

¹ Risk of Bias: Explainable, human-in-the-loop software for general risk-of-bias assessment

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⁷ Summary

⁸ Assessing risk of bias (RoB) is a fundamental component of evidence synthesis, directly ⁹ affecting the credibility and interpretability of systematic reviews and meta-analyses. RoB ¹⁰ assessment clarifies to what extent findings from primary studies can be trusted, guiding both research conclusions and downstream policy or clinical recommendations ([Higgins et al., 2019](#); [Page et al., 2021](#); [P. Whiting et al., 2016](#)). Despite its importance, RoB assessment ¹¹ remains time-intensive and demands specialized expertise. The *risk-of-bias* Python package ¹² provides a general, framework-agnostic software assistant for risk-of-bias assessment, combining ¹³ explainable AI with open, programmable infrastructure. The tool is designed to support any ¹⁴ domain-based risk-of-bias instrument, with the widely adopted Cochrane RoB 2 tool for ¹⁵ randomized trials ([Sterne et al., 2019](#)) implemented as a framework exemplar. By storing ¹⁶ explicit evidence and reasoning for every answer, and providing both command line and web ¹⁷ interfaces, *risk-of-bias* enables explainable, auditable, and efficient assessment, supporting ¹⁸ reproducible research workflows.

¹⁹ Statement of Need

²⁰ Manual risk-of-bias assessment is a critical bottleneck in evidence synthesis, with typical ²¹ reviews requiring 10–60 minutes of expert time per study, repeated across dozens or hundreds ²² of manuscripts ([Savovic et al., 2014](#)). The gold standard remains two independent human ²³ reviewers with a third for adjudication—an approach that is resource intensive and often ²⁴ unattainable in time- or resource-constrained projects. Commercial platforms (e.g., Covidence ²⁵ ([Kellermeyer et al., 2018](#)), DistillerSR) offer user-friendly interfaces, while AI-driven tools like ²⁶ RobotReviewer ([Marshall et al., 2016](#)) provide partial automation for specific tasks, but few ²⁷ options combine openness, programmability, explainability, and affordability. The *risk-of-bias* ²⁸ package addresses this gap by delivering a fully open-source, scriptable tool that provides ²⁹ structured, explainable output, and supports integration with both human and AI-driven ³⁰ workflows. Because the package is open source and developed with modern software best ³¹ practices (including continuous integration), it can be rapidly updated to support the latest AI ³² models as they emerge. Unlike commercial software, where underlying models may be opaque ³³ and lag behind the state of the art, this approach puts the technology directly in the hands ³⁴ of researchers—empowering them to select, use, or even contribute the most powerful and ³⁵ up-to-date AI models for their needs.

³⁶ Software Overview & Architecture

³⁷ *Risk-of-bias* is built around a generic, hierarchical assessment structure:

40 **Framework → Domain → Question → Response**

41 This mirrors all major RoB instruments, enabling use beyond the Cochrane RoB 2 tool. The
42 package offers:

- 43
 - 44 ▪ A modular core, where any framework is defined as a JSON schema capturing its domains,
45 questions, and allowed responses.
 - 46 ▪ Data classes (via Pydantic) that explicitly store, for each answer: the response, supporting
47 evidence (verbatim text from the manuscript), and a natural language reasoning/explana-
48 tion.
 - 49 ▪ Multiple user interfaces: a command-line interface (CLI) for batch assessment and
50 workflow integration, and a web interface for interactive analysis and report download.
51 This enables both technical and non-technical users to use the tool effectively.
 - 52 ▪ An engine that systematically applies the framework to imported manuscripts, walking
53 through the assessment questions and storing structured outputs.
 - 54 ▪ Export functions for RobVis-compatible CSV summaries, facilitating high-quality visualiza-
55 tions using the *robvis* R package or web app ([McGuinness & Higgins, 2021](#)).

56 For batch analysis, the CLI allows processing of entire directories of manuscripts, automatically
57 generating summary CSVs for cross-study visualization or meta-analysis.

57 **Explainable AI & Evidence-linked Reasoning**

58 Unlike “black-box” AI tools, *risk-of-bias* stores and surfaces both the **evidence** (exact textual
59 excerpts) and the **reasoning** (explanation of how evidence informs the answer) for every question
60 in every domain. This design meets the auditability requirements of leading journals and
61 systematic review standards, supporting both transparent reporting and dispute resolution in
62 collaborative review teams. When used alongside independent human reviewers, the software’s
63 explicit justifications make it easy to compare and resolve discrepancies, and to understand
64 why the software or a reviewer made a particular assessment. This explainable approach is
65 particularly valuable as LLM-based and hybrid systems become more common in evidence
66 synthesis, ensuring assessments remain interpretable and verifiable.

67 **Human-in-the-Loop Augmentation**

68 The *risk-of-bias* package is designed to augment, not replace expert human judgment. Its
69 intended workflow is to augment the established approach of two independent human reviewers,
70 with a third human reviewer adjudicating discrepancies. AI can meaningfully enhance this
71 process: for example, the software can serve as an additional reviewer alongside human experts,
72 providing a systematically derived perspective while leaving final adjudication to a human.
73 Incorporating an AI perspective can help reveal potential biases in both directions—including
74 those arising from the AI itself—and offer a complementary lens for evaluating studies. In
75 situations where resource constraints make the gold standard unachievable, AI tools can support
76 more consistent and thorough assessments, helping raise the overall quality of risk-of-bias
77 evaluations as the field moves toward best practice.

78 **Current Framework Support & Extensibility**

79 While RoB 2 for randomized trials is implemented end-to-end (with both CLI and web UI, and
80 export to RobVis/CSV ([McGuinness & Higgins, 2021](#))), the architecture is framework-agnostic
81 by design. Additional frameworks—such as ROBINS-I ([Sterne et al., 2016](#)), ROBINS-D
82 ([Higgins et al., 2024](#)), QUADAS-2 ([P. F. Whiting et al., 2011](#)), and PROBAST ([Wolff et al.,
83 2019](#))—can be registered as JSON schemas immediately, leveraging the same hierarchical logic
84 (framework → domain → question → response), and is in the roadmap for future explicit

85 inclusion in the software. This software is already being utilised to support study design and
86 systematic literature reviews.

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89 the authors of RoB 2 (Sterne et al., 2019), and the wider open-source and evidence synthesis
90 community whose contributions inform both the methodology and the software ecosystem.

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