Why is your paper rejected? Lessons learned from over 5000 rejected transportation papers

Citation for the original published paper (version of record):
Wu, J., Sanchez-Diaz, I., Yang, Y. et al (2024). Why is your paper rejected? Lessons learned from over 5000 rejected transportation papers. Communications in Transportation Research, 4.
http://dx.doi.org/10.1016/j.commtr.2024.100129

Communications in Transportation Research 4 (2024) 100129

Contents lists available at ScienceDirect

Communications in Transportation Research

journal homepage: www.journals.elsevier.com/communications-in-transportation-research

Full Length Article

Why is your paper rejected? Lessons learned from over 5000 rejected transportation papers

Jiaming Wu [a], Ivan Sanchez-Diaz [b], Ying Yang [c,*], Xiaobo Qu [d]

[a] Architecture and Civil Engineering, Chalmers University of Technology, Gothenburg, 41296, Sweden
[b] Technology Management and Economics, Chalmers University of Technology, Gothenburg, 41296, Sweden
[c] School of Management, Shanghai University, Shanghai, 200444, China
[d] State Key Laboratory of Intelligent Green Vehicle and Mobility, School of Vehicle and Mobility, Tsinghua University, Beijing, 100084, China

ARTICLE INFO

Keywords:
Publication
Transportation
Elsevier
Rejection

ABSTRACT

Academic papers are the cornerstone of knowledge dissemination and crucial for researchers' career development. This is particularly true for rapidly evolving research domains such as transportation, as evidenced by the surge of journals and papers in the past decade. While abundant literature offers guidance on successful publication strategies, insights into the reasons for rejection are rare. This study fills in this gap by examining why papers are rejected in the area of transportation. We present concrete evidence based on data from over 5,000 rejected transport papers. Quantitative analyses are conducted to reveal the impacts of similarity rate, duplication submission rate, and topic on desk rejections. Additionally, we shed light on the distinct focus reviewers have when serving different journals. We hope the results could equip transport researchers with a deeper comprehension of publication criteria and a better awareness of common but avoidable mistakes.

1. Introduction

Navigating the academic publishing landscape is both challenging and imperative, as the old saying goes "publish or perish". Apart from producing quality research, successful publication demands a series of correct actions, from writing and visualization to journal selection (Klingner et al., 2005; Schimel, 2012). Students and early-career researchers learn the publication rule of thumb from their mentors, peers, or the vast number of materials on the Internet. Transforming those into actionable steps is, however, a journey that spans years and is sometimes punctuated by the sting of rejections. We celebrate and share acceptances and keep rejections to ourselves. This is partially because of the embarrassment of sharing one's setbacks, and partially because each paper is unique, as are the reasons for rejection.

It is challenging for researchers to generalize lessons learned from their few rejected papers, and these are the kinds of lessons that one would rather not learn. However, rejections carry invaluable information. Suggestions from reviewers help polish the paper, and criticisms show directions for improvement. Unfortunately, they are always behind the scenes, despite great values. While there have been instances of Editors-in-Chief sharing insights on rejections, such perspectives are mostly descriptive and journal-specific advice.

For instance, in Edmans (2023), "Learnings from 1,000 rejections", the author discusses his experience as editor of *Review of Finance* and presents the main reasons for rejections of papers. The author highlights the lack of novel contribution, the importance of the findings, the lack of alignment between the papers and the scope of the journal, the lack of generalization, the appropriateness and execution of the method, and the quality of the writing. Witlox (2019) compiles recommendations based on the author's experience as the Editor-in-Chief of *Journal of Transport Geography*. The key recommendations are to be careful with the selection of the journal, to read the guidelines, to keep a single message for the paper, to select an attractive title, to include figures and tables that are attractive for the reader, to be honest, and modest, and use the experience of being a reviewer to assess your paper. In this research, we present lessons learned from over 5,000 papers rejected by a variety of transport journals and present a quantitative analysis.

In October 2020, Elsevier B.V. (Elsevier) launched a project entitled "Editorial Transfer System" (henceforth, the transfer system). The transfer system is a free service, provided to authors who need to find another journal for their rejected papers. Journals in the transfer system are clustered into several disciplinary portfolios, with transportation being one of the first established portfolios. The transportation portfolio contains nearly all transport-centric Elsevier journals and actively

* Corresponding author.
E-mail address: yyingqxb@gmail.com (Y. Yang).

https://doi.org/10.1016/j.commtr.2024.100129
Received 21 January 2024; Received in revised form 15 March 2024; Accepted 18 March 2024

engages other portfolios such as Operations Research and Computer Science. If authors of a rejected paper choose to use the transfer system, the full submission package and related information will be sent to a Transfer Editor.[1] The transfer editor will carefully review the paper and decide whether and where to transfer the paper. During the project, the transfer system received over 5,000 transport papers. This unique opportunity allowed us to gain a broader and deeper perspective on rejections, transcending the boundaries between journals, and offering insights beyond the reach of individual authors or even journal editors.

We note that this study does not feature innovation in methodology. Instead, we employ standard models for statistical analysis and text mining. The goal is to share our gained experience and knowledge of rejected papers from a quantifiable standpoint, a perspective seldom explored in the existing literature. As an attempt to extend the impact and broaden the beneficiaries of the transfer system, we seek to help students avoid common but unnecessary mistakes, young researchers choose journals more wisely, senior researchers better train juniors, and support editors and reviewers by saving their time from less unsuitable papers.

The remainder of this study is structured as follows. Section 2 presents a summary of the journals and data used for this research. Section 3 presents the findings related to desk rejections. Section 4 summarizes the top reasons for rejection from the reviewers' perspective. Section 5 concludes the paper with discussions.

2. Data

In this section, we present a summary of the data used in our analysis. As previously mentioned, data is sourced from the transfer system, which received rejected papers from the transport portfolio. This portfolio includes 30 journals, but its actual spectrum spans over 56 journals from various disciplines. Over the 27 months from October 2020 to December 2022, the transfer system received 5,168 transport-related papers. Out of these, 845 (16.4%) were rejected after review, with the remainder being desk rejected. The full list of journals included in the transport portfolio can be found in the Appendix. To draw meaningful conclusions, we opted to omit newly established journals or those contributing only a few papers, focusing instead on the well-established and active ones. This leaves us with 5,036 papers in hand, of which 824 (16.4%) were rejected after review. A detailed breakdown of the data is presented in Table 1.

For each paper, we have three categories of data, namely (1) submission files, (2) review and decision letters, and (3) transfer system metadata. The submission files encompass not only the paper itself but also supplementary details required by journals during the submission process. These details encapsulate author identities, email contacts, institutional affliations, keywords, abstracts, and suggested reviewers. The review and decision specifics capture all elements instrumental to making the final decision, such as the editor's comments, reviewers' comments (if available), and a similarity check report. The transfer system metadata, on the other hand, aggregates cross-journal historical records. Such records might pinpoint instances where a manuscript has been previously submitted to other Elsevier journals, highlight duplication rates, and flag specific statuses for papers and authors, indicating unique scenarios, like a warning flag for various reasons. The hierarchy of data accessibility is illustrated in Fig. 1.

The uniqueness and richness of the dataset are summarized as follows.

- To the best of our knowledge, this is the first time that a rejection-side story has been revealed in the area of transport. It offers a holistic view, encompassing comprehensive feedback from both editors and reviewers.

[1] Dr. Long Cheng was the first transfer editor who served from October 2020 to September 2021, and Dr. Jiaming Wu succeeded until December 2022.

Table 1
Selected journals and number of papers in the system.

Journal	Papers in the transfer system	Papers rejected after review
Asian Journal of Shipping & Logistics (AJSL)	22	4
Asian Transport Studies (EASTSJ)	18	4
Case Studies on Transport Policy (CSTP)	125	40
International Journal of Transportation Science & Technology (IJTST)	54	11
Journal of Air Transport Management (JATM)	254	56
Journal of Choice Modelling (JOCM)	44	9
Journal of Public Transportation (JPUBTR)	55	2
Journal of Rail Transport Planning & Management (JRTPM)	44	8
Journal of Transport & Health (JTH)	289	42
Journal of Transport Geography (JTRG)	420	59
Maritime Transport Research (MARTRA)	25	1
Research in Transportation Economics (RETREC)	196	16
Research in Transportation Business & Management (RTBM)	244	32
Transport Policy (TP)	440	76
Travel Behaviour & Society (TBS)	207	36
Transportation Research Part A: Policy & Practice (TRA)	855	96
Transportation Research Part B: Methodological (TRB)	287	33
Transportation Research Part C: Emerging Technologies (TRC)	74	49
Transportation Research Part D: Transport & Environment (TRD)	692	146
Transportation Research Part E: Logistics & Transportation Review (TRE)	358	63
Transportation Research Part F: Traffic Psychology & Behaviour (TRF)	285	19
Transportation Research Interdisciplinary Perspectives (TRIP)	48	22
Total	5,036	824

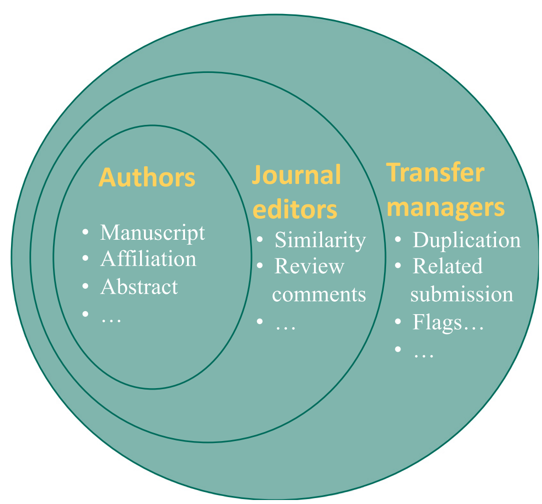


Fig. 1. Dataset access levels: from authors to transfer managers.

- In the transport community, this is the largest dataset that contains rejected papers from a variety of journals with different focuses.
- The dataset is diversified in terms of paper quality. It is pivotal to underscore that a rejection does not necessarily mean low quality. Of the 5,168 papers, over 100 were later accepted or published, many in top-tier journals, and more than 300 were under review at the time of this research's completion.
- The dataset has also good diversity regarding the origins of papers. Specifically, the papers analyzed in this research came from 9396 different institutions all over the world.

Despite its many merits, the dataset is biased in several aspects. Specifically:

- The data is confined to Elsevier transport journals and does not reflect perspectives from journals of other publishers, such as Springer Nature (Springer) and Institute for Operations Research and the Management Sciences (Informs).
- The dataset does not contain all rejected papers from the portfolio journals during the studied period. There are an unknown number of papers that were rejected but the authors chose not to use the transfer system.
- The number of papers stemming from different journals varies considerably, as shown in Table 1. This variance is a natural reflection of the authors' first submission choices and their use of the transfer system. Consequently, this uneven data distribution may result in varied depths of insights gained for different journals.

As such, one should interpret this research as a supporting reference for academic publishing in transportation, rather than a profiling of journals or a criticism of any author, reviewer, or editor.

3. Reasons for desk rejection

Desk rejection constitutes a significant percentage of all paper rejections. For instance, according to the 2023 annual summary of *Transportation Research Part D: Transport and Environment*, 71% of submissions were desk rejected for various reasons (e.g., 35% due to being out of scope and 7% due to poor writing). This resulted in an overall acceptance rate of 13%.[2] Hence, in the case of TRD, desk rejection makes up 81.6% of all rejections. In our dataset, a similar proportion of 83.6% of papers that entered the transfer system were desk rejected, matching the case of TRD and many other journals based on our knowledge.

In analyzing the reasons behind desk rejections, we focus on three quantifiable metrics: similarity rate, duplication submission rate, and out-of-scope submissions. While lack of significant contribution or low quality can also lead to desk rejections, these determinations often hinge on the subjective assessments of editors and are not well quantified in the current Elsevier systems. Moreover, as a kind gesture, editors may not criticize a paper's quality in the decision letter, although that stands as their primary concern. Given the implicit nature of quality judgment, we do not examine the "quality" factor in desk rejections to ensure that the conclusions drawn are meaningful and reliable. Instead, we will later discuss how this factor may be indirectly reflected in decision letters within this section.

3.1. Similarity rate

Original innovation is highly valued in the publishing world, particularly for top-tier journals. As a result, it has become a standard procedure for most publishers to check the similarity rate between the submitted work and existing literature. In the transport portfolio, a similarity rate is calculated for each submission, to help editors assess the "originality" of a work and identify potential plagiarism. Specifically, a similarity check report will be automatedly generated (with iThenticate by Turnitin as the current service provider) once a submission is completed. This report highlights texts that are similar to or direct copies of existing content.

The plagiarism check system is not new. However, the key question is that how this similarity rate influences editorial decisions. The short answer is that the similarity rate acts as an initial filter. However its application is, to some extent, a mystery, arising from three sources. First of all, many journals do not specify their threshold for the similarity rate.

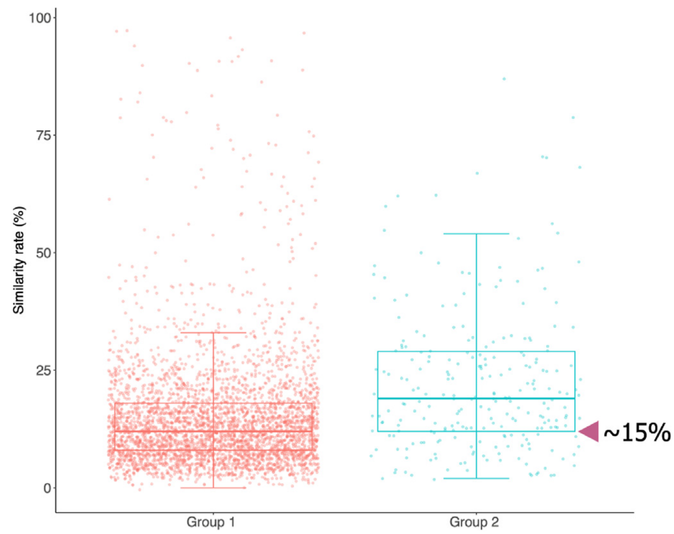


Fig. 2. Similarity rates of two groups: (1) editors did not criticize SR; (2) editors criticized SR.

Secondly, even those journals with a clear requirement do not always enforce it strictly, possibly due to the last factor: the existence of special cases. Special cases refer to instances where a high similarity is reasonable and justifiable, such as overlaps with one's own thesis.

Fortunately, when editors reject a paper due to similarity issues, they usually explicitly bring it up in the decision letter or leave a note for the transfer editor. This practice facilitates our quantitative analysis. To investigate the employed similarity thresholds, we divide desk-rejected papers into two groups and compare their similarity rates (SRs). The first group consists of papers that were not criticized for SR issues, and the second group includes papers where decision letters highlighted SR issues. The box plots of SRs for these two groups are shown in Fig. 2. Fig. 2 demonstrates a clear statistical difference between the two groups, indicating the significant impact of SR. Fig. 3 further illustrates a journal-specific comparison, which reveals similar patterns across almost all journals.[3]

While the SR is a crucial factor, the data in Figs. 3 and 4 suggest that it does not serve as a strict threshold for rejection. Papers with high SRs are not always criticized, and conversely, some with low SR receive criticism. Three plausible explanations emerge from our experience and informed speculation. First, for a particular submission, the single-source similarity rate (SSR, overlaps with one source of literature) holds more significance than the overall SR in principle. It is quite common that a high SSR is masked by a low SR and vice versa. However, SSR can only be accessed after viewing the complete similarity check report, a process that may be time-consuming. This leads some editors to rely on SR, while others use SSR, resulting in the observed inconsistency in decision-making. Second, some journals do not set explicit requirements for SR/SSR, but depend on the verdicts of individual editors. Lastly, some editors may not put much weight on SR/SSR in decision-making.

Additionally, there are a few rules of thumb that are practically applied. For instance, similarities with an author's degree thesis are generally considered acceptable, which explains the upper portions (>75%) of the box plots. The same rules apply to overlaps with preprints, such as those on arXiv, given the identical authorship. In the same vein, similarity with the authors' previous work usually warrants a larger threshold. However, this last scenario might be risky if editors choose not to open the full similarity report.

We recommend that authors carefully review the "guide for authors"

[2] Data from Prof. Jason Cao, the Editor-in-Chief of *Transportation Research Part D: Transport and Environment*.

[3] Only selected journals are presented. Details on other journals can be shared upon request.

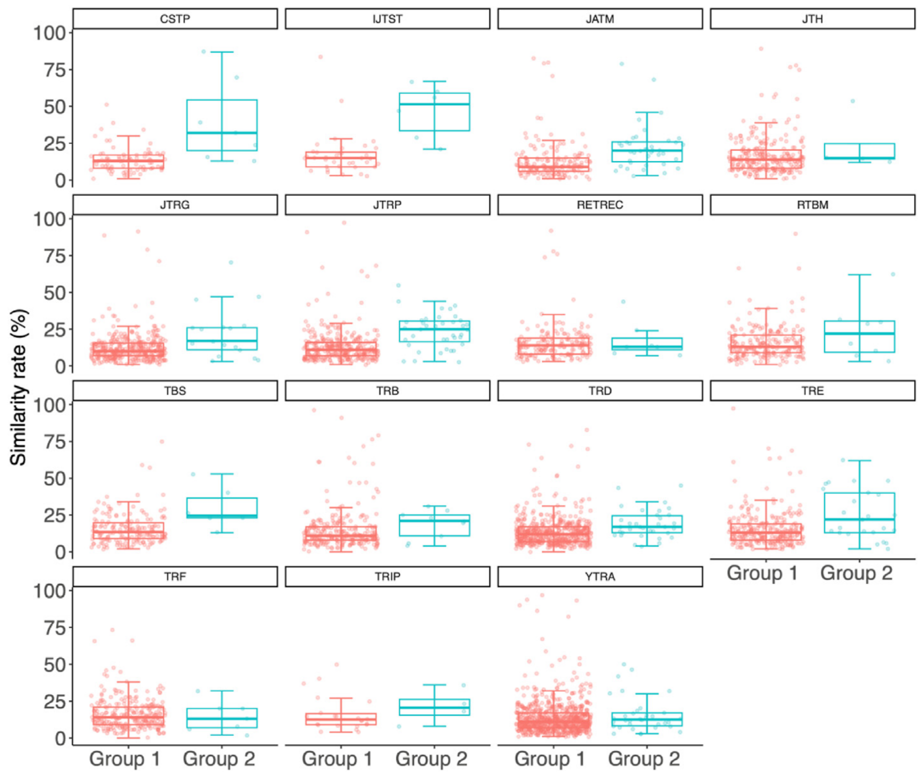


Fig. 3. Journal-specific similarity rates of two groups.

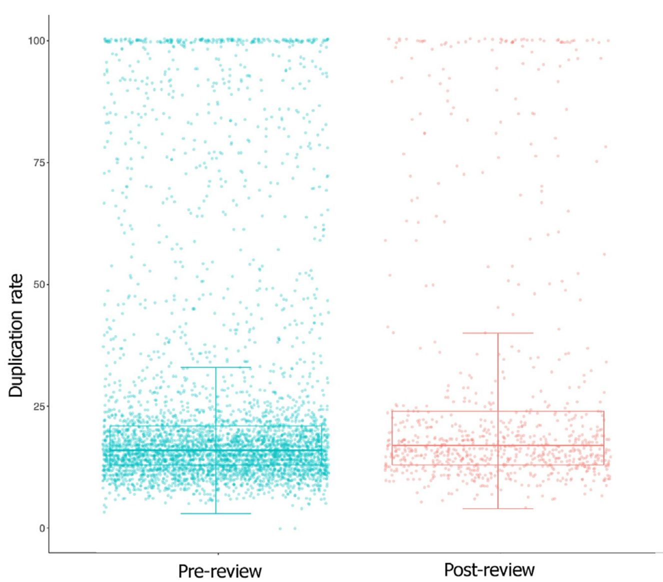


Fig. 4. Duplication submission rates of two groups: (1) pre-review papers; (2) post-review rejected paper.

of their target journal. It is beneficial to revisit the guide before each new submission, even if you are quite familiar with the journal, as guidelines may be updated. This advice can be particularly useful for journals that strictly apply the SR filter. For instance, TP explicitly states that an SR higher than 10% will certainly result in a desk rejection. If there are no instructions on SR, it is probably safe to keep SR below 15%, using the third quartile in Fig. 4 as the threshold.

3.2. Duplication submission rate

Another similar but distinct indicator to SR is the duplication submission rate (DSR). DSR checks if a submitted manuscript is identical or very similar to a pre-existing manuscript within Elsevier. Through DSR, editors could immediately identify duplicated submissions (one paper simultaneously submitted to several journals), resubmissions of previously rejected papers, or spam submissions.

Like SR, we wonder about the impacts of DSR on editorial decisions. Unlike SR, editors rarely criticize nor explicitly mention DSR issues. As a result, it is impossible to firmly ascertain if a rejection is closely related to DSRs. Thus, we make a comparison between the DSRs of pre-review (desk rejection) papers and post-review papers as an indirect attempt to reveal the impacts of DSR. The overall and journal-specific distributions of the two groups are shown in Figs. 4 and 5, respectively. In Figs. 4 and 5, there are no systematic differences between the two groups. Specifically, in Fig. 4, the average DSR for pre-review rejected papers is 16%, and the average DSR for post-review papers is 17%, almost identical to each other.

Figs. 4 and 5 imply that DSR is not a deciding factor in editorial decision-making, at least not as significant an indicator as SR. The rationale behind this phenomenon is threefold. Most importantly, not all journal editors currently have access to this indicator, as it is an optional function of the submission system. Additionally, it is reasonable to allow resubmissions of a rejected paper. Finally, a major portion of the DSR is closely tied to authors' previous successful publications within Elsevier, which is usually deemed as a solid foundation and thus a positive sign.

However, this should not be interpreted as a chance for spamming submissions. In this research, spamming refers to a series of trial-and-error submissions to a large number of journals, regardless of topic and quality. For instance, the transfer manager has witnessed several instances where the same work was repeatedly submitted and rejected by over ten different journals. Such spam submissions are irresponsible and are not appreciated by any journal. Every time, they resulted in a desk rejection. Another reason to discourage spamming is that major academic publishers (e.g., Elsevier) can easily establish cross-journal indicators to mark such papers and authors. Currently, authors of suspiciously duplicated submissions are marked with a flag within the editorial system in

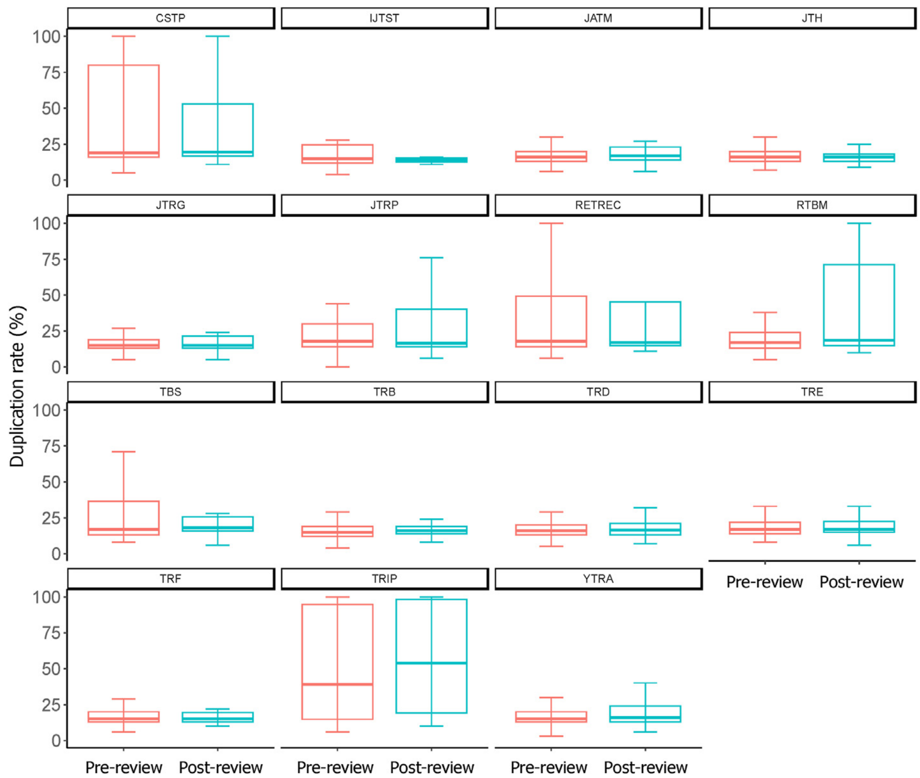


Fig. 5. Journal-specific DSRs of two groups: (1) pre-review papers; (2) post-review rejected paper.

Elsevier, calling for extra caution from editors.

3.3. Out of scope

"Out of scope" is probably the most commonly seen reason for desk rejection. In our dataset from the transfer system, 55% of desk rejections were attributed to issues related to topic and scope. This high percentage is both notable and unexpected, especially considering that many papers seem to align well with the scopes of their target journals. So, what is truly at play here?

To shed light on the situation, we establish a benchmark group comprised of papers published within the transport portfolio. This benchmark allows us to assess the extent to which the topics of rejected papers diverge from those of accepted ones. Specifically, we extract data from papers published during the same period and from the same journals in Table 1. The benchmark data is sourced from Web of Science. Among all dimensions, we use "keywords" as the indicator to represent the topics of a paper, as they are naturally tokenized, concise, and intended to summarize the key content of a work. To quantify the similarity of the two groups of keywords, we employ the Jaro–Winkler distance method for measuring the edit distance between two sequences. The Jaro–Winkler distance is normalized, with 0 indicating identical keywords and 1 signifying no similarity (Van der Loo, 2014).

However, having a topic in common with a few published papers does not necessarily guarantee a good fit for a journal. Yet, if a paper's topic aligns with a significant number of published works, it is reasonable to consider it "within scope". Therefore, we first define a distance threshold φ to determine whether a rejected paper i shares similar topics with a published paper j or not. Specifically, we use the threshold of $\varphi = 0.3$, meaning that if the Jaro-Winkler distance $d_{i,j}$ is less than 0.3, the two papers are considered to have similar topics. This is a relatively tight threshold, considering that the average Jaro–Winkler distance between published papers is 0.34. To facilitate understanding of this threshold, we provide a few examples of different Jaro–Winkler distances between keywords in Fig. 6.

The threshold enables us to convert the continuous Jaro–Winkler distance $d_{i,j}$ to a binary variable $T_{i,j,\varphi}$ as Eq. (1):

$$T_{i,j,\varphi} = \begin{cases} 0, & \text{if the Jaro–Winkler distance is smaller than a predefined threshold } d_{i,j} \le \varphi \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

where i, j are paper indices, and φ is the pre-defined threshold. Based on $T_{i,j,\varphi}$, we finally define a scope fitness indicator SF_i for a rejected paper with regard to the submitted journal, as Eq. (2):

$$SF_i = \frac{\sum_j T_{i,j,\varphi}}{N}, j \in 1, 2, \ldots, N \tag{2}$$

The meaning of SF_i is the proportion of published papers in the submitted journal that have similar topics. As an example, if a rejected paper has $SF_i = 0.2$, it has similar topics to 20% of its successful counterparts from the same journal. In this case, we should probably not criticize that it is an out-of-scope paper. Building upon this understanding, we showcase the distribution of SF_i values for selected journals in our dataset, as displayed in Fig. 7. In Fig. 7, a greater degree of left-skew in the distribution signals a higher probability that rejected papers were, in fact, within the journal's scope.

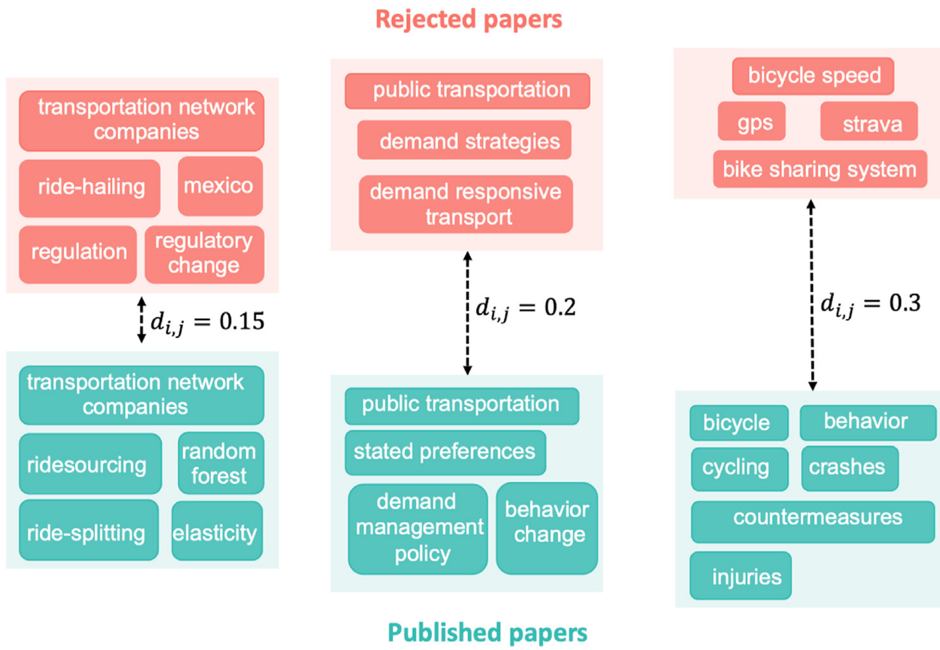


Fig. 6. Examples of keyword groups with various Jaro–Winkler distances.

Although the distribution varies from journal to journal, there is a consistent pattern that a large portion of rejected papers deemed "out of scope" align well with the journal's thematic focus. A possible explanation for this phenomenon is that editors may opt for the less critical "out of scope" comment as a polite replacement for their real critical thoughts, e.g., "the paper is just not good enough". Alternatively, the phenomenon could be attributed to topic saturation. In cases where editors receive an overwhelming number of submissions on a particular topic, they may become more selective, even if the submissions are relevant to the journal's scope.

During our discussions with several Editors-in-Chief, "out of scope" rejections can also be linked to papers that applied methods and models inappropriately or wrongly. For example, if a stated preference paper collected data from highly biased participants, it may indicate the authors lack basic knowledge of survey-based research in the editor's eyes. The scope of a journal is, less rigorously speaking, what the journal or

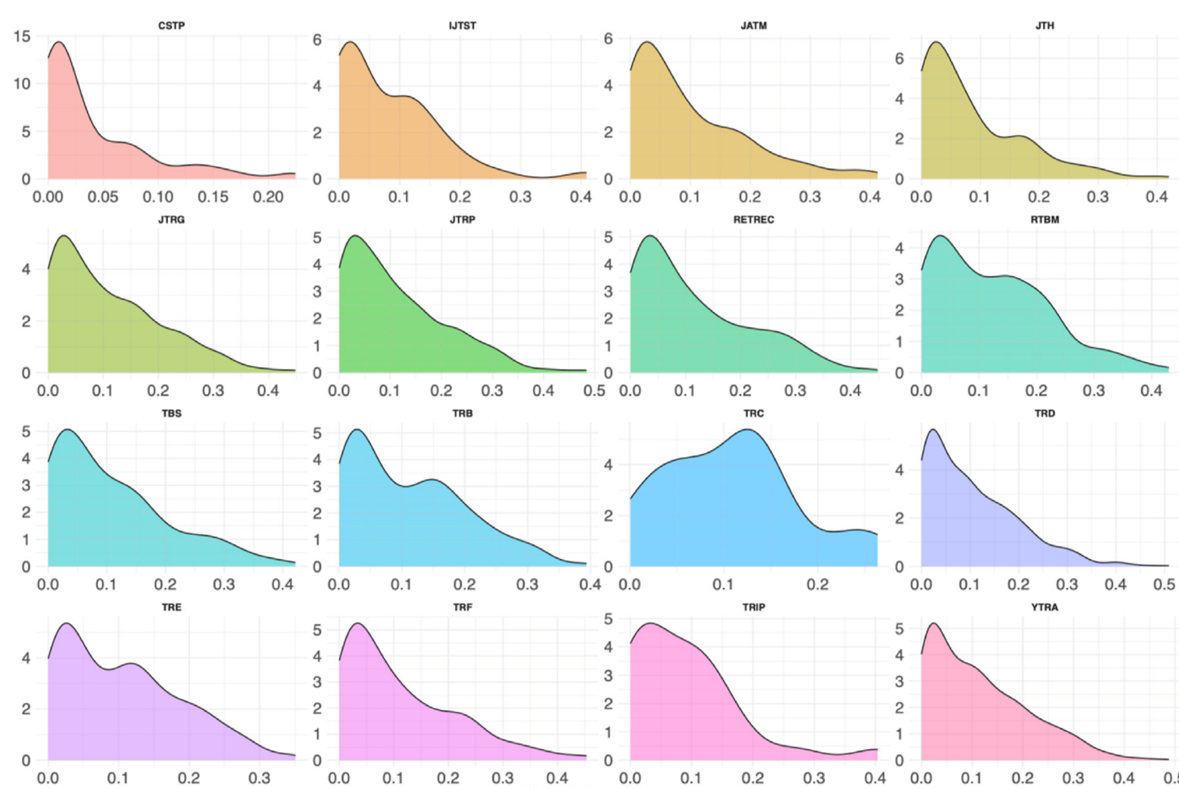


Fig. 7. SF_i distribution of rejected papers from different journals.

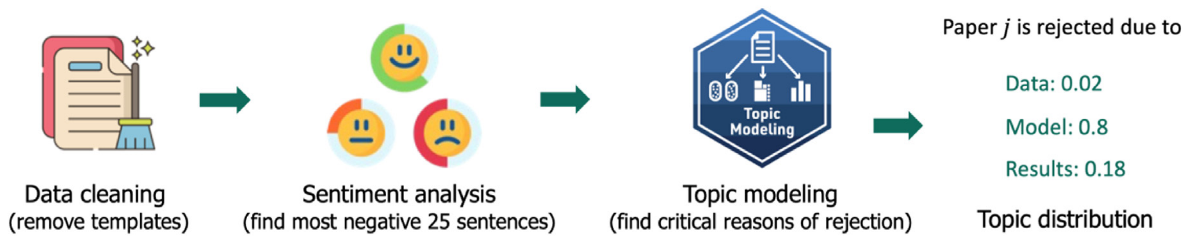


Fig. 8. Framework for reviewers' comments text mining.

Editor-in-Chief wishes to accept for publication, and thus can relate to all dimensions of the submitted paper, such as topic, impact, quality, and contribution. Any significant drawbacks in those metrics may lead to a verdict of "out of scope".

In this research, it is intractable to unveil and confirm the reasons behind all "out of scope" rejections. The results shown in Fig. 7 are presented to raise awareness that decision letters may not always reflect the true reasons for desk rejection, particularly when issues of scope and topic are mentioned. This does not imply, however, that authors could be casual in selecting journals. Every journal has its unique thematic focus or flavor, a point which will be further elaborated on in the next section.

4. Perspectives from reviewers

In this section, we examine the reasons for rejection from the perspectives of reviewers. The objective is to find out the most criticized aspects of papers, which can inform researchers for their future submissions. The corpus to be used are comments from 824 rejected papers in Table 1. More specifically, decision letters were downloaded and utilized to guarantee the capture of comments from both editors and reviewers.

A typical decision letter is structured into three components: (1) templated text, which includes headers and other standardized elements; (2) comments from editors, which often summarize the reviewers' reports and may include additional feedback if the editors have reviewed the paper themselves; and (3) comments from reviewers. The templated text serves as the framework for the decision letter, incorporating acknowledgments, useful links, and information on optional services. When crafting their comments, many editors employ templated phrases as starting points. This practice, while not widely known, is understandable given the volume of papers editors must handle monthly. Utilizing templates can significantly streamline their workload.

Reviewers' comments, while typically personalized, often adhere to a specific structure. The conventional approach to crafting review comments begins with a description of the submitted work. This is usually followed by positive feedback (e.g., commendation for good writing or acknowledgment of solid data), and then real criticisms and suggestions are presented. In cases where a paper is ultimately rejected, the criticisms section of the review is decisive. With this in mind, we developed a text-mining framework designed to elucidate the reasons reviewers cite for rejecting papers (Fig. 8).

Specifically, we first remove the templating words from both journals and editors, leaving only real comments that matter. Secondly, sentiment scores were evaluated for each remaining sentence, using the "sentiment" package from R (Rinker, 2021). Afterward, we retain the top 25 negative sentences to further filter out the paper descriptions and potential compliments, so as to highlight key criticisms. Otherwise, using all sentences may bury the critical comments with enormous less informative phrases. With the selected negative sentences, the Latent Dirichlet Allocation (LDA) model is applied for topic modeling. The result of LDA is a distribution over a few topics, each consisting of a set of terms. For example, the results could attribute the rejection 2% to data issues, 80% for modeling problems, and 18% due to results. In this research, we utilize the standard LDA model from the "topicmodels" package in R (Grün and Hornik, 2011).

As stated at the beginning of this paper, we exclude the description of standard procedures and details of standard models such as LDA, to focus on the presentation of key results. After 12 h of training, the LDA model exhibits 7 topics, representing different aspects that reviewers value for different journals. In specific, the topics are

1) Results and findings;
2) Impact and policy;
3) Methodology;
4) Literature review;
5) Data and scope;
6) Writing and clarity;
7) Others.[4]

The heatmap of topic distribution for selected journals is presented in Fig. 9. Evidently, different journals present distinct distributions over topics, reflecting various flavors and valued aspects. For example, TRB, TRC, and TRE show exceptional focus on methodology innovation; TRA and TRD are all-rounders that value all aspects equally; TRF reviewers focus more on the results of research; and CSTP naturally prioritizes data and scope issues, as the journal is focused on case studies.

We emphasize again that, although Fig. 9 exhibits clear patterns, this should not be considered a stereotype of journals. The dataset only includes a part of all rejected papers, hence the unrevealed full picture may look different. More importantly, the results in Fig. 9 are only meaningful from a statistical perspective. When it comes to a specific paper, peer review can lead to very different directions and results. For example, one of the TRB papers was rejected due to poor writing although the methodology was fine for reviewers. After all, a high-quality publication should always be clear in writing, logical in organization, solid in methodology, and meaningful in results, etc.

The purpose of Fig. 9 is to foster an understanding of the distinct characteristics of different journals, underscoring the importance of strategic decision-making when selecting a journal for submission. Supporting this notion, the desk rejection rate dropped from over 60%–32% following the recommendations provided by the transfer system, highlighting the benefits of making informed, strategic choices.

5. Conclusions and discussion

In this research, we examine common reasons for rejections in the area of transportation research. Based on data from over 5,000 rejected papers, the impact of several key factors on desk rejections and reviewers' objections was studied in a quantitative fashion. Our findings indicate:

- The similarity rate is a filter that journals generally apply, but the strictness varies.

[4] Mixed issues, such as analysis, visualization, and discussion on specific variables.

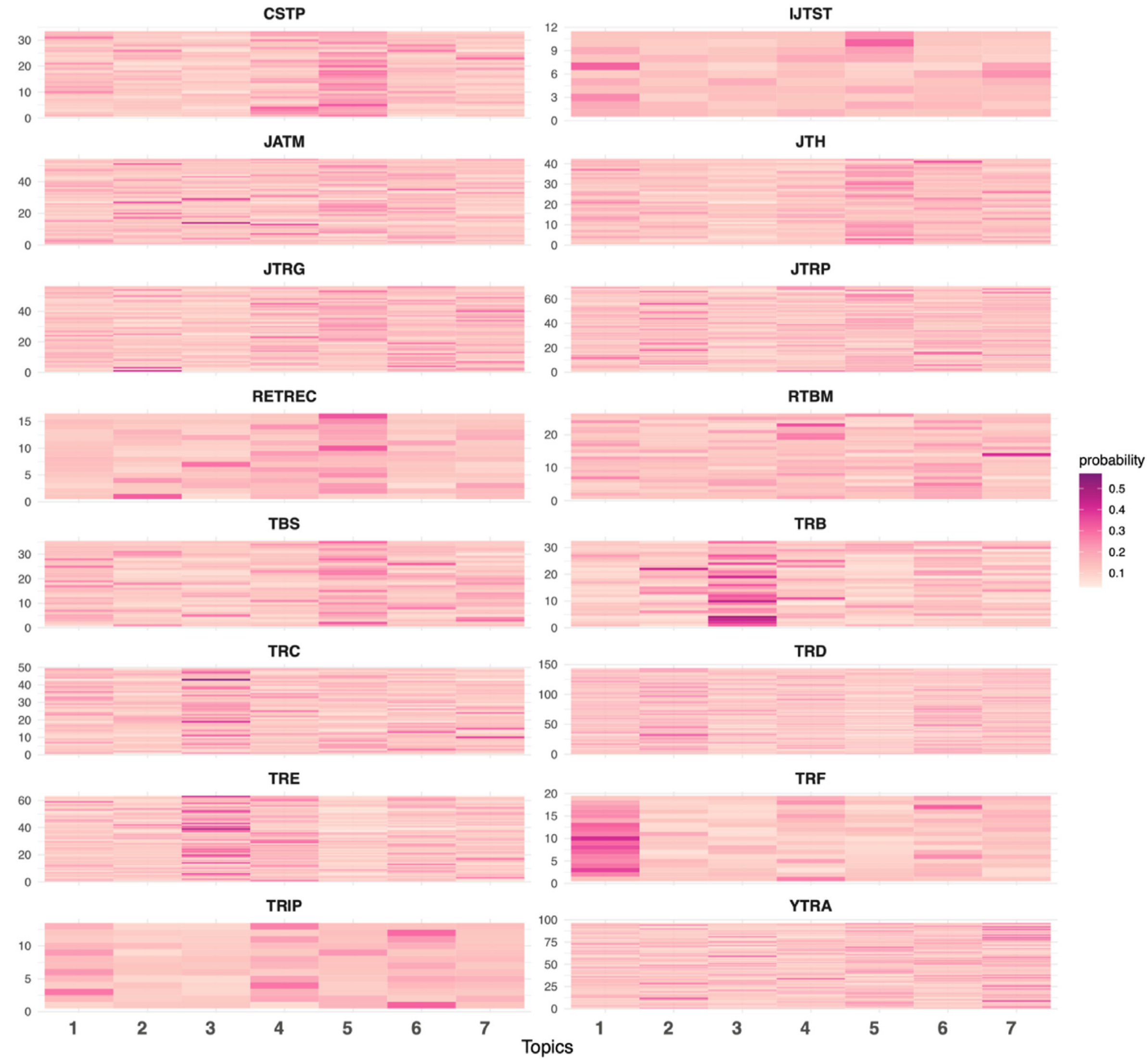


Fig. 9. Topic distribution of rejected papers from different journals.

- The duplication rate does not have significant impacts on decision-making.
- Sometimes, the decision letter may not reflect the real reasons for rejection for various reasons.
- Reviewers' perspectives and values can vary significantly in reviewing for different journals.

Based on the above findings and our experience, the following recommendations are summarized to facilitate the publication process.

- **Read carefully the "Guide for authors".** It contains more information than researchers might anticipate. For example, *Transport Policy* may desk reject papers that do not use page numbers, and this rule is explicitly written on their website. Some journals may specify their similarity bar in the guide, and others may be picky in word limits. To avoid unnecessary setbacks during the lengthy publication process, it is wise to adhere closely to these guidelines.
- **Keep the similarity rate low.** Keep SR below 15% (even 10% to be on the safe side), and single similarity rate below 1%.
- **Choose journals strategically and seriously.** The right journal should not only have a great match between its reputation and the quality of your paper but also appreciate the topics and flavor of the work.
- **Do not spam submissions.** Although it is unclear to the authors of this research how spam detection works, authors suspected of spamming are flagged in the transfer system. Moreover, transportation is a big yet small community, a paper may reach the same pool of reviewers, albeit submitted to different journals.
- **Make a good first impression.** Editors need to handle hundreds of papers per month, so they have to make quick decisions. It can be risky if the editors have to dig deep to discover the merits of your work (e.g., the real research question and original contribution) or clear any doubts (e.g., the source of similarity). The Editor-in-Chief of JTRG also acknowledged the importance of attractive titles and figures in promoting a paper's impact and viability (Witlox, 2019).

Writing plays a critical role in making a good first impression. It has been emphasized by multiple Editors-in-Chief that if they cannot easily understand the idea of the paper in normal reviewing time, which is often short, they will most likely desk reject it. Moreover, symptoms of unprofessionalism, such as wrong formats, compiling errors from Latex or citations, poor quality of figures, and typos in the title, also significantly undermine the first impression. It is thus worth devoting as much effort as needed to improve writing and ensure readability.

- **Have critical thinking regarding a desk rejection.** When it comes to desk rejections, the decision letter might be drafted based on journal- or editor-specific templates. Some templates can be even very long, making one believe it is tailored to his/her work. Therefore, if your work is unfortunately desk rejected, think critically about the real reasons for the rejection, which may help in your next submission.

Regarding resubmissions, it is important to differentiate three types of them: (1) submitting simultaneously to several journals, which is strictly forbidden for almost all publishers, (2) after rejection, revising and resubmitting the work, which is reasonable and is the logic of the transfer system, and (3) trying multiple journals by trial and error, which is considered a spam.

It is also worth noting that the evaluation of research submissions is conducted by the Editor-in-Chief, alongside various editors and reviewers. These experts have diverse backgrounds, different standards, and unique understandings of the journal's scope and criteria, all of which significantly influence the acceptance or rejection of submitted papers. Furthermore, publishers periodically reconfigure journal editorial boards, a practice that inevitably reshapes a journal's character and expectations. Therefore, it is beneficial for researchers to regularly recalibrate their perceptions of target journals to align with these dynamic changes.

In the end, we emphasize again that the present study is naturally empirical, based on a biased dataset collected within a specific period. One can expect different results if the data is changed. As such, it should not be used to profile any journal but as a supporting reference for publication in the transport area.

Replication and data sharing

Since this research is based on the editorial system from Elsevier, we will not be able to share the raw data for GDPR compliance.

CRediT authorship contribution statement

Jiaming Wu: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Ivan Sanchez-Diaz:** Formal analysis, Funding acquisition, Writing – review & editing. **Ying Yang:** Formal analysis, Resources, Writing – review & editing. **Xiaobo Qu:** Formal analysis, Resources, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

This work received support from Transport Area of Advance, Chalmers University of Technology. Special thanks to Pringle Chris, Executive Publisher of Transport Journals at Elsevier, for his generous support in conducting this research. This research also benefits a lot through the discussions with Prof. Juan de Dios Ortuzar (former Co-Editor-in-Chief of TRA), Prof. Xinyu (Jason) Cao (Co-Editor-in-Chief of TRD), Prof. Kay Axhausen (Editor-in-Chief of *Transportation*), Prof. Maria Attard (Co-Editor-in-Chief of RTBM), and Prof. Shuaian Wang (Co-Editor-in-Chief of TRE). We appreciate their invaluable comments and insights, which nurtured this research.

Appendix

Table A1
Journal list in the transportation portfolio (ranked alphabetically).

Journal	Total number of papers	Number of reviewed papers
Accident Analysis and Prevention (AAP)	9	0
Asian Journal of Shipping & Logistics (AJSL)	22	4
Asian Transport Studies (ATS)	18	4
Case Studies on Transport Policy (CSTP)	125	40
Communications in Transportation Research (COMMTR)	13	0
Economics of Transportation (ECOTRA)	1	0
Green Energy and Intelligent Transportation (GEITS)	0	0
International Journal of Transportation Science & Technology (IJTST)	54	11
Journal of Air Transport Management (JATM)	254	56
Journal of Choice Modelling (JOCM)	44	9
Journal of Public Transportation (JPT)	55	2
Journal of Rail Transport Planning & Management (JRTPM)	44	8
Journal of Transport & Health (JTH)	289	42
Journal of Transport Geography (JTRG)	420	59
Journal of Urban Mobility (JUM)	13	3
Maritime Transport Research (MARTRA)	25	1
Multimodal Transportation (MULTRA)	15	7
Research in Transportation Economics (RETREC)	196	16
Research in Transportation Business & Management (RTBM)	244	32
Social Sciences and Humanities Open (SSHO)	0	0
Transport Policy (TP)	440	76

(*continued on next page*)

Table A1 (*continued*)

Journal	Total number of papers	Number of reviewed papers
Travel Behaviour & Society (TBS)	207	36
Transportation Research Part A: Policy & Practice (TRA)	855	96
Transportation Research Part B: Methodological (TRB)	287	33
Transportation Research Part C: Emerging Technologies (TRC)	74	49
Transportation Research Part D: Transport & Environment (TRD)	692	146
Transportation Research Part E: Logistics & Transportation Review (TRE)	358	63
Transportation Research Part F: Traffic Psychology & Behaviour (TRF)	285	19
Transportation Research Interdisciplinary Perspectives (TRIP)	48	22
Urban Governance (UG)	0	0
Total	5,168	845

References

Edmans, A., 2023. Learnings from 1,000 rejections. https://dx.doi.org/10.2139/ssrn.4336383.

Grün, B., Hornik, K., 2011. Topicmodels: an *R* package for fitting topic models. J. Stat. Soft. 40, 1–30.

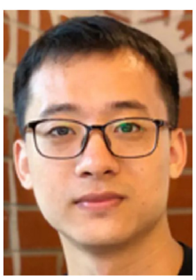
Klingner, J.K., Scanlon, D., Pressley, M., 2005. How to publish in scholarly journals. Educ. Res. 34, 14–20.

Rinker, T.W., 2021. Sentimentr: Calculate Text Polarity Sentiment. Buffalo, New York. https://github.com/trinker/sentimentr.version2.9.0.

Schimel, J., 2012. Writing Science: How to Write Papers that Get Cited and Proposals that Get Funded. Oxford University Press, California, USA.

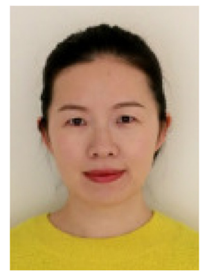
Van der Loo, Mark PJ., 2014. The stringdist package for approximate string matching. https://journal.r-project.org/archive/2014-1/loo.pdf.

Witlox, F., 2019. Getting your paper reviewed and finally published in Journal of Transport Geography: the do's and don'ts from the viewpoint of the editor-in-chief. J. Transport Geogr. 81, 102545.



Jiaming Wu received his B.S. and M.S. degrees in the School of Transportation Science and Engineering from Harbin Institute of Technology in 2014, and his Ph.D. degree from Southeast University in 2019. He is currently a Researcher in the Department of Architecture and Civil Engineering at Chalmers University of Technology, Gothenburg, Sweden. His research interests include electric vehicle fleet management (routing and charging), connected and automated vehicle platooning, and intersection control.

Ivan Sanchez-Diaz is an Associate Professor at the Division of Service Management and Logistics at Technology Management and Economics, Chalmers University of Technology, Sweden. His research focuses on freight demand modeling and the design of urban freight transportation policy. His work involves the development of statistical analysis, behavioral models, and analytical models for freight transportation systems planning.



Ying Yang is currently a Professor at Shanghai University, China. She received her B.S. degree from Renmin University of China and her Ph.D. degree from Beijing Normal University in 2012. Her research is focused on cross-cultural psychology, behavioral decision theory, and traffic psychology. She has great interest and passion in understanding how people from different cultures perceive, think, and behave. She is an awardee of the prestigious Australian Government Endeavour Research Fellowship in 2016, and earned ACU Women researcher award in 2020. Her studies were published at *Journal of Cross-Cultural Psychology*, *Personality and Individual Differences*, *Transportation Research Part A*, *Part D*, and *Part F*.

Xiaobo Qu is a Changjiang Chair Professor in Intelligent Transportation, Tsinghua University in China. His research is focused on improving large, complex, and interrelated urban mobility systems by integrating with emerging technologies. He has published over 180 journal articles published at top tier journals in the area of transportation. He is an elected member in Academia Europaea-The Academy of Europe since 2020.