques erronées. Leur intérêt réside dans une exploration préliminaire, l'utilisateur devant conserver un rôle central, combinant assistance computationnelle et jugement scientifique pour un choix éclairé.

Mots clés : Biais algorithmique, Bibliométrie, Diffusion de la recherche, Éthique éditoriale, Facteur d'impact, Normes de publication, Recherche d'information, Scimago, Scopus, Validation logicielle, Web of Science

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Introduction

Publishing in a reputable peer-reviewed journal is vital for scientific communication, shaping visibility, credibility, and research impact (1-4). Journal selection is a strategic decision influencing readership, citations, and career progression, yet it is challenged by over 42,500 journals (until early July 2025), predatory outlets, and shifting standards (3, 5-11). Navigating such an extensive landscape makes it increasingly difficult and time-consuming for researchers to identify the most suitable venue for their work (5). Researchers face complex decisions regarding journal scope, impact factor, indexing requirements, and ethical standards (11-14). These considerations become more challenging due to frequent changes in journal rankings, indexing criteria modifications, and annual impact factor fluctuations (15, 16). The proliferation of predatory journals further complicates the decision, necessitating careful scrutiny to avoid unethical publishing practices (3, 6, 8).

Furthermore, journals differ in their acceptance rates and editorial expectations, making it critical to align manuscript content with the journal's scope (12-14, 17). This meticulous selection process demands considerable effort, requiring authors to navigate various journal finders, publisher databases, and peer recommendations. Historically, journal selection has evolved from manual searches to structured, publisher-specific tools and, more recently, artificial intelligence (AI)-driven innovations (18-27). Early classical finders from publishers like Springer (18), Wiley (19), Elsevier (20) laid the groundwork (Box 1), followed by text-matching tools such as Jane (Journal/Author Name Estimator) (21), Jot (Journal Targeter) (22), and Edanz (23), which expanded beyond publisher limits. Till late April 2025, AI solutions like Manuscript Matcher (24) and Trinka Journal Finder (25) (Box 2), alongside Chatbots like Chat Generative Pre-trained Transformer (ChatGPT) (26) and Grok (27) offer advanced analytics and speed to streamline the process.

Box 1. Publishers' tools that help finding journals.

Publisher	Name	Link
Elsevier	Elsevier journal finder	https://journalfinder.elsevier.com
Springer	Springer journal finder	https://journalsuggester.springer.com
Wiley	Wiley journal finder	https://journalfinder.wiley.com/search?type=match
Sage	Sage journal recommender	https://journal-recommender.sagepub.co
Taylor & Francis	Taylor & Francis journal suggester	https://authorservices.taylorandfrancis.com/publishing-your-research/choosing-a-journal/journal-suggester/
MDPI	MDPI Journal Finder	https://www.mdpi.com/about/journalfinder

Box 2. Text-matching & artificial intelligence tools that help finding journals.

Full name Abbreviated name	Link	Free access
Text-matching tools		
Journal/Author Name Estimator Jane	https://jane.biosemantics.org	Yes
Journal Targeter Jot	https://jot.publichealth.yale.edu/	Yes
Editor advance Edanz	https://www.edanz.com/journal-selector	Yes (Limited)
Artificial intelligence tools		
Manuscript matcher -	https://mjl.clarivate.com/manuscript-matcher	No
Trinka journal finder Trinka	https://www.trinka.ai/features/journal-finder	Yes (Limited)

This narrative review presented an overview of classical and AI-driven journal selection tools, before evaluating their capacity to recommend suitable journals for unpublished research. We inputted an unpublished, accepted study on heat and vibration therapies for nonspecific back pain (NSBP) (28), into the following tools, using the abstract for the first four tools (ie; Sringer journal finder, Jane, Manuscript matcher, and Trinka journal finder) and the full paper for two chatbots (ie; ChatGPT and Grok):

i. Springer journal finder (classical) (18): A publisher-specific tool matching abstracts to Springer journals via Abstract and keyword similarity (Appendix 1) (29).

ii. Jane (text matching tool) (21): Uses advanced text matching techniques (Appendix 2) (30).

iii. Manuscript matcher (AI-driven) (24): Uses clustering algorithms and Web of Science data for journal recommendations (Appendix 3) (31).

iv. Trinka journal finder (AI-driven) (25): Employs concept-matching technology across a vast publication database (Appendix 4) (32).

v. ChatGPT (26) (Box 3, Appendix 5) (33) and **Grok** (27) (Box 4, Appendix 6) (34) (AI chatbots): Prompted to suggest journals based on their knowledge bases and, respectively).

Box 3. ChatGPT prompt for journal suggestions.

ChatGPT prompt

Attached is the full text of a manuscript entitled "Influence of heat therapy and/or vibration on nonspecific back pain: A prospective, open, randomized, controlled, parallel-group clinical study". I ask you to suggest 10 journals and to recommend the best one. For each journal, please report the following data (if available) into this table: Journal name, Publisher, Impact factor, Quartile, Review speed, Acceptance rate, Production speed, Open access, Open access fee, Embargo period.

ChatGPT Response

	Journal name	Publisher	Impact factor	Quartile	Review speed (days)	Acceptance rate	Production speed (days)	Open access	Open access fee	Embargo period
1	Journal of Pain Research	Dove Medical Press	2.5	Q2	~30	~30%	~10	Yes	$1,980	None
2	Pain Management	Future Medicine	2.0	Q3	~45	~25%	~15	Optional	$3,000	12 months
3	Journal of Back and Musculoskeletal Rehabilitation	IOS Press	1.8	Q3	~60	~35%	~20	Optional	$1,500	12 months
4	Clinical Rehabilitation	SAGE Publications	3.1	Q1	~50	~20%	~15	Optional	$3,000	12 months
5	Archives of Physical Medicine and Rehabilitation	Elsevier	3.5	Q1	~45	~25%	~20	Optional	$3,500	12 months
6	Journal of Orthopaedic Surgery and Research	BMC (Springer Nature)	2.2	Q2	~40	~30%	~10	Yes	$2,190	None
7	Healthcare	MDPI	2.0	Q2	~20	~40%	~5	Yes	$2,000	None
8	PLOS ONE	PLOS	3.7	Q2	~45	~30%	~10	Yes	$1,695	None
9	BMC Musculo skeletal Disorders	BMC (Springer Nature)	2.1	Q2	~40	~30%	~10	Yes	$2,190	None
10	Frontiers in Pain research	Frontiers	2.3	Q2	~35	~35%	~7	Yes	$2,950	None

Box 4. Grok prompt and Response for journal suggestions.

Grok's Prompt

Attached is the full text of a manuscript entitled "Influence of heat therapy and/or vibration on nonspecific back pain: A prospective, open, randomized, controlled, parallel-group clinical study". I ask you to suggest 10 journals and to recommend the best one. For each journal, please report the following data (if available) into this table: Journal name, Publisher, Impact factor, Quartile, Review speed, Acceptance rate, Production speed, Open access, Open access fee, Embargo period.

Grok's Response

	Journal Name	Publisher	Impact Factor	Quartile	Review Speed	Acceptance Rate	Production Speed	Open Access	Open Access Fee	Embargo Period
1	Pain	Wolters Kluwer (IASP)	7.4	Q1	~6-8 weeks	~20%	~4-6 weeks	Hybrid	$3,500	12 months
2	The Journal of Pain	Elsevier	5.0	Q1	~6 weeks	~25%	~4-5 weeks	Hybrid	$3,000	12 months
3	European Journal of Pain	Wiley	3.7	Q2	~5-7 weeks	~30%	~4-6 weeks	Hybrid	$3,200	12 months
4	Physical Therapy	Oxford University Press (APTA)	3.1	Q2	~4-6 weeks	~35%	~3-5 weeks	Hybrid	$3,000	12 months
5	Archives of Physical Medicine and Rehabilitation	Elsevier	4.0	Q1	~6-8 weeks	~30%	~4-6 weeks	Hybrid	$3,400	12 months
6	Clinical Rehabilitation	SAGE Publications	2.9	Q2	~6 weeks	~40%	~4-5 weeks	Hybrid	$3,000	12 months
7	Journal of Rehabilitation Medicine	Foundation for Rehabilitation Information	2.5	Q3	~4-6 weeks	~45%	~3-4 weeks	Gold OA	$2,000	None
8	BMC Musculoskeletal Disorders	BioMed Central	2.3	Q3	~8-10 weeks	~50%	~3-4 weeks	Gold OA	$2,690	None
9	Pain Medicine	Oxford University Press	2.8	Q2	~6-8 weeks	~35%	~4-6 weeks	Hybrid	$3,500	12 months
10	Scandinavian Journal of Pain	De Gruyter	1.8	Q3	~5-7 weeks	~50%	~3-5 weeks	Hybrid	$2,500	12 months

Methods

Classical methods

Traditionally, journal selection has relied on manual searches, publisher-based tools, and bibliographic databases such as PubMed, Scopus, and Web of Science (4, 35, 36). Tools like Springer (18), Wiley (19), Elsevier (20), Sage (37), MDPI (38), Taylor & Francis (39) journal finders/Suggesters, have long provided structured recommendations by matching the title and abstract words similarities to published research in their respective data bases (4, 35, 36). Box 1 exposes the link for some publishers' tools. However, these classical methods often involve extensive manual filtering and are publisher-specific, limiting the pool of suitable journals.

Text-matching tools

Tools like Jane (21) and Jot (22) rely on text-matching techniques using the Lucene search engine to analyze manuscript titles and abstracts for similarity to journal content. These platforms operate on rule-based algorithms, which depend on predefined criteria such as keyword frequency or title similarity to generate recommendations. While they excel at static pattern recognition, they lack machine learning or predictive capabilities, thus not fully qualifying as AI-driven (5, 40). Similarly, Edanz journal selector (23) employs semantic technology to match manuscripts with journals, offering a sophisticated yet non-AI approach. Box 2 exposes the link for the aforementioned tools.

AI-tools

The advent of AI has transformed journal selection by introducing tools that enhance efficiency and broaden options beyond publisher-specific limitations (41). In contrast, to text-matching tools, AI-powered solutions, such as Manuscript matcher (24), leverage sophisticated clustering algorithms to analyze millions of citation connections, offering data-driven journal recommendations. Machine learning enables these tools to refine recommendations over time, accommodating shifts in journal scopes, impact factors, and publication landscapes. Another notable AI-driven tool, Trinka journal finder (25), uses advanced concept-matching technology to compare a manuscript's concepts against millions of publications, ensuring recommendations align with current trends and journal scopes. These advancements highlight a shift toward more automated, intelligent systems in navigating the complex publishing landscape. Box 2 also exposes the link for these latter tools.

Generative AI

Beyond specialized tools, AI chatbots like ChatGPT (26) and Grok (27) offer valuable support in journal selection. By analyzing a manuscript abstract or research summary or the manuscript full text, both can suggest relevant journals based on their understanding of scope and focus, drawing from vast knowledge bases. They streamline the process by providing quick, tailored recommendations, and can clarify journal traits like prestige or audience. However, their lack of real-time database access and potential for overgeneralization mean they complement, rather than replace, dedicated tools and human expertise. Indeed, recent work has shown that over-reliance on AI chatbots in peer review can erode scientific rigor and transparency, underscoring the need for human oversight (42).

Practical evaluation

For classical journal selection tools like Springer Journal Finder and Jane, as well as AI-driven platforms such as Manuscript Matcher and Trinka, the title and abstract of the study "Influence of Heat Therapy and/or Vibration on Nonspecific Back Pain: A Prospective, Open, Randomized, Controlled, Parallel-Group Clinical Study" (28) were analyzed. For the generative AI systems (ChatGPT and Grok), we provided the complete manuscript text with customized instructions detailed in Box 5. We selected ChatGPT's ephemeral mode (https://chatgpt.com/?temporary-chat=true) for data security purposes, as this version automatically removes all session data, including prompts and responses, immediately after use. The resulting output featured a comparative table of 10 journals, detailing critical metrics such as publisher, impact factor, quartile ranking, review speed, acceptance rate, production timelines, open access availability, associated fees, and embargo periods.

We tried this method with the full text of our published article "Influence of Heat Therapy and/or Vibration on Nonspecific Back Pain: A Prospective, Open, Randomized, Controlled, Parallel-Group Clinical Study" (28) on April 10, 2025. Appendix 5 (33) exposes the outputs of the request. The table provided by ChatGPT ephemeral includes available information for 10 journals, including publisher, impact factor, quartile, review speed, acceptance rate, production speed, open access options, open access fees, and embargo periods. The decision to use the 'ephemeral' mode of ChatGPT was motivated by the need for a secure, transient interaction that ensures data privacy while enabling focused, real-time exploration.

Comparative assessment

Classical Tools

The Springer Journal Finder tool suggested BMC Anesthesiology as its highest-ranked option (Appendix 1) (29), which represents a notable thematic misalignment for research concerning a musculoskeletal randomized clinical trial (RCT). This illustrates that while Springer's tool is confined to its own portfolio and sometimes ranks less-relevant titles first, it can still surface appropriate journals within the publisher's domain.

Box 5. Request to be completed and to be pasted in chatbots.

Prompt

Attached is the full text of a manuscript titled entitled "XXXXXX.". I ask you to suggest 10 journals and to recommend the best one. For each journal, please report the following data (if available) into this table: Journal name, Publisher, Impact factor, Quartile, Review speed, Acceptance rate, Production speed, Open access, Open access fee, Embargo period.

	Journal name	Publisher	Impact factor	Quartile	Review speed	Acceptance rate	Production speed	Open access	Open access fee	Embargo period
1										
2										
3										
4										
5										
6										
7										
8										
9										
10										

The Jane tool ranked *Zhurnal Nevrologii i Psikhiatrii imeni S.S. Korsakova* as its primary recommendation (Appendix 2) (30), which was inappropriate for the manuscript. Additional suggestions from this platform (eg; *Brain Sciences, Journal of Clinical Medicine*) lacked sufficient topical specificity or relevance to the research subject. Only *Journal of Back and Musculoskeletal Rehabilitation and Healthcare* aligned well with the manuscript's focus on NSBP and non pharmacological therapies. Jane's text matching approach yields mixed relevance, and it offers no impact factors, review times, or fees, requiring users to independently research these aspects, making it more informative than directive.

AI driven tools

Manuscript Matcher recommended *Journal of Clinical Medicine* (Appendix 3) (31) first. Although it publishes clinical trials, its broad scope dilutes specificity for a back-pain intervention. The remainder of its top page included journals such as *journal of ondodontics, Military Medicine*, which bear little thematic connection to physical therapy or pain research. This suggests that citation cluster analysis can struggle with narrowly defined clinical topics. Trinka Journal Finder put PLOS ONE at the top (Appendix 4) (32). As a multidisciplinary open access journal, it accepts RCTs across fields, making it a viable but non specialized outlet for NSBP research. Additional recommendations from the Trinka Journal Finder, including *Pain and Therapy and BMC Musculoskeletal Disorders*, demonstrated stronger thematic congruence with the manuscript's focus on physical interventions for back pain.

Generative AI tools

The ChatGPT ephemeral model identified *Journal of Pain Research* as its primary recommendation (Box 3, Appendix 5) (33), which represents an appropriate match for a randomized controlled trial examining nonspecific back pain interventions. Beyond the comparative table (impact 2.5; Q2; ~30 days review; 30% acceptance; $1980 APC; no embargo), ChatGPT also grouped its recommendations into three actionable categories:

- High Impact & Broad Reach: PLOS ONE, *Archives of Physical Medicine and Rehabilitation*
- Specialized Focus: Journal of Back and Musculoskeletal Rehabilitation, *Journal of Orthopaedic Surgery and Research*
- Rapid Publication: *Healthcare* (MDPI), *Frontiers in Pain Research*

The categorization schema proposed by ChatGPT offers a structured evaluation framework that considers three key publication variables: impact metrics, subject specialization, and publication timeline. However, verification against established sources, including official journal websites and Journal Citation Reports data, revealed several discrepancies in the reported bibliometric parameters and processing timeframes. The thematic groupings themselves are solid, yet authors must validate all quantitative details before acting on them.

Grok (Box 4, Appendix 6) (34) identified the journal Pain as its highest-ranked recommendation, which despite its Q1 status and high impact factor, focuses predominantly on mechanistic and fundamental pain science research, potentially limiting its receptiveness to clinical intervention trials with rehabilitation modalities. A more appropriate choice from Grok's list is the European Journal of Pain, which routinely publishes RCTs and interventional studies and better aligns with the study's clinical focus. Other solid fits include Physical Therapy and Clinical Rehabilitation. As with ChatGPT, Grok's detailed metadata could not be fully corroborated, so all figures

should be independently confirmed.

Our analysis demonstrates that traditional journal selection tools (eg; Springer, Jane) identify thematically appropriate journals but exhibit significant limitations in database coverage and omit essential publication metrics, necessitating substantial researcher effort for complete evaluation. Platforms utilizing artificial intelligence (eg; Manuscript Matcher, Trinka) frequently recommend journals with excessively broad scope such as Journal of Clinical Medicine or PLOS ONE which, while accepting clinical trials, lack sufficient subject specificity for specialized research topics. The generative language models examined (eg; ChatGPT, Grok) demonstrate superior capability in identifying discipline-appropriate journals and presenting structured comparative analyses, yet their reported quantitative parameters (eg; impact factors, review timelines, article processing charges) frequently contain inaccuracies or lack verifiable sources. Thus, generative AI should be viewed as a powerful preliminary guide rather than an authoritative source: it broadens your horizon and speeds discovery, but all figures must be independently confirmed. Building on these insights, Box 6 presents a concise seven step framework to optimal journal selection.

Box 6. Practical steps for choosing the right journal.

Step	Action item
1	Define target audience and research focus. Ensure the journal aligns with the study's field and target readership.
2	Use both classical and AI-driven journal finders. Compare publisher-restricted tools and AI-powered solutions to expand options.
3	Evaluate journal impact factor, indexing, and ethical compliance. Check databases like PubMed, Scopus, and Web of Science.
4	Assess peer review policies and transparency. Opt for journals with rigorous editorial processes to ensure scientific integrity.
5	Check publication fees, funding support, and open access options. Weigh accessibility against costs.
6	Avoid common pitfalls: verify indexing claims, beware of predatory journals, and do not over-prioritize impact factor over scope fit.
7	Review submission guidelines carefully and tailor the manuscript accordingly to increase acceptance chances.

Assessing the limitations of AI-based tools in selecting journals for manuscript submission

One major limitation of generative AI systems is the phenomenon of "hallucination," whereby the model generates information that appears plausible but is factually incorrect, unverifiable, or entirely fabricated (43). In the context of journal selection, hallucinations may manifest as inaccurate impact factors, misleading acceptance rates, or fictitious processing timelines, potentially misguiding researchers who rely on such outputs without independent verification. This underscores the importance of treating AI-generated recommendations as preliminary insights that must be critically validated against authoritative sources. Beyond hallucinations, the misclassification of journals by AI tools has a significant impact on researchers' decision-making during the submission process and can lead to confusion and doubt about the credibility of these systems. These concerns are legitimate as evidenced by documented technical limitations. The AJPC system, an AI-driven tool designed to differentiate between legitimate scholarly journals and suspected predatory ones, misclassified 37.9% of journals considered 'predatory' (44) Similarly, Elsevier's AI tools have been accused of having serious shortcomings that discourage users (45).

Despite their promise in selecting journals for article submission, AI tools face significant technological limitations that can affect their reliability, particularly in terms of algorithmic accuracy or bias issues affecting the data. Indeed, there are many challenges linked to algorithmic accuracy during journal selection, due to the high dependence of these AI tools on pre-established algorithmic models based on manuscript content. Yet the accuracy of these models is subject to a major concern secondary to the fact that their:

i) Precision varies according to discipline (more precise in Science, Technology, Engineering, and Mathematics fields than in the humanities or social sciences) (46);

ii) Inappropriate classification of journals, one of the major problems of AI tools, which in practice translates into imprecision in arranging the order of priority of journals or inability to distinguish between scholarly and predatory journals (44);

iii) Disputed accuracy in predicting journals' impact factors, which varies according to the models used (75% accuracy for BERT (for Bidirectional Encoder Representations from Transformers) , lesser performance for XGBoost (for Extreme Gradient Boosting) or logistic regression) (47); and

iv) Lack of correlation with human decisions (generative AI models, such as ChatGPT-4 and Microsoft Copilot, have shown no significant correlation with human decisions, casting doubt on their ability to reproduce the nuanced judgment of experienced editors) (48).

Similarly, the reliability of these AI tools is disadvantaged by pervasive challenges related to biases affecting the data. These include bias:

i) Affecting the quality of AI models used for training. This bias explains the existing disparities in journal rankings and the consequent persistence of this problem (self-reinforcing cycle), which results in certain journals being disproportionately recommended, thus reinforcing their dominance (49);

ii) In journal recommendation algorithms, where AI systems prioritize journals with the highest number of citations or those affiliated with prestigious publishers, at the risk of neglecting high-quality specialized journals that are better suited to the user-researcher's query (50). This bias is responsible for limiting the diversity of options presented and may compromise the interest of the manuscript;

iii) Relating to the lack of transparency in decision-making, explained by the "black box" nature of AI models, making it difficult to identify and correct technological biases affecting decision-making (51); and

iv) Induced by the user-researcher, who introduces

incomplete or biased input data (eg; keywords, manuscript titles, abstract content) (52).

Conclusion

Although AI tools have the potential to revolutionize journal selection for article submission, their technological limitations, particularly in terms of algorithmic accuracy and data bias, must be taken into account. Our findings reveal that while these systems efficiently generate initial recommendations, they frequently misclassify journals and present unverifiable bibliometric data. This pattern of limitations aligns with previous research across multiple healthcare domains, where generative AI demonstrated insufficient specialized expertise despite technical sophistication. In mental health assessment, ChatGPT showed substantial shortcomings in clinical reasoning and diagnostic precision (53). Similar deficiencies appeared in exercise prescription and nutrition counselling contexts, where AI systems lacked the contextual understanding necessary for truly personalized recommendations (54, 55). The journal selection process requires researcher expertise that current algorithms cannot replicate. As Washif et al. (56) demonstrated in resistance training applications, AI offers computational efficiency but lacks the specialized judgment developed through professional experience. This expert knowledge gap consistently emerges across specialized domains where AI functions more effectively as a screening tool than as an autonomous decision system. The academic community benefits most from hybrid approaches that combine AI tools during search while maintaining human supervision. Effective implementation requires diverse training data, integrating journals from various disciplines and regions to ensure equitable representation (57). Regular algorithm audits help maintain quality control through comparison of AI recommendations with expert-curated journal lists (51). Additionally, researcher education about AI capabilities and limitations optimizes the use of these systems (52). This researcher-centered approach addresses both the practical challenges of navigating thousands of potential journals and the scholarly requirement for appropriate manuscript submissions.

DECLARATION. The authors wish to disclose that two artificial intelligence tools (ie; Deep L translator, ChatGPT ephemeral, and QuillBot) were utilized to enhance the clarity and coherence of the manuscript's writing. The tool was utilized for language refinement purposes only, ensuring the text was clear and coherent without altering the scientific content (58). After using these tools, the authors have reviewed and edited the content as necessary and take full responsibility for the content of the publication.

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APPENDICES

Appendix 1 (29). Output of the Springer Journal Finder: Publisher-Based Journal Recommendation Using Abstract Matching. DOI: https://doi.org/10.5281/zenodo.15865749

Appendix 2 (30). Output of Jane (Journal/Author Name Estimator): Text-Matching Journal Recommendation Based on Abstract Similarity. DOI: https://doi.org/10.5281/zenodo.15866088

Appendix 3 (31). Output of Manuscript Matcher: AI-Based Journal Recommendation Using Citation Clustering and Web of Science Integration Ask ChatGPT. DOI: https://doi.org/10.5281/zenodo.15866125

Appendix 4 (32). Output of Trinka Journal Finder: AI-Driven Journal Recommendation Based on Concept-Matching Algorithms. DOI: https://doi.org/10.5281/zenodo.15866149

Appendix 5 (33). Output of ChatGPT (Ephemeral Mode): Generative AI-Based Journal Recommendations from Full-Text Analysis. DOI: https://doi.org/10.5281/zenodo.15866167

Appendix 6 (34). Output of Grok: Generative AI-Based Journal Recommendations Using Full-Text Input. DOI: https://doi.org/10.5281/zenodo.15866174

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