

Machine learning and patient-reported outcomes in oncology: A systematic literature review on methodological quality

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BACKGROUND

Machine learning (ML), as a subfield of artificial intelligence, offers various opportunities for the medical field (e.g. risk assessment, screening, detection), but it may also bring along methodological challenges and pitfalls.

The objectives of the herein presented review are threefold:

- To assess the prevalence of reporting on ML-models including patient-reported outcome (PRO) data in scientific publications in oncology, more specifically
 - whether there has been an increase in research publications about ML with PROs as a feature or an outcome over the years and
 - which PRO instruments were most commonly used in ML studies
- To assess which ML-algorithms are most commonly used in oncological PRO research
- To evaluate the quality of applied ML - according to a modified version of the "minimum information about clinical artificial intelligence modeling" (MI-CLAIM) checklist¹

TAKE HOME MESSAGE: Current reporting practice shows only moderate compliance with existing reporting guidelines. The use of modern technology requires methodological rigor in application and reporting to result in reliable and reproducible evidence.

METHODS

- systematic literature review
- two-level screening (abstract & full-text), double-review
- exclusion criteria
 - study type: systematic review, narrative review (used for backward search)
 - no cancer patients
 - no supervised machine learning/deep learning
 - no PRO as a feature or outcome
 - time filter: until December 2022
- quality appraisal of ML models according to the MI-CLAIM checklist¹

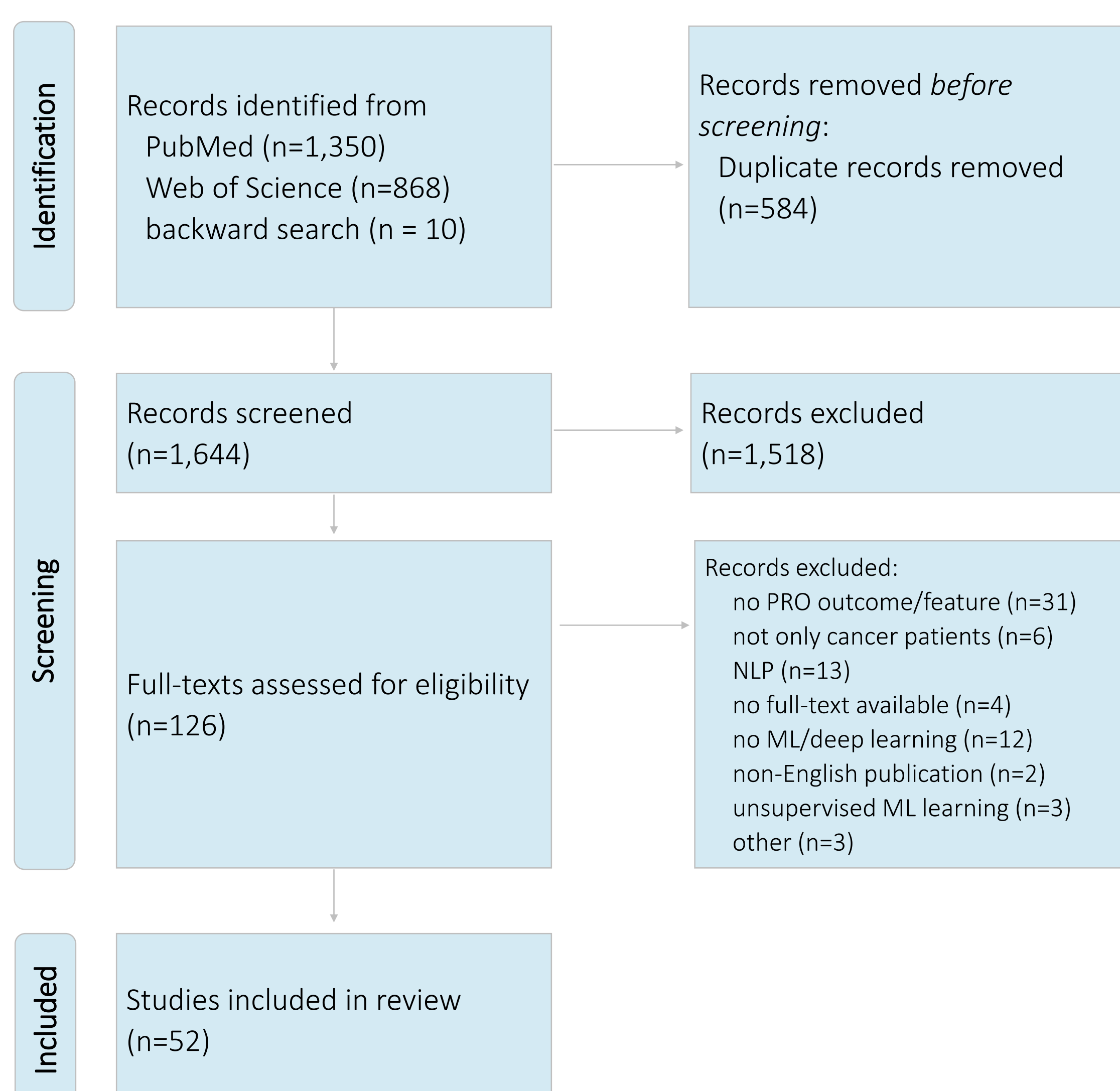
Take a look at the review protocol for details on the methodology. Scan the QR code to access the PROSPERO registration.



ELIGIBLE REFERENCES

Screening of 1,644 abstracts resulted in 52 eligible publications
Fig. 1 gives an overview of the selection of sources.

Fig. 1 PRISMA Flow chart adapted from Page et al (2021)²



RESULTS

- Objective 1a.: number of publications in the field has doubled over the last decade
- Objective 1b.: most frequently used PRO instruments: EORTC measures: 10 (19.2%), SF12/36: 6 (11.5%)
- Objective 2: most frequently applied ML models: artificial neural networks: 14 (26.9%), random forest classifiers: 11 (21.2%)
- Objective 3: Table 1 includes detailed results of the quality appraisal

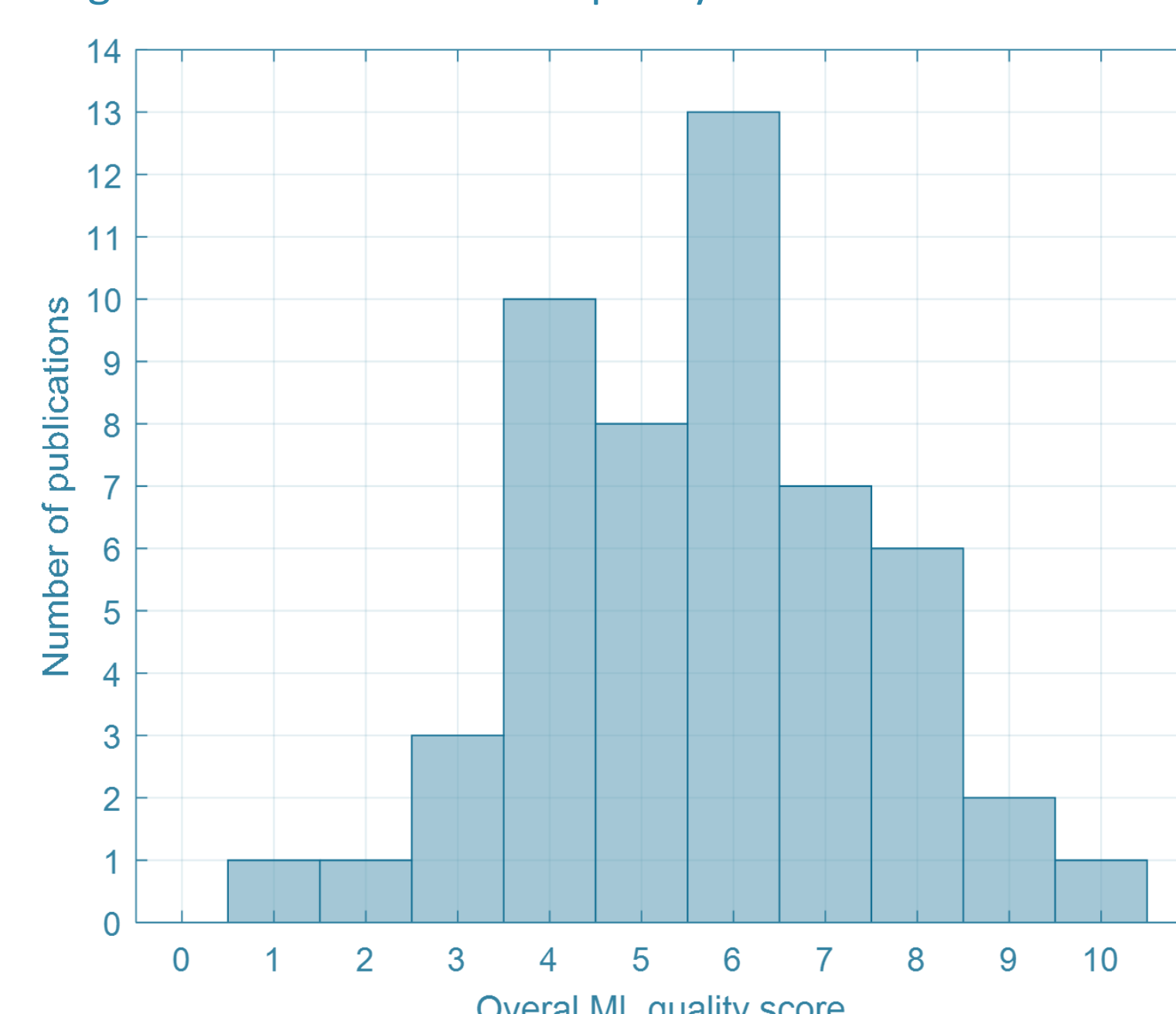
Table 1 MI-CLAIM checklist¹ results

		N	%
STUDY DESIGN	research task	48	92.3%
	data characteristics	35	67.3%
DATA PREPARATION & PARTIONING	data transformations	13	25.0%
	validation method	40	76.9%
MODEL DEVELOPMENT & SELECTION	train/test independency	42	80.8%
	model configuration & parameters	16	30.8%
MODEL PERFORMANCE	performance metric	49	94.2%
MODEL EXAMINATION	examination technique	39	75.0%
	reliability & robustness discussed	9	17.3%
REPRODUCIBILITY & TRANSPARENCY		3	5.8%

RESULTS: QUALITY SCORE (Fig. 2)

- mean quality score (out of 10): 5.7
- 9 (17.3%) studies had a quality score of at least 8
- the majority of studies had a quality score between 5 and 7

Fig. 2 Distribution of total quality score



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References: ¹B. Norgeot et al., 'Minimum information about clinical artificial intelligence modeling: the MI-CLAIM checklist', Nat. Med., vol. 26, no. 9, pp. 1320–1324, Sep. 2020, doi: 10.1038/s41591-020-1041-y.

²M. J. Page et al., 'The PRISMA 2020 statement: an updated guideline for reporting systematic reviews', BMJ, vol. 372, p. n71, 2021, doi: 10.1136/bmj.n71.

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