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RESEARCH NOTE

Questioning the Classification of the Highest SJR-Ranked Organizational Behavior and Human Resource Management Journals by an Artificial Intelligence Tool

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Abstract

Although human endeavor lies at the heart of the mission of organizational behavior and human resource management (OBHRM), artificial intelligence (AI) might threaten that endeavor. Ethical OBHRM journals play a crucial role in ensuring that strictly and rigorously vetted research gets published, and this requires editorial management that does not engage in "predatory" behavior. Using an AI-driven tool (Academic Journal Predatory Checking System) that claims to differentiate "normal" from "suspected predatory" journals, the SCImago Journal Rank's top OBHRM journals ($n=59$ Q1 journals) were assessed on 23 October 2024. Surprisingly, 49% of these legacy journals were classified as "suspected predatory", a result that we consider inaccurate. A replication test of the same 59 journals on 1 November 2025 revealed that 34/59 or 58% of them were classified as "suspected predatory" journals, even though no justification or evidence was provided for this classification. Moreover, several of the journals' classifications in 2024 changed in 2025, from "normal" to "suspected predatory" ($n=14$), and vice versa ($n=9$), again without any stated reasons. Journal and publisher endeavor, including of authors, peer reviewers, editors and other stakeholders invested in ensuring quality control in these journals would surely be negatively impacted by such erroneous characterization. OBHRM researchers are alerted to this AI tool's inability to correctly or accurately classify a journal, placing it into direct conflict with human endeavor of those journals' stakeholders.

Keywords Accountability · Blacklists or watchlists · Predatory journal detector · Transparency

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1 Introduction

An impactful aspect of organizational behavior and human resource management (OBHRM) is its focus on humans as the central subject matter of excellence and achievement—or of failure—especially as humanity attempts to continually assert its place and maintain a focus on human-centric societal endeavor [1], even more so in an evolving industrial revolution that is seeing the amplified importance of artificial intelligence (AI). There is thus interest in appreciating whether AI-driven tools would be able to assist humans in important decision-making processes. Since OBHRM journals play an important societal ecosystem function by providing an understanding of human-AI interactions and interfaces as a function of organizational behavior [2], there is interest in appreciating quality-related aspects of those journals, such as their editorial management, rigor of peer review, and ethical policies.

Predatory behavior impacts both society and human resources, so it is important to be able to differentiate predatory and exploitative behaviors, including in academic publishing [3], and to seek integrated ways, such as with the use of AI, to minimize the negative impact of such behavior—including misconduct—in academic publishing [4]. There is also interest by ethicists and policy-makers in appreciating the level of scientific rigor employed by journals' editors during peer review and whether editorial management is able to detect and filter out submitted papers with questionable research practices and misconduct in the fields of OBHRM, as their publication may render the reputation of those journals questionable [5–7]. A scientifically questionable OBHRM journal, or one that engages in publication bias [8], could also result in it gaining a negative reputation if it were to publish irreproducible findings [9] or findings derived from misconduct [10]. However, there is very little empirical research—to our knowledge—that has shown and provided a fail-safe and robust method of differentiating an unreliable or questionable OBHRM journal [11] from a "predatory" one, except for some lexical differences [12]. One reason is that the taxonomy related to research misconduct is highly diversified, lending itself to subjective classifications [13]. To that end, an AI-driven tool, the Academic Journal Predatory Checking System (AJPCS),[1] was created in 2023 with the claim that it was able to differentiate "normal journals" (NJs) from "suspected predatory journals" (SPJs) [14].

The objective of this study was to apply the AJPCS to top-ranked OBHRM journals that would most likely be considered as non-predatory by OBHRM peers, as a way to test and validate the strength and legitimacy of this AI tool.

[1] http://140.113.207.51:8000/

2 Methodology

The AJPCS was used to probe whether any of the 59 Q1 SJR[2]-indexed OBHRM journals (Suppl. Table),[3] which we assumed would highly likely not be SPJs, were classified as such. To achieve this, following the instructions for use provided by the AJPCS website, the top-page URLs of these journals were manually harvested then inputted into AJPCS on 23 October 2024, and their output (NJ/SPJ status) was noted (Suppl. Table). An attempted replication was conducted on 31 October 2025, although the AJPCS website was dysfunctional. Following a complaint to the authors and architects of AJPCS (Chen et al.), the website was swiftly reactivated, and a replication was conducted on 1 November 2025.

3 Findings

Visual evidence of the 2024 and 2025 AJPCS output has been provided in the form of screenshots for each of the 59 journals (Suppl. Figure) while the NJ or SPJ classification has also been tabulated (Suppl. Table). In 2024, of the 59 journals, 29 or 49%, were classified as SPJs, and among the SPJs, 14 were published by Sage (Suppl. Table; Suppl. Figure). In 2025, the number of SPJs had increased dramatically to 58% (34/59 journals), with 16 of these having been published by Sage (Suppl. Table; Suppl. Figure). There were also a number of “flips” in classification: 14 NJ → SPJ “flips” (i.e., classified as a NJ in 2024, but reclassified as a SPJ in 2025) and nine SPJ → NJ “flips” (i.e., classified as a SPJ in 2024, but reclassified as a NJ in 2025).

4 Discussion

The issue of predatory publishing affects all authors [15], including those of OBHRM journals. The results by the AJPCS found in this study for the top-ranked 59 OBHRM journals—according to the SJR—are likely to be inaccurate, considering that all of these journals claim on their websites to implement strict peer review, editorial screening and subject matter quality control,[4] albeit with possible minor exceptions and inter-journal or inter-publisher variations. Consequently, as we see it, their publishing management is not characteristic of “predatory” behavior, nor is there systemic malfeasance related to peer review or editorial handling. This suggests that AJPCS as an AI-driven tool to assist humans in deciphering the “predatory” nature of OBHRM (or other) journals is sub-optimal [16].

The highly likely misclassification of leading OBHRM journals as SPJs by the AI-based AJPCS tool in both 2024 and 2025 fortifies similar findings and trends related to mischaracterization of thematically closely related FT50 journals [17].

[2] SCImago Journal Rank background: https://www.scimagojr.com/aboutus.php

[3] https://www.scimagojr.com/journalrank.php?category=1407

[4] Caveat emptor: just because an indexed journal’s website claims to conduct peer review does not necessarily imply that this is so, or, if it has been conducted, that it is free of imperfections.

This reinforces previous concerns about the precision and dependability of AI-based evaluations in academic publishing [18]. As far as we could tell,[5] most of these journals have established long-term credibility by ensuring the integrity of published research through rigorous editorial and peer-review processes. Consequently, their incorrect classification as a SPJ can damage the reputation of these journals, create unnecessary and invalidated distrust in the editors and publishers, and undermine the value of legitimate research efforts of authors who have decided to publish in those journals. In other words, if the AJPCS classifies a journal as a SPJ, but provides no evidence of so-called "predatory" behavior or editorial malfeasance, then that output would damage the journal's brand, and by association, that of the publisher. Therefore, improvements to such AI tools are crucial for maintaining the credibility of academic institutions, journals and publishers. More importantly, the reliance on journal management or prospective authors on the AJPCS as an AI-driven tool to guide and advise them about the correct choice of journal—even more so considering that its output is inconsistent and thus unreliable depending on the URL that is inputted [19]—is not advisable based on the likely erroneous output (false positives) that we recorded for the 59 SJR-ranked OBHRM journals, and the flux in classification (NJ → SPJ and SPJ → NJ "flips") between 2024 and 2025.

The use of AI in and by organizations and human resource management appears to be both inevitable and likely irreversible, considering current trends [20, 21]. These trends will not limit themselves to the workplace, but will also impact research and publishing, where AI will be—and is already being—abused to gain a competitive edge over competitors using dishonest and deceptive practices [22]. Prospective authors of OBHRM journals must not only not abuse AI, they should also not employ unreliable AI-driven tools like the AJPCS to base their journal-related decision-making. In addition, editors of OBHRM journals need to keep a watchful eye for authors who abuse AI to gain a competitive advantage by using their journals as a "cuckoo's nest" (i.e., for the deposit of illegitimate research) because journal content that contains undisclosed AI-generated content or whose authors have not transparently declared their reliance on AI or AI-driven tools, may suffer reputational harm should AI-related violations in academic ethics be discovered post-publication.

How then can an AI-driven detector be improved? Like large language models, such as ChatGPT, this requires the training dataset and code to be accurate and free of false positives or negatives and incorrect classifications. The architects and authors of the AJPCS not only have the responsibility of explaining the likely erroneous classification of the majority of the top (i.e., Q1) 59 OBHRM journals ranked by SJR as SPJs, they also have the responsibility of providing concrete and substantiated evidence of those journals' malfeasance, editorial misconduct or mismanagement that would have led them to be classified as "suspected predatory". In addition, and very importantly, concrete evidence and justification that clearly explains why 14 journals became SPJs in 2025 when they were NJs in 2024 (i.e., NJ → SPJ "flips") and nine

[5] This was tested crudely by running each journal's name in Google, coupled with the keywords "misconduct" and "scandal", and also assessed for volumes of retractions in the Retraction Watch database (https://retractiondatabase.org/RetractionSearch.aspx), with the assumption that excessive volumes of retractions would surely serve as an indirect reflection of poor editorial and journal management.

journals became NJs in 2025 when they were SPJJs in 2024 (i.e., SPJ → NJ “flips”), is needed. In the absence of such evidence, those journals could argue that this AI tool has falsely characterized their journals, and could thus cause harm to their brand.

An AI tool is only as good as the prompts it is fed. Thus, to ensure that accurate information is used by the AJPCS, this would require that journals be assessed individually, using a comprehensive series of quality-related benchmarks pertaining to journal management [23], which might allow a legitimate academic journal to be differentiated from a suspected “predatory” journal. Absent rigorous screening and classification, a machine-driven tool that employs inaccurate information about journals will likely mislead authors and editors alike [24].

5 Limitations

This short report provides evidence of top-ranked OBHRM journals using a single AI tool. Although we are aware of some additional efforts by other research groups to develop AI-based tools to test the non-predatory versus predatory nature of journals, those pilots appear to be even worse and more ineffective than the AJPCS, so they are not cited here. We have also relied exclusively on the SJR rankings, because it is a popular source of journal ranking, although we are conscientious of criticisms leveled at SJR due to its reliance on Scopus [25]. However, that ranking is also based on citation-based data, such as the Clarivate journal impact factor, which is a pseudo-quality parameter [26], so we recognize that reliance on the SJR rankings is likely imperfect, although we were hard-pressed to identify a more reliable listing or ranking of OBHRM journals. Finally, we decided to limit our assessment to Q1 journals, as these were decidedly the most respected and highly ranked, but a future exercise could examine all 240 journals in this SJR category.

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