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Do competitive forces tend to correct choice errors in journal selection due to imperfect attention on the part of researchers?

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Abstract

For scientists, one of the most important points to consider is the right journals for research, current awareness, and publication of results. However, if scientists suffer from imperfect attention, they would pay attention to only a subset of journals in the subject category. Under this scenario, chief editors might affect preferences by using the journal's salience to influence what scientists pay attention to. In this paper, we are going to address two related research questions: First, do competitive forces tend to correct choice errors in journal selection due to imperfect attention on the part of researchers? Second, does journal selection based on the choice of journal impact factor (JIF) quartiles produce the best journals in a multivariate indicator space? Using an attention game, we find that the competition between journals in the presence of positive externalities between the visibility of journals, pushes the best journals to increase their salience enough to overcome the distorting effects of imperfect attention. However, a visibility strategy based on JIF quartiles exhibits negative externalities between the ability of journals to attract attention. Therefore, we cannot guarantee that the most visible journals using quartiles are the preferred journals based on their impact on the development of the discipline. To illustrate this theoretical result, for the subject categories of Information Science & Library Science, and Computer Science, Artificial Intelligence (both in 2022), we found that the JIF quartiles do not reveal the impact classification of journals in a multivariate space of seven indicators.

Keywords Imperfect attention · Journal impact · Journal visibility · Competitive forces · JIF quartiles · Multivariate indicator space · Unsupervised statistical classification

Introduction

For scientists working in academia and in public and private companies, one of the most important points to consider is the selection of the appropriate journals for publication of results, current awareness, and research (Tenopir & King, 2007; Tenopir et al., 2009). However, if scientists suffer from imperfect attention, they would pay attention to only a subset of journals in the subject category (Bordalo et al., 2016; Garcia et al., 2018). For example, the researcher's salient journals in a journal citation reports (JCR) category may be

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the journals in the first quartiles (Garfield, 2006; Garcia et al., 2012; Campanario, 2018). However, the JCR subject classification system has inherent limitations. In the Library and Information Science classifications, for example, subfields such as information retrieval, librarianship, and health information management co-exist, but receive different levels of citation attention. This discrepancy affects how journals are ranked within quartiles, which is not only a function of competitive forces, but also of structural biases within the citation databases (Mech et al., 2020; Larivière & Sugimoto, 2019). In this scenario, Albarran and Ruiz-Castillo (2011) also found that "around 70% of the scientific publications receive fewer citations than average and 9% of the publications can be designated as highly-cited." In the sample data set used in Albarran and Ruiz-Castillo (2011), "this 9% of highly cited articles accounts for 44% of all citations received." Furthermore, Seglen (1992) found that "the citational variability between articles in a journal is less (semilog linearity) than in the corresponding field as a whole, suggesting that each journal represents a select, stratified sample of the field."

When selecting a journal for publication, a scientist could, for example, search for an answer within the scope of the journal impact factor (JIF) quartiles (Liu et al., 2016; Bormann & Marx, 2014). The journal impact factor was originally proposed to help librarians decide on journal subscriptions, after ranking them according to their impact factor (Garfield, 2006). Thus, the JIF score is the average number of citations received by papers published in a particular journal within the immediate two proceeding years (Garfield, 2006): "the total number of citations, received by a journal in a given year, to articles published in the two immediately preceding years, divided by the total number of citable items published by that journal in the past two years, such as primary research articles, reviews, and commentary, not news items, editorials, or other non-research materials." However, a good impact factor score depends on the discipline of the journals. For example, while an impact factor of 2 may be considered high in a certain field (e.g., history), it may be low in a different field of research (e.g., oncology) (Mech et al., 2020; Larivière & Sugimoto, 2019). In addition to the discipline of the journals, the impact factor is also affected by its calculation formula, because only citations from the previous two years are considered and in some fields it takes longer to discover new findings for dissemination and citations (Mech et al., 2020; Larivière & Sugimoto, 2019). Furthermore, some researchers think that it is not a valid tool because the JIF scores are skewed from the normal distribution (Seglen, 1992). For example, general journals receive more citations than specific journals, or some types of citable articles, for example, review articles are cited more than any other type of research articles, such as case reports. Moreover, the impact factor has been encouraging exploitative practices such as self-citation, non-source publications, duplicate publications, and selective publication of highly citable literature, seeking to increase the quality and prestige of journals (Opthof, 2013; Heneberg, 2016; Chorus & Waltman, 2016; Cronin & Sugimoto, 2015; Wilhite & Fong, 2012; Alberts, 2013).

Although the system is highly debated and criticized for distorting good scientific practices (Callaway, 2016; Nature, 2016; Larivière & Sugimoto, 2019; Mech et al., 2020; Waltman & Traag, 2021), the JIF quartiles determine a classification system that is easy to use in practice as an indicator of the relative importance of a journal in a certain field of research (Liu et al., 2016). Therefore, journals in the first or second quartile tend to attract the attention of academics, policymakers, and practitioners in the research field to a greater extent than journals in the third or fourth quartile (Liu et al., 2016; Bormann & Marx, 2014). The classifications of journals based on the JIF score are so relevant that there are even editors who try to manipulate this indicator (Campanario, 2018; Yang et al., 2016; Davis, 2017). There are several ways a journal can artificially inflate its JIF, from inviting or accepting more citable types of articles (for example, review articles rather than original research) to scheduling those more citable articles earlier in the calendar (allowing more time to accumulate citations), some editors may even encourage authors to cite recent articles from their journal during peer review (Betts et al., 2024). In any case, in this introduction we do not attempt to make an in-depth analysis of the journal impact factor. Instead, we refer for example to the works of Larivière and Sugimoto (2019); Mech et al. (2020); Waltman and Traag (2021); Triggle et al. (2021); Zeng et al. (2024) which presented a systematic survey of the pros and cons, and an overview of alternative measures.

Under this scenario, when scientists select the right journal for research and publication, an attention game emerges that describes a natural competition between journals (Heintzelman & Nocetti, 2009; Bordalo et al., 2016). In this competition, journals want to be selected by those researchers with imperfect attention. For example, journal editors can establish the journal's salience by accepting certain articles with high visibility and reach (Garfield, 2006; Campanario, 2018). In a significant percentage of subject categories (17.5%), the leading journals according to their JIF score are review journals that did not publish any articles considered original research articles (Campanario, 2018). The 'Nature effect' in academic communication described in (Garcia et al., 2018) represents another good example of a scientific journal introducing a different strategy that allowed Nature to achieve greater visibility. This strategy consisted of a drastic and unilateral reduction in the complexity of writing. At the same time, the rejection rate increased significantly when more demanding manuscript selection was carried out. As a result, Nature gained reader attention by increasing the importance and accessibility of its articles (Garwin & Lincoln, 2003; Garcia et al., 2018).

In such a way, the journal editors might affect preferences by using salience to influence what scientists pay attention to (Heintzelman & Nocetti, 2009; Bordalo et al., 2016). If each editor-in-chief has chosen a visibility strategy and no journal can benefit from changing strategies while the others keep theirs unchanged, then the current set of strategic options constitutes a Nash equilibrium (Nash, 1951; Osborne, 2004).

In this way, journal editors can influence the subset of salient journals that scientists actively considers. However, do competitive forces tend to correct selection errors due to imperfect attention on the part of scientists? Does journal selection based on the choice of quartiles produce the best journals in a multivariate indicator space? What leads us to ask this question is the existence of negative externalities in the attention game that uses journal impact factor (JIF) quartiles to define a visibility strategy. For example, journals can increase their JIF scores and still decrease their visibility by moving from an upper quartile to a lower quartile, because other journals have increased their JIF scores even further. On the contrary, Campanario (2018) found that "being a JIF leader in a given subject category does not necessarily mean being the most productive journal in that category." This may happen, for example, because the leader is the journal that published the lowest number of citable items [see Campanario (2018) for further details].

In this paper we find that for this problem that can appear when using a certain visibility strategy, a possible solution would be to require properties to the probabilities of the journal being noticed that guarantee external benefits in the attention game (Manzini & Mariotti, 2016; Garcia et al., 2019). These properties would be the positive effect that one journal imposes on another in the subject category. Under these external benefits, the editors-in-chief of the best journals do not care whether worse journals attract attention or not. In this situation, the journal's profitability only depends on the probability that scientists will notice even better journals in the category. Therefore, the consequence of positive externalities will be that a better journal will gain greater benefit from increasing salience than an inferior journal because there are more situations in which it is selected conditional on attracting attention (Manzini & Mariotti, 2016; Garcia et al., 2019). As a result, in attention games with positive externalities, the editor-in-chief of the top journal generally has a stronger incentive to invest in salience. In this article we are going to present a basic series of positive externalities that can be introduced for this purpose.

In this paper, we also find that a visibility strategy based on JIF quartiles does not support the properties of positive externalities, and the attention game does not behave well. Therefore, we cannot guarantee that the most visible journals using quartiles are the preferred journals based on their overall impact on the development of the discipline. To further illustrate this point, we also perform a classification of journals that share similar characteristics in a multivariate indicator space, and we study the relationship between the JIF quartiles and the journal classification in this multivariate space (Palacios-Huerta & Volij, 2004; Garcia et al., 2012). For this analysis, we consider the subject categories of Information Science & Library Science, and, Computer Science, Artificial Intelligence, both in 2022.

In the following, Sect. 2 presents a well-behaved attention game that describes a natural competition between journals that want to be selected by scientists who exhibit imperfect attention. In these attention games, the journal editors can establish the salience of journals using a visibility strategy. Next, Sect. 3 shows that there are negative externalities in an attention game that uses the JIF quartiles to define a visibility strategy. In this section we find that the competition between journals, in the presence of positive externalities, pushes the best journals to increase their salience enough to overcome the distorting effects of imperfect attention. Section 4 presents a classification of journals that share similar characteristics in a multivariate indicator space. In this section we find the relationship between the JIF quartiles and the journal classification in the multivariate space. Finally, we conclude by suggesting some implications and limitations of our analysis in Sect. 5.

Basic model

In today's dynamic and highly competitive landscape of scientific publishing, establishing a strong journal presence is essential to success. However, following (Bordalo et al., 2016; Garcia et al., 2018, 2019), researchers in the research field can suffer from imperfect attention. This means that they only pay attention to a subset of journals in the subject category. We consider the finite set of journals $A = \{a_1, \dots, a_n\}$ in a subject category (see Table 1). Within the finite set A, the salient journals are the subset of publication venues to which a researcher pays attention.

In this scenario, let σ_i, with $\sigma_i \in S$, be the visibility of journal a_i. Therefore, in the ever-evolving world of scientific publishing, the value of journal visibility σ_i can be the cornerstone of a successful publishing strategy for journal a_i. The aim of a journal's visibility strategy is to promote the academic journal, for example, to ensure that the contributions of the different published studies are effectively communicated to readers and relevant stakeholders. This value of journal visibility σ_i plays a pivotal role in shaping readers' perceptions and influencing authors' decisions when choosing a journal to publish their research work.

In this situation, the visibility of an academic journal, as measured by σ_i, refers to the degree to which the journal is exposed to its target audience (see Table 1). It involves making the journal recognizable and familiar across various classifications. For

Table 1 Model parameters and their meaning

Set A	The finite set of journals $\{a_1, \ldots, a_n\}$ in a subject category
Visibility score σ_i	The visibility of journal a_i. It refers to the degree to which the journal a_i is exposed to its target audience
A journal's visibility strategy	It involves promoting the academic journal, giving it visibility on a regular basis and positioning it positively in the most widely used rankings
Visibility profile σ	The list of visibility scores $\sigma = (\sigma_1, \ldots, \sigma_n)$
Attention probability $p_i(\sigma)$	For each journal a_i, $p_i(\sigma)$ associates a visibility profile σ with the probability of being a salient journal in a subject category. Salience refers to the degree to which a particular journal stands out and captures a researcher's attention within a given category
Preference order *Impact*$(\cdot)$	Scientists evaluate the salient journals using the preference order *Impact*$(\cdot)$ based on the recognition of the journal impact on the development of the discipline
Probability $P_i(\sigma)$	The probability that a researcher prefers journal a_i. It is the probability that a_i is in the subset of salient journals and that none of the most preferred journals a_k in the subject category, with $k < i$, is also in the subset of salient journals (i.e., they do not attract attention)
Cost $c_i(\sigma_i)$	The costly effort of achieving a certain visibility σ_i
$Pay_i(\sigma) = P_i(\sigma) - c_i(\sigma_i)$	The payment to each journal a_i at a visibility profile σ
(A, S, Pay)	An attention game in a subject category, with S being the visibility strategy for each journal

example, the value of journal visibility σ_i can refers to the Journal Impact Factor (JIF) score for the journal a_i. Therefore, using the JIF score to measure the visibility of journal a_i, it follows that the visibility value σ_i is given by the average frequency with which an article is cited in the journal a_i, during a given time period (Hoeffel, 1998; Garfield, 2006; Waltman & Traag, 2021).

When the journal is visible, potential authors can easily find it, for example, while exploring digital spaces. But what does a journal's visibility strategy consist of? It involves promoting the academic journal, giving it visibility on a regular basis and positioning it positively in the most widely used rankings. In our model, we assume that the probability of a_i being a salient journal depends on the value of journal visibility σ_i. For the finite set of academic journals $A = \{a_1, \ldots, a_n\}$, a visibility profile σ denotes the list of visibility scores $\sigma = (\sigma_1, \ldots, \sigma_n) \in S^n$.

Let $p_i(\sigma)$ be the the probability that a_i is a salient journal in the subject category, given that the list of visibility scores is σ (see Table 1). Therefore, the effectiveness of the visibility profile $\sigma = (\sigma_1, \ldots, \sigma_n)$ is described by the probability values $p_i(\sigma)$. For each journal a_i, $p_i(\sigma)$ associates a visibility profile σ with the probability of being a salient journal in a subject category. Salience refers to the degree to which a particular journal stands out and captures a researcher's attention within a given category.

We also assume that every researcher maximizes a preference order *Impact*$(\cdot)$ on the researcher's set of salient journals (see Table 1). To this end, scientists evaluate the salient journals using a preference order *Impact*$(\cdot)$ based on the recognition of the journal impact on the development of the scientific discipline (González-Pereira et al., 2010). For example, scientists can compare the impact of the salient journals in a multivariate indicator space [see Garcia et al. (2012) for further details). Thus, the position of a journal a_i in the preference ranking is: $Impact(a_i) > Impact(a_j)$ iff $1 \le i < j \le n$. In this situation, journal a_i is preferred over journal a_j and would therefore be selected if it is able to attract the researcher's attention.

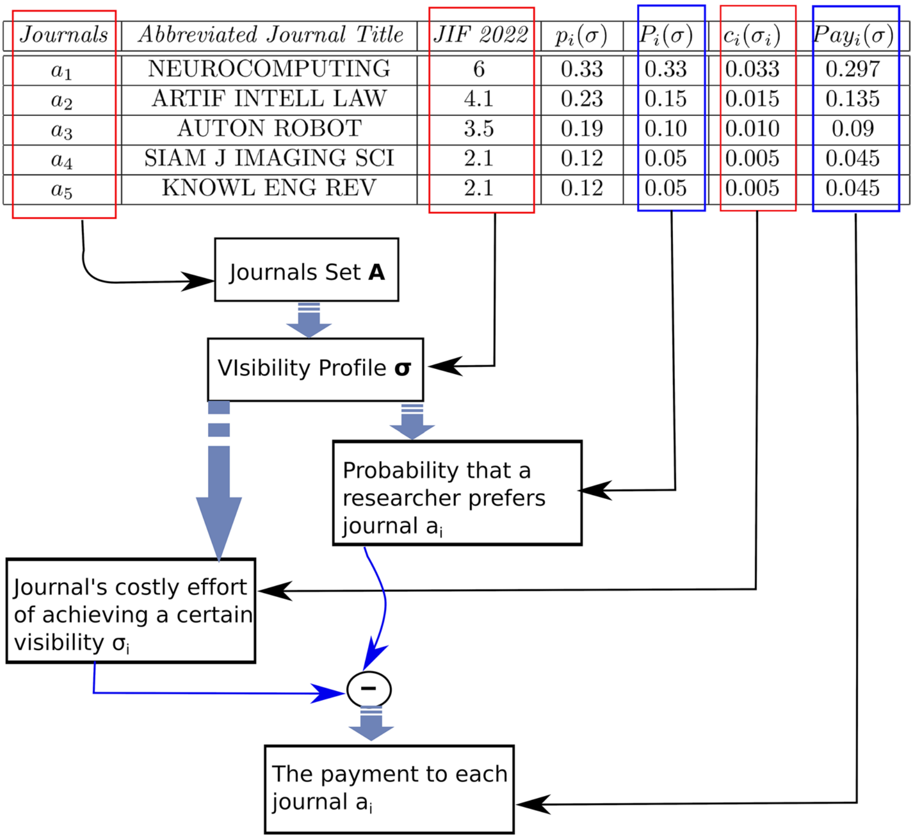
Therefore, given a visibility profile σ, it follows that the probability that a researcher prefers a journal a_i is the probability that this journal a_i is in the subset of salient journals and that none of the most preferred journals a_k in the subject category, with $k < i$, is also in the subset of salient journals (i.e., they do not attract attention):

$$P_i(\sigma) = p_i(\sigma) \prod_{k<i} (1 - p_k(\sigma)). \tag{1}$$

In this attention game, the payment to each journal a_i is the probability $P_i(\sigma)$ that a researcher prefers journal a_i, at a visibility profile σ, minus a cost $c_i(\sigma_i)$ that represents the costly effort of achieving a certain visibility σ_i:

$$Pay_i(\sigma) = P_i(\sigma) - c_i(\sigma_i). \tag{2}$$

Therefore, $(A,\ S,\ Pay)$ denotes an attention game in a subject category, where A is the set of journals $\{a_1, \ldots, a_n\}$, S is the visibility strategy set for each journal, and $Pay = (Pay_1, Pay_2, \ldots, Pay_n)$ represents the payment to each journal. Figure 1 and Table 1



Journals	*Abbreviated Journal Title*	*JIF 2022*	$p_i(\sigma)$	$P_i(\sigma)$	$c_i(\sigma_i)$	$Pay_i(\sigma)$
a_1	NEUROCOMPUTING	6	0.33	0.33	0.033	0.297
a_2	ARTIF INTELL LAW	4.1	0.23	0.15	0.015	0.135
a_3	AUTON ROBOT	3.5	0.19	0.10	0.010	0.09
a_4	SIAM J IMAGING SCI	2.1	0.12	0.05	0.005	0.045
a_5	KNOWL ENG REV	2.1	0.12	0.05	0.005	0.045

Fig. 1 The different elements integrated into an attention game in a subject category

illustrate the different elements integrated into the research model. In the following we define when an attention game is well-behaved.

A well-behaved attention game in a subject category: Increasing the a_i's visibility score σ_i strictly increases the probability of journal a_i to attract attention $p_i(\sigma)$.

Figure 2 illustrates a well-behaved attention game and shows its main difference from a non-well-behaved game. Therefore, a well-behaved attention game describes a natural competition between journals that want to be selected by researchers who show imperfect attention. In this attention game, journal editors can establish the salience of the journal, for example, by accepting certain articles with high visibility and reach. If each editor-in-chief has chosen a visibility strategy and no journal can benefit from changing strategies while the others keep theirs unchanged, then the current set of strategic options constitutes a Nash equilibrium, (Nash, 1951; Osborne, 2004; Bordalo et al., 2016; Manzini & Mariotti, 2016). However, do competitive forces tend to correct choice errors due to imperfect attention on the part of researchers? In the next section we will find an answer to this question.

The importance of positive externalities in an attention game

In this digital and information-rich age, journal quartiles often serve as beacons guiding researchers toward journals that amplify the visibility of their articles (Garfield, 2006). However, selecting a right journal for research or publication based on quartile choice does not necessarily have to produce the best journal (Garcia et al., 2012). Using a game theory-based approach, the reason is that there are negative externalities in an attention game that uses JIF quartiles to define the visibility strategy (Campanario, 2018). Thus, journals can increase their JIF scores and still decrease their visibility and reach by moving from an upper to a lower quartile because other journals have increased their JIF scores further.

For example, in the subject category of Computer Science, Artificial Intelligence, Neurocomputing increased the JIF score from 5.71 to 5.77 between 2020 and 2021, but nevertheless, this journal moved from the Q1 quartile to the Q2 quartile (see Fig. 3). This

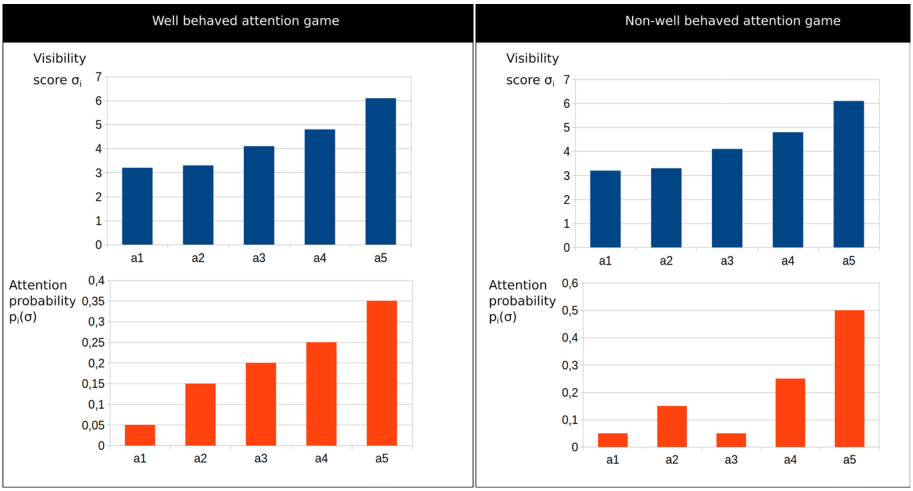


Fig. 2 (Left) A well-behaved attention game; (Right) A non-well-behaved attention game

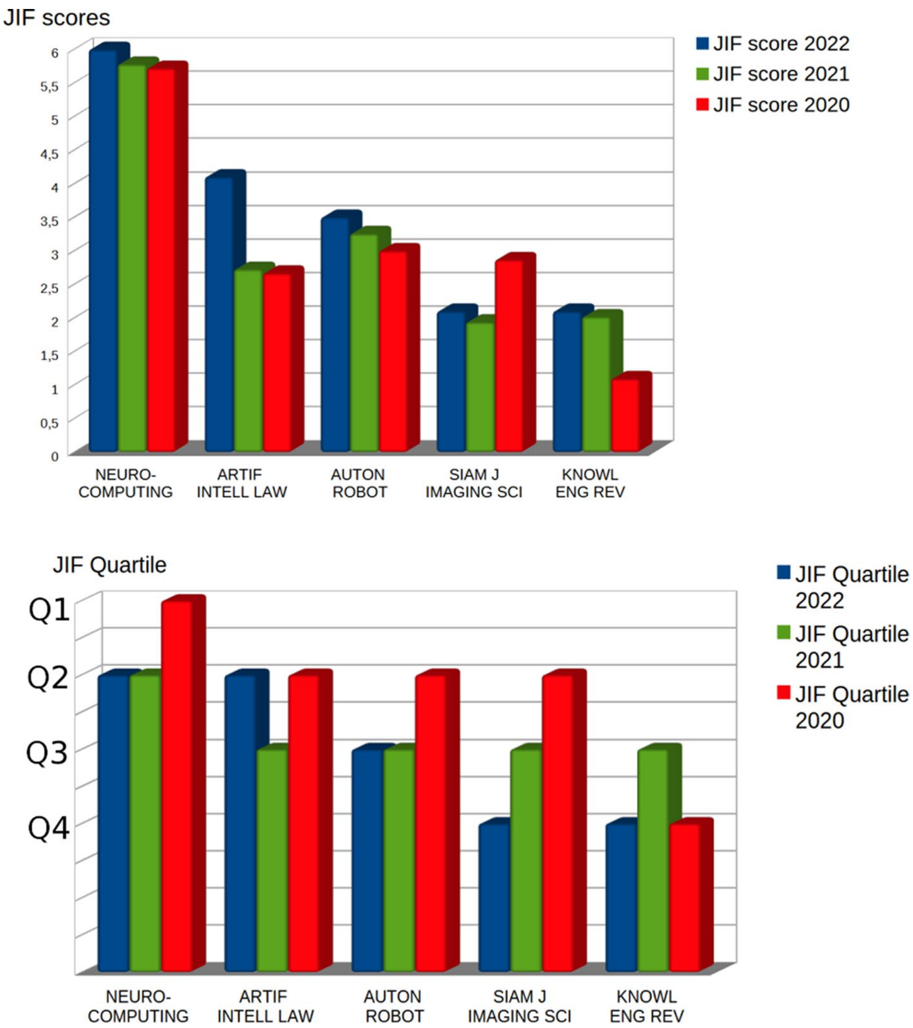


Fig. 3 In the subject category of Computer Science, Artificial Intelligence, journals can increase their JIF scores and still decrease their visibility by moving from upper to lower quartiles

is illustrated in Table 2. Similarly, Autonomous Robots increased the JIF score from 3 to 3.255 between 2020 and 2021, but this journal moved from the Q2 quartile to the Q3 quartile (see Fig. 3). The same table and figure also show other similar examples.

In the subject category of Information Science & Library Science, Scientometrics increased the JIF score from 2.86 to 3.23 between 2019 and 2020, but nevertheless, this journal moved from the Q1 quartile to the Q2 quartile (see Fig. 4). This is illustrated in Table 3. Similarly, MIS Quarterly Executive increased the JIF score from 4.08 to 4.37 between 2019 and 2020, but this journal went from the Q1 quartile to the Q2 quartile (see Fig. 4). Table 3 shows several similar situations in the subject category.

The visibility problem using journal quartiles arises from the negative externalities between the ability of journals to attract attention. A possible solution would be to impose conditions on the probabilities of the journal being noticed, p_i, that guarantee external

Table 2 In Computer Science, Artificial Intelligence, journals can increase their JIF scores and still decrease their visibility by moving from an upper quartile to a lower quartile

JCR Category: COMPUTER SCIENCE, ARTIFICIAL INTELLIGENCE						
Abbreviated journal title	JIF 2022	JIF quartile 2022	JIF 2021	JIF quartile 2021	JIF 2020	JIF quartile 2020
NEUROCOMPUTING	6	Q2	5.779	Q2	5.719	Q1
ARTIF INTELL LAW	4.1	Q2	2.723	Q3	2.667	Q2
AUTON ROBOT	3.5	Q3	3.255	Q3	3	Q2
SIAM J IMAGING SCI	2.1	Q4	1.938	Q3	2.867	Q2
KNOWL ENG REV	2.1	Q4	2.016	Q3	1.094	Q4

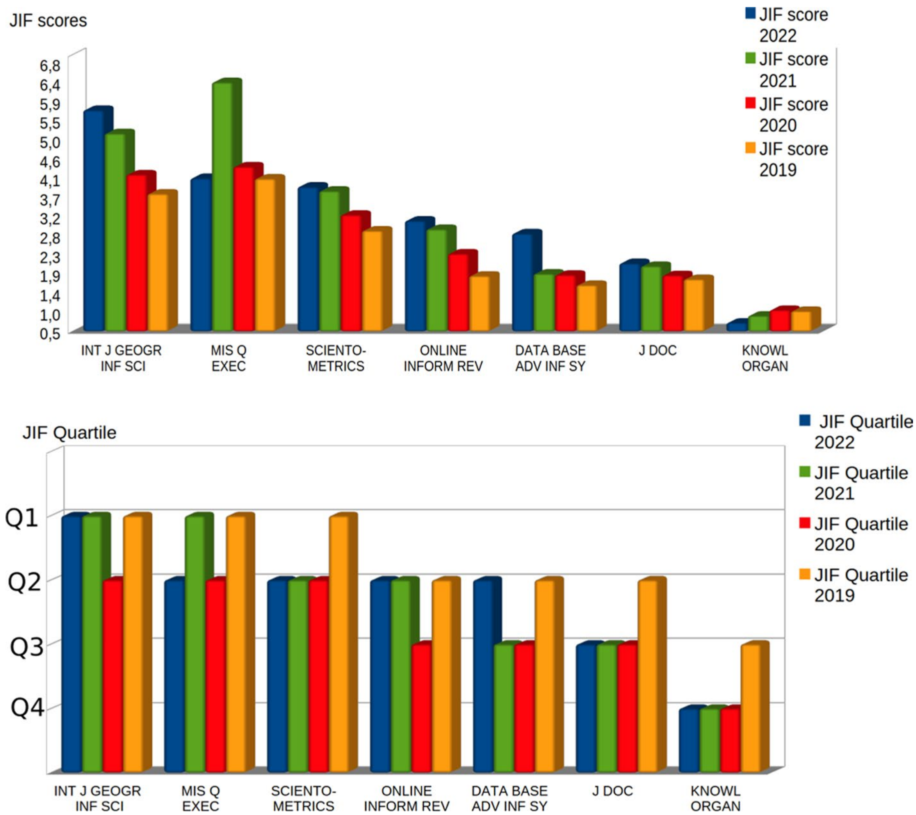


Fig. 4 In the subject category of Information Science & Library Science, journals can increase their JIF scores and still decrease their visibility by moving from upper to lower quartiles

benefits in the attention game. These conditions would be the positive effect that one journal imposes on another in the subject category. In this situation, the editor of the best journal in a category should only worry about the own probability p_i of being noticed. On the contrary, if the probabilities p_i decrease with the visibility of other journals, an increase in

Table 3 In Information Science & Library Science, journals can increase their JIF scores and still decrease their visibility by moving from an upper quartile to a lower quartile

JCR category: INFORMATION SCIENCE & LIBRARY SCIENCE								
Abbreviated journal title	JIF 2022	JIF quartile 2022	JIF 2021	JIF quartile 2021	JIF 2020	JIF quartile 2020	JIF 2019	JIF quartile 2019
INT J GEOGR INF SCI	5.7	Q1	5.152	Q1	4.186	Q2	3.733	Q1
MIS Q EXEC	4.1	Q2	6.353	Q1	4.371	Q2	4.088	Q1
SCIENTOMETRICS	3.9	Q2	3.801	Q2	3.238	Q2	2.867	Q1
ONLINE INFORM REV	3.1	Q2	2.901	Q2	2.325	Q3	1.805	Q2
DATA BASE ADV INF SY	2.8	Q2	1.854	Q3	1.828	Q3	1.588	Q2
J DOC	2.1	Q3	2.034	Q3	1.819	Q3	1.725	Q2
KNOWL ORGAN	0.7	Q4	0.867	Q4	1.000	Q4	0.977	Q3

the journal's visibility would be more profitable the lower the visibility of its competitors. This effect is illustrated in Fig. 5. However, the external benefit of a "cross-monotonicity" property eliminates this effect. This positive externality can be expressed as follows:

Cross-monotonicity: A journal cannot harm the visibility of other journals in the category by increasing its own visibility.

Under this scenario, the better journal may still not want to follow a worse journal in increasing its visibility if that increase becomes less useful when the worse journals also increase theirs. However, a "weak supermodularity" property eliminates precisely this adverse situation. It is expressed in the following way.

Weak supermodularity: The effectiveness of a journal in gaining visibility is greater with the salience of the other journals in the category.

This property of weak supermodularity is illustrated in Fig. 6.

These properties are, therefore, external benefits in the attention game between journals in the category. Such externalities impose positive effects of their own salience on the other journals: the condition of 'weak supermodularity' that acts on the first differences of the probabilities p_i, and the condition of 'cross-monotonicity' that acts on the absolute salience levels.

However, we also need conditions to ensure that if journals with lower quality do not produce greater salience in equilibrium, it does not derive from either lower levels of resources or higher unit costs to produce salience. This way, each journal can achieve a certain visibility at exactly the same cost or benefit (e.g., journals a_2 and a_3 in Fig. 7). These conditions are defined as follows.

A symmetric attention game in a subject category: (i) Holding the salience of all journals in a category fixed except for journals a_i and a_j, if a_i and a_j reach a certain visibility through their editorial criteria and processes, the effectiveness of this visibility profile to attract attention in the field is the same for each journal; (ii) the costly effort to achieve a given visibility score is the same for a_i and a_j.

The consequence of the positive externalities that result from the stated conditions is that the better journal has a greater benefit from increasing its salience than an inferior journal because there are more situations in which it is selected conditional on attracting

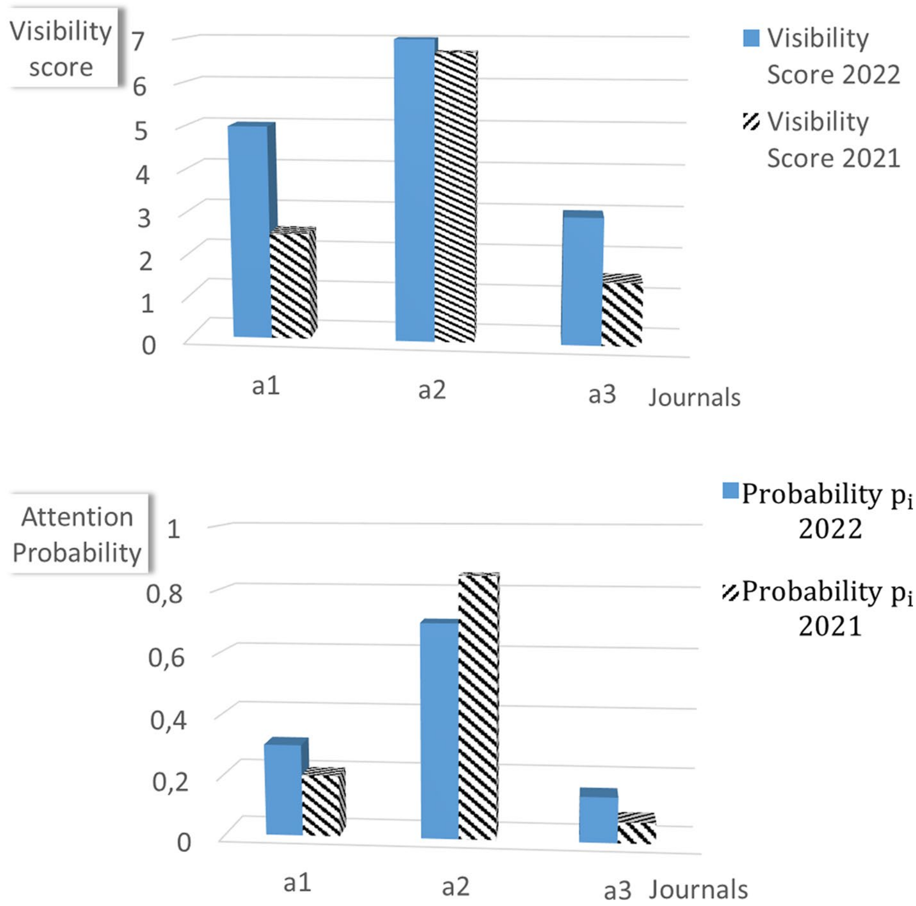


Fig. 5 If the attention probability of journal a_2 decreases with the visibility of journals a_1 and a_3, an increase in the journal's visibility would be more profitable the lower the visibility of its competitors. However, the external benefit of a "cross-monotonicity" property eliminates this effect

attention. Therefore, the editor-in-chief of the top journal generally has a stronger incentive to invest in salience. Next, a mathematical result demonstrates that, under these positive externalities, competition between journals pushes the best journals to increase their salience enough to overcome the distorting effect of imperfect attention.

Proposition. *Let σ be a pure strategic equilibrium of an attention game (A, S, Pay) that is symmetric, well-behaved, and has the properties of weak supermodularity and cross monotonicity.*

In equilibrium, the best journals in the subject category A are also the ones most likely to attract attention in the category (i.e., they are also the most salient journals).

Proof To prove this mathematical result we have to find the equilibrium σ of the pure Nash strategy for the attention game (A, S, Pay) that verifies the properties of positive externalities, symmetry, and behaves well. Since Proposition 2 of Manzini and Mariotti (2016) proposed a similar game with the same properties and behavior, here we have used the same

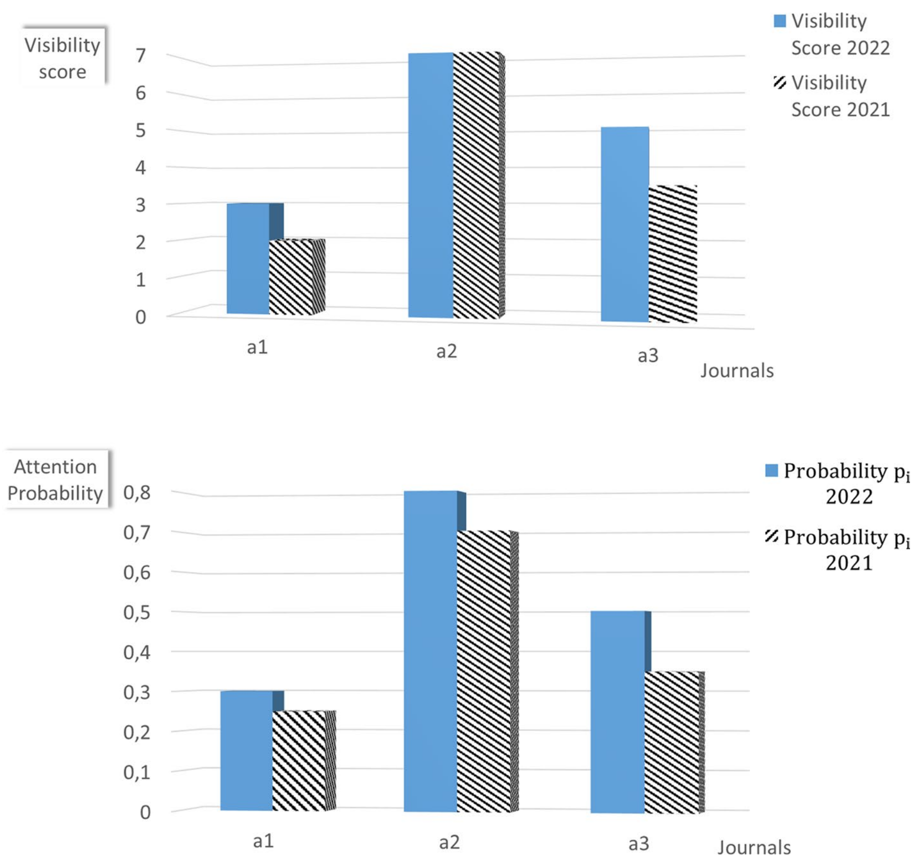


Fig. 6 The effectiveness of journal a_2 in gaining visibility is greater with the salience of the other journals a_1 and a_3 in the category

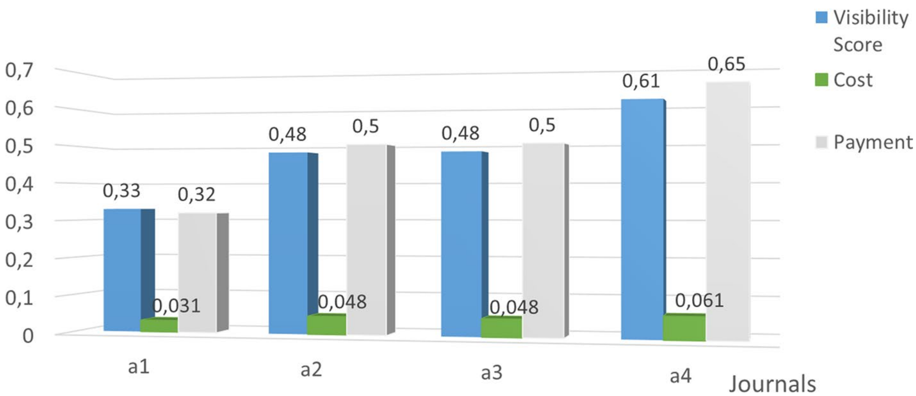


Fig. 7 Journals a_2 and a_3 can achieve a certain visibility at exactly the same cost or benefit

approach described in Manzini and Mariotti (2016) to calculate this equilibrium. For brevity, we have not shown the details of the demonstration in this work, but we can do so upon request. □

However, when the attention game is not symmetric, does not behave well, or does not verify the conditions of weak supermodularity or cross monotonicity, these equilibrium properties may break down and the most salient journals may not faithfully reveal their overall impact.

For example, we have already shown in Tables 2 and 3, that a visibility strategy based on JIF quartiles does not support the properties of positive externalities, and the attention game does not behave well. Therefore, in this situation we cannot guarantee that the most visible journals are the preferred journals based on their impact. In the next section we will analyze this point in greater detail.

Journal classification in a multivariate indicator space

Now, we find the relationship between the JIF quartiles and the journal classification in a multivariate indicator space. To this analysis we consider the subject categories of Information Science & Library Science, and, Computer Science, Artificial Intelligence, both in 2022. We performed an unsupervised statistical classification of journals in three impact classes: highest impact, medium impact, and lowest impact journals. The seven variables considered in the multivariate indicator space were (see Garcia et al. (2012) for further details): Scimago journal ranking, h-index, eigenfactor score, article influence score, immediacy index, journal impact factor, and 5-year impact factor.

In unsupervised statistical classification, the optimal impact classes are those whose multivariate within impact class variance is minimal (Garcia et al., 2012). In our experiment to achieve this optimization we followed the approach used in (Abonyi et al., 2011; Garcia et al., 2012) and therefore the unsupervised statistical classification was calculated using fuzzy maximum likelihood estimation (FMLE) clustering. This is because fuzzy clustering algorithms take into account uncertainty related to the transition zones of impact classes. This allows overlapping impact classes and therefore introduces a property of some degree of confusion regarding the attribution of impact classes. Furthermore, it also allows for a certain level of vagueness in terms of the definition of impact classes in the sense, for example, of when a journal has a medium impact within the subject category.

In our study, we implemented a fuzzy clustering using the FMLE algorithm (Abonyi et al., 2011). However, the FMLE was initialized with the membership values obtained using the fuzzy k-means algorithm. In this way we correct the sensitivity problems of the FMLE algorithm that can make it unstable and dependent on the initial values. This problem arises from the fuzzy cluster membership distance that follows an exponential dependence in the FMLE algorithm. However, by initializing it using a fuzzy k-means we correct this problem, since in this case the class membership follows the inverse square law, which avoids problems of sensitivity to the initialization conditions (Gath & Geva, 1989).

For the subject category of Information Science & Library Science (in 2022), Tables 4 and 5 (fifth column) illustrate the membership probabilities of the fuzzy partition using the FMLE algorithm. In these tables, the value of u_{ki} represents the membership probability of the ith journal to the kth class group, with $k = 1, 2, 3$. Thus, u_{1i} corresponds to the highest impact (HI) class, u_{2i} to the medium impact (MI) class, and, u_{3i} to the lowest impact (LI)

Table 4 Relationship between the JIF quartiles (at the 2022 edition) in Information Science & Library Science and the journal classification in three impact classes

JCR category: INFORMATION SCIENCE & LIBRARY SCIENCE (2022)

JIF quartile	JIF	Abbreviated journal title	Impact class	Membership values		
				u_{1i}	u_{2i}	u_{3i}
Q_1	21.0	INT J INFORM MANAGE	HI	1.000000	0.000000	0.000000
	9.5	EUR J INFORM SYST	HI	1.000000	0.000000	0.000000
	8.6	INFORM PROCESS MANAG	HI	1.000000	0.000000	0.000000
	7.8	GOV INFORM Q	HI	1.000000	0.000000	0.000000
	6.5	J ENTERP INF MANAG	MI	0.000001	0.999999	0.000000
	6.3	INFORM ORGAN-UK	HI	1.000000	0.000000	0.000000
	5.7	INT J GEOGR INF SCI	HI	0.982407	0.017593	0.000000
	5.6	J INF TECHNOL-UK	HI	0.999997	0.000003	0.000000
	5.6	TELECOMMUN POLICY	MI	0.000000	1.000000	0.000000
	4.9	INFORM SYST RES	HI	1.000000	0.000000	0.000000
Q_2	4.4	INFORM TECHNOL PEOPL	MI	0.000000	1.000000	0.000000
	4.4	J HEALTH COMMUN	MI	0.003024	0.996976	0.000000
	4.2	PROF INFORM	MI	0.000000	1.000000	0.000000
	4.1	SOC SCI COMPUT REV	MI	0.000000	1.000000	0.000000
	3.9	SCIENTOMETRICS	HI	1.000000	0.000000	0.000000
	3.8	HEALTH INFO LIBR J	MI	0.000000	1.000000	0.000000
	3.7	J INFORMETR	HI	1.000000	0.000000	0.000000
	3.6	ETHICS INF TECHNOL	MI	0.000000	1.000000	0.000000
	3.5	J ASSOC INF SCI TECH	HI	1.000000	0.000000	0.000000
	3.4	LIBR HI TECH	MI	0.000000	1.000000	0.000000
	3.3	RES EVALUAT	MI	0.000000	1.000000	0.000000
	3.2	KNOWL MAN RES PRACT	MI	0.000000	0.999995	0.000005
	3.1	ONLINE INFORM REV	MI	0.000000	1.000000	0.000000
	2.9	LIBR INFORM SCI RES	LI	0.000000	0.024808	0.975192
	2.8	LEARN PUBL	MI	0.000000	1.000000	0.000000

class of journals. Tables 4 and 5 (fourth column) also show the journal's class label (i.e., HI, MI, or LI) after applying the standard defuzzification process. In this process, each journal was assigned to the class with the highest membership probability value.

Now, what is the link between the JIF quartiles and the journal classes in the multivariate space? Are there $Q1$ journals in Information Science & Library Science (in 2022) which are not of the highest impact? Or on the contrary, are there journals with the highest impact that are not in the $Q1$ quartile?

We found that two $Q1$ journals were assigned to the medium impact class (see Table 4): Journal of Enterprise Information Management, and Telecommunications Policy. On the contrary, three $Q2$ journals were assigned to the highest impact class in the multivariate space (see Table 4): Scientometrics, Journal of Informetrics, and, Journal of the Association for Information Science and Technology.

We also found that there are $Q2$ journals in the three impact classes, i.e., HI, MI, and LI. For example, Library & Information Science Research was assigned to the lowest impact

Table 5 Relationship between the JIF quartiles (at the 2022 edition) in Information Science & Library Science and the journal classification in three impact classes

JCR category: INFORMATION SCIENCE & LIBRARY SCIENCE (2022)						
JIF quartile	JIF	Abbreviated journal title	Impact class	Membership values		
				u_{1i}	u_{2i}	u_{3i}
Q_3	2.6	J ACAD LIBR	MI	0.000000	1.000000	0.000000
	2.6	ASLIB J INFORM MANAG	MI	0.000000	0.984025	0.015975
	2.4	J INF SCI	MI	0.000000	1.000000	0.000000
	2.1	J DOC	MI	0.000000	1.000000	0.000000
	2.0	J MED LIBR ASSOC	MI	0.000000	1.000000	0.000000
	1.9	INFORM DEV	LI	0.000000	0.005817	0.994183
	1.9	ELECTRON LIBR	LI	0.000000	0.057615	0.942385
	1.8	LIBR QUART	LI	0.000000	0.008641	0.991359
	1.8	INFORM TECHNOL LIBR	LI	0.000000	0.006447	0.993553
	1.8	COLL RES LIBR	LI	0.000000	0.001887	0.998113
	1.7	J LIBR INF SCI	LI	0.000000	0.033683	0.966317
	1.6	DATA TECHNOL APPL	LI	0.000000	0.016937	0.983063
	1.3	MALAYS J LIBR INF SC	LI	0.000000	0.002785	0.997215
	1.3	J AUST LIB INF ASSOC	LI	0.000000	0.000754	0.999246
	1.2	PORTAL-LIBR ACAD	LI	0.000000	0.001848	0.998152
	1.2	REV ESP DOC CIENT	LI	0.000000	0.001055	0.998945
Q_4	1.1	SOC SCI INFORM	LI	0.000000	0.036800	0.963200
	1.0	REF SERV REV	LI	0.000000	0.002404	0.997596
	1.0	LIBRI	LI	0.000000	0.002193	0.997807
	0.9	SERIALS REV	LI	0.000000	0.001282	0.998718
	0.8	INFORM RES	MI	0.000000	1.000000	0.000000
	0.8	LIBR TRENDS	LI	0.000000	0.043528	0.956472
	0.7	KNOWL ORGAN	LI	0.000000	0.001479	0.998521
	0.6	TRANSINFORMACAO	LI	0.000000	0.000075	0.999925
	0.6	INFORM CULT	LI	0.000000	0.000102	0.999898
	0.5	LIBR RESOUR TECH SER	LI	0.000000	0.000578	0.999422
	0.5	LIBR INFORM SC	LI	0.000000	0.000042	0.999958
	0.4	INVESTIG BIBLIOTECOL	LI	0.000000	0.000027	0.999973
	0.4	CAN J INFORM LIB SCI	LI	0.000000	0.000757	0.999243
	0.4	AFR J LIBR ARCH INFO	LI	0.000000	0.000049	0.999951
	0.2	LAW LIBR J	LI	0.000000	0.000211	0.999789
	0.1	Z BIBL BIBL	LI	0.000000	0.000006	0.999994

class. Research Evaluation was assigned to the medium impact class. Meanwhile, Scientometrics was assigned to the highest impact class. Furthermore, we found that there are $Q3$ and $Q4$ journals in the medium impact class (see Table 5). For example, the Journal of Information Science ($Q3$) and Information Research ($Q4$) were both assigned to the medium impact class.

We now repeat the same analysis but in this case for the subject category of Computer Science, Artificial Intelligence (in 2022): what is the link between the JIF quartiles and the journal impact classes? Are there $Q1$ journals which are not of the highest impact? Are there journals with the highest impact that are not in the Q1 quartile?

In Computer Science, Artificial Intelligence (2022), we found that there are $Q1$ journals in the three impact classes (see Table 6). For example, Advanced Engineering Informatics, and, International Journal of Intelligent Systems were assigned to the lowest impact class in the multivariate space. Artificial Intelligence, and, Pattern Recognition were assigned to the medium impact class. Meanwhile, IEEE Transactions on Pattern Analysis and Machine Intelligence, and, International Journal of Computer Vision were assigned to the highest impact class in the multivariate space.

Regarding the $Q2$ quartile, we also found that there are $Q2$ journals in three impact classes (see Table 6). For example, Journal of Machine Learning Research was assigned to the highest impact class, IEEE Intelligent Systems was assigned to the medium impact class, and Complex & Intelligent Systems was assigned to the lowest impact class. As can be seen in Table 7, we even found a $Q4$ journal in the medium impact class: Journal of Intelligent and Fuzzy Systems.

In summary, as a result of this experimentation using the subject categories of Information Science & Library Science and Computer Science, Artificial Intelligence (both in 2022), we have found that the JIF quartiles do not always accurately reveal the impact classification of journals in a multivariate space of seven indicators.

Conclusions

The first research question in our study was: Do competitive forces tend to correct selection errors due to imperfect attention on the part of researchers? Regarding this first question, we found that, under positive externalities, competition between journals pushes the best journals to increase their visibility enough to overcome the distorting effects of imperfect attention by researchers in the field.

These external benefits would be the positive effect that one journal imposes on another in the subject category: the conditions of weak supermodularity and cross-monotonicity. These externalities impose positive effects due to their own salience on other journals.

However, we also need conditions to ensure that if lower quality journals do not produce higher salience in equilibrium, this does not derive from either lower levels of resources or higher unit costs to produce salience: the attention game is symmetric. In this way, each journal of the category can achieve certain visibility at exactly the same cost or benefit.

The consequence of positive externalities is that a better journal has a greater benefit in increasing its salience than an inferior journal because there are more situations in which it is selected conditional on attracting attention. Therefore, the editor-in-chief of the best journals generally has a stronger incentive to invest in journal visibility.

However, when the attention game is not symmetric, does not behave well, or does not verify the conditions of weak supermodularity or cross-monotonicity, the equilibrium properties can be broken and the most salient journals may not faithfully reveal their overall impact on the development of the research field.

The second research question in our study was: Does journal selection based on the choice of journal impact factor quartiles produce the best journals in a multivariate indicator space? Firstly, we have found that a visibility strategy based on JIF quartiles does not support the properties of weak supermodularity and cross-monotonicity, and the attention game does not work well. Therefore, we cannot guarantee that the most visible

Table 6 Relationship between the JIF quartiles (at the 2022 edition) in Computer Science, Artificial Intelligence and the journal classification in three impact classes

JCR category: COMPUTER SCIENCE, ARTIFICIAL INTELLIGENCE (2022)						
JIF quartile	JIF	Abbreviated journal title	Impact class	Membership values		
				u_{1i}	u_{2i}	u_{3i}
Q_1	23.6	IEEE T PATTERN ANAL	HI	1.000000	0.000000	0.000000
	19.5	INT J COMPUT VISION	HI	1.000000	0.000000	0.000000
	14.4	ARTIF INTELL	MI	0.004578	0.995422	0.000000
	12.0	ARTIF INTELL REV	MI	0.000000	0.999991	0.000009
	11.9	IEEE T FUZZY SYST	HI	0.999888	0.000112	0.000000
	10.4	IEEE T NEUR NET LEAR	HI	1.000000	0.000000	0.000000
	9.0	IEEE COMPUT INTELL M	MI	0.000000	1.000000	0.000000
	8.8	ADV ENG INFORM	LI	0.000000	0.232293	0.767707
	8.8	KNOWL-BASED SYST	MI	0.000000	1.000000	0.000000
	8.5	EXPERT SYST APPL	MI	0.000000	1.000000	0.000000
	8.3	J INTELL MANUF	MI	0.000000	0.999926	0.000074
	8.2	IEEE T INTELL VEHICL	MI	0.000000	1.000000	0.000000
	8.0	PATTERN RECOGN	MI	0.000000	1.000000	0.000000
	8.0	ENG APPL ARTIF INTEL	MI	0.000000	1.000000	0.000000
	7.8	NEURAL NETWORKS	MI	0.000000	1.000000	0.000000
	7.5	ARTIF INTELL MED	MI	0.000000	0.681519	0.318481
	7.5	MACH LEARN	MI	0.000000	1.000000	0.000000
	7.4	MIND MACH	MI	0.000000	1.000000	0.000000
	7.0	INT J INTELL SYST	LI	0.000000	0.017502	0.982498
Q_2	6.5	INTEGR COMPUT-AID E	MI	0.000000	1.000000	0.000000
	6.4	IEEE INTELL SYST	MI	0.000000	1.000000	0.000000
	6.0	NEURAL COMPUT APPL	MI	0.000000	1.000000	0.000000
	6.0	J MACH LEARN RES	HI	0.985606	0.014394	0.000000
	6.0	NEUROCOMPUTING	MI	0.000010	0.999990	0.000000
	5.8	COMPLEX INTELL SYST	LI	0.000000	0.002483	0.997517
	5.6	INT J MACH LEARN CYB	LI	0.000000	0.016612	0.983388
	5.3	APPL INTELL	MI	0.000000	1.000000	0.000000
	5.3	IEEE T EM TOP COMP I	MI	0.000000	0.999203	0.000797
	5.3	CONNECT SCI	LI	0.000000	0.007765	0.992235
	5.1	PATTERN RECOGN LETT	MI	0.000000	1.000000	0.000000
	5.1	CAAI T INTELL TECHNO	LI	0.000000	0.000919	0.999081
	5.0	ACM T INTEL SYST TEC	MI	0.000000	1.000000	0.000000
	5.0	J ARTIF INTELL RES	MI	0.000000	1.000000	0.000000
	5.0	IEEE T COGN DEV SYST	MI	0.000000	1.000000	0.000000
	4.7	FUZZY OPTIM DECIS MA	LI	0.000000	0.008008	0.991992
	4.3	INT J FUZZY SYST	LI	0.000000	0.001812	0.998188
	4.1	ARTIF INTELL LAW	LI	0.000000	0.025360	0.974640
	3.9	PATTERN ANAL APPL	LI	0.000000	0.000282	0.999718
	3.9	INT J APPROX REASON	LI	0.000000	0.006729	0.993271

Table 7 Relationship between the JIF quartiles (at the 2022 edition) in Computer Science, Artificial Intelligence and the journal classification in three impact classes

JCR Category: COMPUTER SCIENCE, ARTIFICIAL INTELLIGENCE (2022)						
JIF quartile	JIF	*Abbreviated journal title*	Impact class	*Membership values*		
				u_{1i}	u_{2i}	u_{3i}
Q_3	3.6	IEEE T HUM-MACH SYST	LI	0.000000	0.002613	0.997387
	3.6	INT J INTERACT MULTI	LI	0.000000	0.000160	0.999840
	3.5	AUTON ROBOT	LI	0.000000	0.002573	0.997427
	3.4	ACM T INTERACT INTEL	LI	0.000000	0.000902	0.999098
	3.4	J INTELL INF SYST	LI	0.000000	0.000240	0.999760
	3.3	EXPERT SYST	LI	0.000000	0.000070	0.999930
	3.3	J INTELL ROBOT SYST	LI	0.000000	0.000672	0.999328
	3.1	NEURAL PROCESS LETT	LI	0.000000	0.000393	0.999607
	3.1	FRONT NEUROROBOTICS	LI	0.000000	0.000984	0.999016
	2.8	COMPUT INTELL-US	LI	0.000000	0.000073	0.999927
	2.8	APPL ARTIF INTELL	LI	0.000000	0.000098	0.999902
	2.8	J ARTIF INTELL SOFT	LI	0.000000	0.003116	0.996884
	2.7	J HEURISTICS	LI	0.000000	0.000460	0.999540
	2.7	KNOWL INF SYST	LI	0.000000	0.000100	0.999900
	2.6	SWARM INTELL-US	LI	0.000000	0.000293	0.999707
	2.6	ARTIF LIFE	LI	0.000000	0.000904	0.999096
	2.5	NAT LANG ENG	LI	0.000000	0.000060	0.999940
	2.3	IEEE T GAMES	LI	0.000000	0.000051	0.999949
	2.2	J EXP THEOR ARTIF IN	LI	0.000000	0.000049	0.999951
Q_4	2.1	KNOWL ENG REV	LI	0.000000	0.000633	0.999367
	2.1	AI EDAM	LI	0.000000	0.000031	0.999969
	2.0	J INTELL FUZZY SYST	MI	0.000000	1.000000	0.000000
	2.0	INTELL AUTOM SOFT CO	LI	0.000000	0.001769	0.998231
	1.9	AUTON AGENT MULTI-AG	LI	0.000000	0.000116	0.999884
	1.7	INTELL DATA ANAL	LI	0.000000	0.000028	0.999972
	1.6	ADAPT BEHAV	LI	0.000000	0.000050	0.999950
	1.6	CONSTRAINTS	LI	0.000000	0.000609	0.999391
	1.5	INT J UNCERTAIN FUZZ	LI	0.000000	0.000030	0.999970
	1.5	INT J PATTERN RECOGN	LI	0.000000	0.000045	0.999955
	1.2	ANN MATH ARTIF INTEL	LI	0.000000	0.000060	0.999940
	1.1	J AUTOM REASONING	LI	0.000000	0.001090	0.998910
	1.1	INT J ARTIF INTELL T	LI	0.000000	0.000020	0.999980
	0.9	INT J SOFTW ENG KNOW	LI	0.000000	0.000022	0.999978
	0.9	AI MAG	LI	0.000000	0.010882	0.989118
	0.8	AI COMMUN	LI	0.000000	0.000036	0.999964

journals in that case are the preferred journals based on their impact. Coincidentally with the previous result, we also found that the JIF quartiles did not always accurately reveal the impact classification of journals in a multivariate space of seven indicators.

This analysis was performed using the subject categories of Information Science & Library Science, and, Computer Science, Artificial Intelligence (both in 2022).

However, what are the limitations of our study? First, we cannot assure that the proposed positive externalities are the only possible system to guarantee that the best journals have the greatest visibility. That is, they determine a sufficient but not necessary condition. Secondly, the classification of the impact of the journals in a multivariate space of seven indicators was carried out using fuzzy clustering. Therefore, using a different unsupervised statistical classification technique we could have obtained a different result for the impact classes in the analyzed categories. Third, a problem encountered was the absence of an indicator score on a particular dimension for some journals. To overcome this obstacle, those journals with missing indicator values were removed from the analysis. Fourth, although we have shown that a visibility strategy based on journal quartiles does not verify the positive externalities of the attention game, we have not proposed an alternative visibility strategy that does verify them. This remains an open research problem that we will address in the future.

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