International Journal of Evaluation and Research in Education (IJERE)
Vol. 15, No. 4, August 2026, pp. 3583~3590
ISSN: 2252-8822, DOI: 10.11591/ijere.v15i4.38930

Writing a research paper with artificial intelligence: a step-by-step guide for junior researchers

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Article Info

Article history:

Received Feb 1, 2026
Revised Jun 26, 2026
Accepted Jul 6, 2026

Keywords:

Academic writing
Artificial intelligence
IMRaD
Plagiarism
Publication ethics
Research design

ABSTRACT

Early-career researchers often have a sound idea yet struggle to turn it into a publishable manuscript that reviewers can trace and evaluate. This paper synthesizes practical guidance on structuring and drafting research articles using the introduction-methods-results-and-discussion (IMRaD) convention, while addressing emerging concerns about the responsible use of generative artificial intelligence (AI) in academic writing. A documentary narrative synthesis was conducted using 36 high-authority sources, including writing guides, guidance from journal editors, publisher and ethics policies, and recent empirical studies on AI-assisted writing. Recommendations were coded using an explicit IMRaD-aligned codebook and then consolidated into a step-by-step workflow from question formulation to submission checks. The synthesis indicates that treating IMRaD as a traceability checklist improves alignment between research questions, methods, results, and claims, and that iterative revision is more effective than one-pass drafting. AI support is most defensible when limited to language and process assistance, combined with disclosure, reference verification, and full human accountability for all content. The paper concludes with an actionable checklist and a visual 'traceability map' that can be adapted for research training and supervision.

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1. INTRODUCTION

Across many universities (including Indonesia and internationally), early-career researchers often receive limited formal training in academic writing. Without structured guidance and feedback, they may produce manuscripts that fail peer review, slowing career progression and weakening institutional research output by increasing rejection cycles and resubmissions [1]–[3]. Research articles are the main vehicle for communicating findings in a form that enables scrutiny, replication, and further development. Yet many junior researchers report that the craft of turning a strong idea into a traceable manuscript is learned informally and unevenly. Practical writing guides emphasize that clarity is achieved through deliberate structure, disciplined revision, and explicit signaling of what was done and why [1]–[3].

The introduction-methods-results-and-discussion (IMRaD) convention has become the dominant reporting scaffold across many empirical fields because it answers, in order, the questions that reviewers and readers use to judge credibility: why the study matters, how it was conducted, what was found, and what those findings mean. Surveys of publishing practice show sustained use of IMRaD and related variants, with discipline-specific flexibility in the separation or combination of results and discussion [4]–[6]. Generative artificial intelligence (GenAI) tools are now widely used for drafting, editing, and literature scoping, creating both opportunities and integrity risks. Recent studies report productivity gains (particularly for multilingual authors), but also document risks including fabricated references, unverified claims, and blurred accountability for authorship [7]–[11].

In response, publishers, universities, and ethics bodies have issued guidance that generally permits limited language support, rejects AI authorship, and stresses disclosure, verification, and safe handling of data. However, this guidance is evolving rapidly and is often presented separately from mainstream writing pedagogy, leaving authors uncertain about what constitutes defensible practice at submission [12]–[17]. Few sources provide an integrated, end-to-end workflow that combines IMRaD scaffolding with responsible AI use, leaving junior researchers without practical, traceable support. This paper integrates IMRaD-based writing guidance with current publication-ethics positions on AI into a single, traceable workflow. The study addresses three research questions (RQs):

- What core information should each IMRaD section contain to allow evaluation of validity and reproducibility?
- What drafting and revision workflow best supports early-career authors?
- How can generative AI be used to improve clarity and efficiency without undermining originality, accountability, and ethics?

Methodologically, a documentary narrative synthesis of 36 sources was conducted and coded using an IMRaD-aligned codebook. The main contributions are: i) a consolidated checklist that links manuscript sections to evaluability requirements and ii) a visual traceability map highlighting points where ethical checks (including AI disclosure and reference verification) should be applied [18]–[22]. To our knowledge, it is among the first guides to synthesize IMRaD writing principles with current publication-ethics positions on AI into a single checklist-driven workflow. The resulting checklist is configurable for supervision, research-methods modules, and institutional writing support, helping programs improve manuscript quality and reduce avoidable criticism from reviewers.

2. METHOD

2.1. Design and corpus

The study used a documentary narrative synthesis in which published guidance and research on academic writing and AI-assisted writing were treated as the data corpus. This design is appropriate when the objective is to consolidate actionable recommendations from heterogeneous sources rather than to estimate the effect of an intervention [18], [19].

2.2. Source identification and selection

Sources were identified through targeted keyword searching (IMRaD, scientific writing, publication ethics, authorship, and AI) and citation chaining from editorial and ethics organizations. Inclusion criteria were: i) recognized writing guides or writing-center resources; ii) publisher, journal, or ethics-body policy statements; and iii) peer-reviewed studies examining benefits and risks of generative AI in academic writing. The final corpus comprised 36 sources. Sources were selected for authority and relevance, but the synthesis is narrative rather than systematic, so outputs should be interpreted as guidance rather than definitive evidence [12], [17], [20], [23].

2.3. Data extraction and coding

Each source was coded using a predefined codebook with two domains: i) IMRaD traceability requirements (problem framing, methodological transparency, result presentation, interpretation, and conclusion claims) and ii) AI-related integrity considerations (disclosure, verification, confidentiality, and accountability). Codes were consolidated into a step-by-step workflow and a checklist for drafting and revision. Recommendations were coded into IMRaD categories and cross-checked for internal consistency to reduce consolidation bias [22], [24], [25].

2.4. Descriptive analysis

To increase transparency about the evidence base, sources were summarized by type (journal article, book/handbook, and policy/guidance) and by publication year band. These descriptive statistics support the interpretation of the synthesis and show the balance between foundational writing guidance and recent AI-focused literature [7], [8], [10].

3. RESULTS AND DISCUSSION

3.1. Profile of included sources

The corpus combined foundational writing guidance with a recent surge of policy and empirical work on generative AI. Table 1 summarizes the distribution by source type and publication year band. With the added journal articles, peer-reviewed studies now represent 47.2% (17/36) of the corpus. Most items (25/36) were published from 2021 to 2026, reflecting rapid policy development and a growing evidence base on feedback literacy, learning analytics, and GenAI-related assessment governance and integrity [26]–[35].

Table 1. Profile of documentary sources included (n=36)

Category	Count (n)	Share (%)
Source type: journal article	17	47.2
Source type: book/handbook	7	19.4
Source type: policy/guidance	11	30.6
Source type: news article	1	2.8
Publication year band		
<=2010	4	11.1
2011-2015	2	5.6
2016-2020	5	13.9
2021-2026	25	69.4

3.2. IMRaD as a traceability checklist

Across sources, a consistent message is that IMRaD is not only a formatting convention but also a traceability mechanism: each section should provide the minimum information readers need to assess appropriateness, credibility, and limitations [1], [4]. Table 2 consolidates the core 'moves' and recommended checks for each section. While Swales and Feak [24] emphasize rhetorical moves, the present synthesis extends that tradition by adding AI literacy checks that improve accountability at each drafting stage. To illustrate evidential links, structured abstract guidance was drawn from European Association of Science Editors (EASE) [20], while ethical AI use principles were based on Committee on Publication Ethics (COPE) [12] and International Committee of Medical Journal Editors (ICMJE) [17].

Table 2. Consolidated IMRaD checklist for traceable reporting and revision

Section	Core information for evaluability (abridged)
Title and abstract	State topic, design, and key contribution; in the abstract, include background, aim, method/corpus, headline findings, and conclusion.
Introduction	Establish context and relevance; synthesize related work; articulate a specific gap/problem; state aims/RQs; preview approach and contributions.
Methods	Describe design; data sources/participants; inclusion and exclusion criteria; instruments/materials; procedures; analysis steps; ethics and disclosure (where relevant).
Results	Report findings in the order of objectives/RQs; use tables/figures for data; highlight the most important patterns without interpretation; avoid repeating the same data in multiple formats.
Discussion	Interpret key findings; compare with prior work; explain consistencies and inconsistencies; discuss implications; state strengths and limitations; avoid over-claiming; propose future work.
Conclusion	Answer objectives/RQs; state the main contributions and implications; note remaining issues; propose focused future research directions grounded in the limitations.
References	Ensure every reference is cited; ensure every citation appears in the list; use a consistent style and verify accuracy (including AI-assisted checks).

3.3. Drafting and revision workflow

The synthesis supports an iterative workflow in which authors separate 'content generation' from 'quality control'. Early drafts are used to test the argument's logic against the IMRaD checklist, followed by successive rounds of structural, paragraph-level, and sentence-level revision. This matters because writing is recursive: each revision cycle clarifies the argument and reduces avoidable error, aligning with Booth *et al*. [18] view of drafting as iterative problem-solving.

A practical sequence is: [1], [18], [21], [23] draft a 'zero draft' rapidly to expose gaps and missing logic, without polishing language. Revise for structure: reorder sections and paragraphs so that objectives, methods, results, and claims align. Revise for clarity by tightening topic sentences, improving transitions, and removing redundancy. Edit at the sentence level: reduce wordiness, standardize terminology, and check tense/voice consistency. Run submission checks: verify every citation and reference, ensure figure/table labelling, and confirm AI disclosure and confidentiality compliance.

3.4. Responsible use of generative AI in academic writing

3.4.1. Potential benefits

Studies suggest that AI-assisted tools can improve efficiency in routine writing tasks such as grammar correction, tone adjustment, and early-stage summarization. These benefits are most defensible when the author retains control over meaning and verifies any suggested claims or references [7], [8], [10].

3.4.2. Risks and integrity concerns

The most frequently highlighted risks are fabricated or inaccurate citations, 'plausible' but wrong factual statements, confidentiality breaches, and reduced traceability in argumentation. Such failures can occur because generative models predict likely text patterns rather than verify facts against sources, so uncritical use can introduce fabricated references or unsupported claims. Ethics bodies also emphasize that AI systems cannot meet authorship criteria because they cannot take responsibility for the work. Reports from higher education indicate widespread student use of AI, reinforcing the need for explicit AI literacy and disclosure norms [12]–[15], [36].

3.4.3. Practical disclosure and verification guidance

A convergent recommendation is to treat AI as a writing assistant rather than a co-author: use it for language and process support, not for generating unverified claims, deciding analysis, or drafting core interpretations. When AI use is non-trivial, authors should disclose the tool and purpose, verify every reference and factual claim against primary sources, and follow both journal policy and institutional guidance. At the programmed level, universities can embed disclosure, verification, and data-protection routines into research methods and academic integrity training, thereby making expectations explicit before submission [13], [14], [16], [17]. Figure 1 summarizes the integrated workflow from idea formulation to submission checks, highlighting points where ethical safeguards (especially around AI use and reference verification) should be applied.

3.4.4. Embedding the workflow in supervision and research training

Use peer-review workshops where students evaluate anonymized drafts against the checklist. Require a short 'traceability appendix' showing where each research question is answered (section and table/figure). Beyond individual writing habits, the workflow can be embedded in research-methods teaching and supervision so that expectations are explicit and assessable. A practical approach is to align each IMRaD element with a weekly milestone: a one-page problem–gap–aim brief (introduction), a reproducible protocol and analysis plan (methods), a 'one figure–one message' results pack (results), and a defensible claims matrix that links each conclusion to supporting evidence and limits (discussion). This makes the writing process easier to coach because supervisors can comment on recurring moves rather than rewriting drafts line by line. When the scaffold is used consistently, junior researchers also develop feedback literacy and become more willing to revise structure before polishing language, which typically reduces late-stage rework.

For multilingual cohorts, pairing the checklist with short micro-lessons on rhetorical moves (establishing territory, identifying a niche, and stating contribution) helps writers translate disciplinary thinking into readable prose without relying on template copying [24]. Learning analytics can be used cautiously to monitor progress (timeliness of drafts and frequency of revisions) without turning writing into surveillance; the emphasis should remain on improvement rather than policing. At the programmed level, the checklist can be adapted into rubrics for authentic assessment, helping departments design tasks that reward reasoning, transparency, and domain judgement rather than fluent text alone [4], [32], [34].

3.4.5. Maintaining an audit trail for AI-assisted writing

Given the speed at which generative tools and publisher policies evolve, the most defensible stance is to maintain a lightweight audit trail that demonstrates human control over content. In practice, this means recording what tool was used, for which bounded purpose, and how outputs were verified before entering the manuscript. This record supports disclosure expectations and can be retained privately unless a journal or institution requests clarification. It also helps authors avoid two common failure modes: importing confident-sounding claims without checking the underlying evidence, and 'citation laundering' where fabricated references propagate through revisions.

– Keep the exact disclosure wording used in the manuscript.
– Record the human verification step taken (source check, recalculation, re-analysis).
– Note the prompt purpose and date (a short description is sufficient).
– State the task category (language editing, summarizing, outlining, code assistance).
– Log the tool name/version and access mode (local vs cloud).

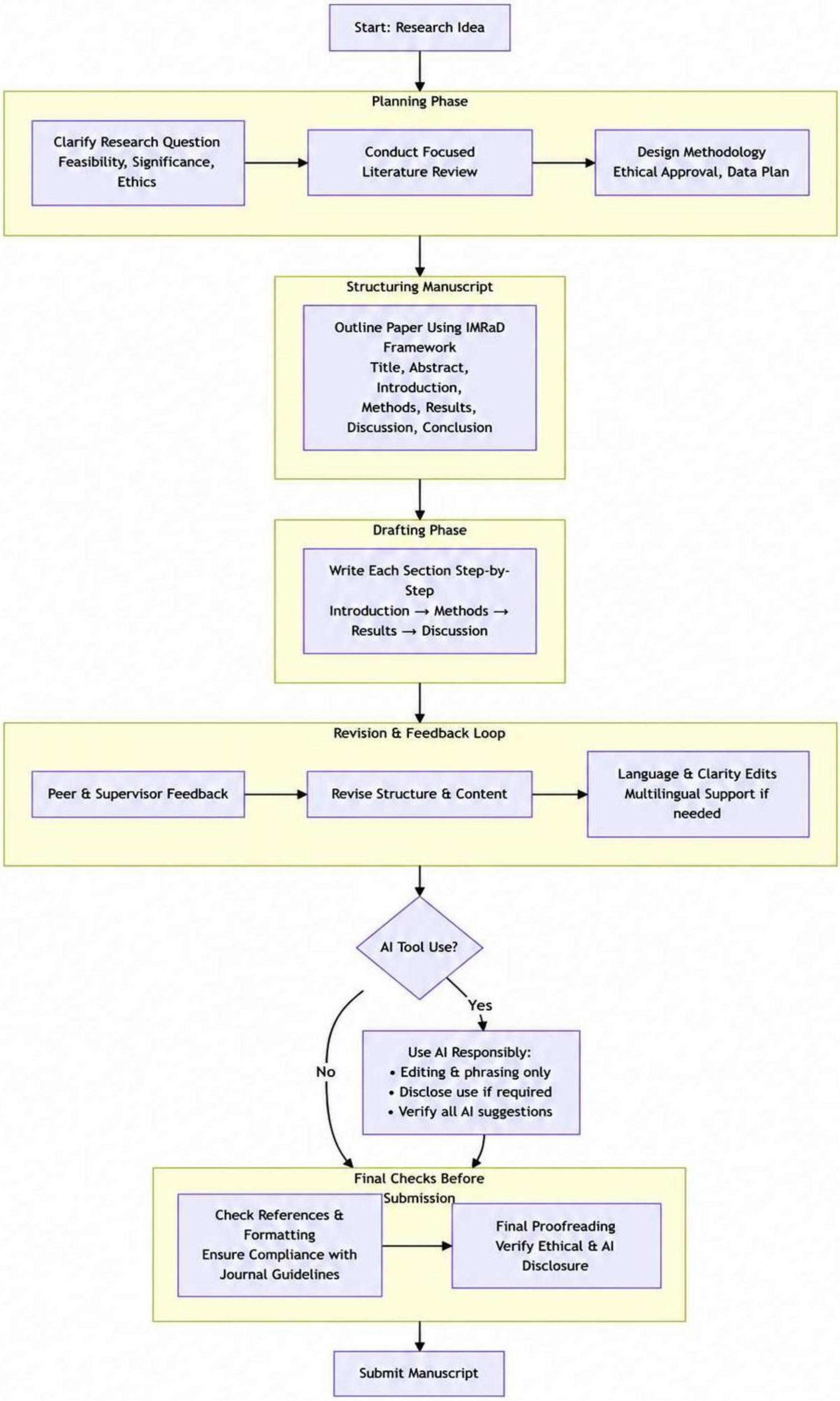

Figure 1. A flowchart for step-by-step writing of a research paper with ethical AI integration

A simple log can be combined with a pre-submission integrity check: verify every citation against the original source, confirm that quoted numbers match the cited table/figure, and ensure that any AI-assisted paraphrase still reflects the source meaning. When sensitive material is involved, the log should also note what was not shared with external tools, reinforcing confidentiality and data-protection expectations [14]. If the manuscript undergoes multiple rounds of revision, updating the log helps keep the disclosure statement aligned with the final text, especially when co-authors contribute at different stages. Such routines align with editorial guidance that authors, not software, remain accountable for accuracy and originality [12], [16], [17].

3.5. Limitations

This study synthesizes documentary sources rather than reporting primary empirical data, so its outputs are best interpreted as evidence-informed guidelines rather than tested interventions. The synthesis is influenced by English-language publishing norms and by rapidly evolving AI policies, which may require periodic updating. While a predefined codebook was used to improve consistency, documentary coding inevitably involves interpretation and may reflect the author's judgment in consolidating recommendations [15], [18], [20].

4. CONCLUSION

This paper consolidates guidance from 36 documentary sources into a practical, IMRaD-aligned workflow that strengthens traceability from the research question to the claims. The main contributions are a consolidated checklist and an integrated workflow map that supports planning, drafting, and submission-stage quality control. In practice, the synthesis suggests that reviewers' trust is most effectively built when authors make design and analysis decisions explicit, align results reporting with stated objectives, and state the limitations that bound the claims.

In relation to generative AI, the paper highlights an emerging consensus: limited language and process support can be acceptable, but authors must remain fully accountable for accuracy, interpretation, and originality. Remaining challenges include inconsistent disclosure thresholds across journals and institutions, and the need for more discipline-specific guidance on safe data handling and reference verification. Future research should empirically test the proposed workflow (for example, through controlled training interventions for MSc. and Ph.D. cohorts) and evaluate outcomes such as manuscript quality, the number of revision rounds, and the transparency of AI disclosure practices.

FUNDING INFORMATION

The authors have a workplace fellowship (MidKent College Training), which is funding this research paper on their own account.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Emad Al-Mahdawi	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓			✓
Nkaepe Olaniyi	✓	✓				✓		✓	✓	✓		✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

DATA AVAILABILITY
All data are available via DOI links, URLs, book titles, and organization names.

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