# AIMS.au: A Dataset for the Analysis of Modern Slavery Countermeasures in Corporate Statements

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Prepared for ICLR 2025











# Background

## Modern Slavery: A Global Issue

- Over 50 million people were affected globally (2021), with 28 million in forced labor.
- Limited transparency in corporate supply chains remains a significant barrier to eradication.

## **Regulatory Response**

- Modern Slavery Acts (MSAs) were introduced in jurisdictions such as California (2010), the UK(2015), Australia (2018), and Canada(2023), mandating large corporations to report annually on their anti-slavery efforts, but often lack clarity and specificity in their reporting and enforcement mechanisms.
- The Australian MSA notably requires over 3,000 companies to disclose annual statements against mandatory criteria.

## **Persistent Compliance Challenges**

- Compliance assessment is resource-intensive; thousands of corporate statements remain unreviewed each year.
- Corporate disclosures frequently include vague language, complicating the differentiation between superficial compliance and meaningful action.









# Objectives

## Address a significant research gap:

- Existing datasets and ML models target general domains (medical/legal).
- A clear gap exists as no dataset or ML models exist specifically for legally mandated disclosures from corporate modern slavery statements.

## **Develop AIMS.au**, a novel annotated dataset to:

- Extract key disclosures required by modern slavery legislation and filter vague sentences.
- Support fine-tuning of ML models for compliance tasks.

#### **Benchmark and evaluate:**

- Fine-tune and assess ML models using AIMS.au.
- Compare against larger LLMs in zero-shot settings.

## **Ensure practical relevance:**

- Develop in consultation with diverse stakeholders (including the Australian Government).
- Published open source to support broader research and cross-jurisdiction adaptation (e.g., UK, Canada).



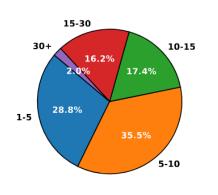


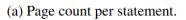


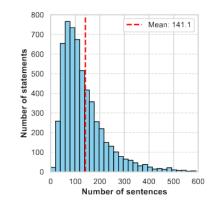
## AIMS.au is the largest publicly available dataset addressing this issue.

## **Dataset Description**

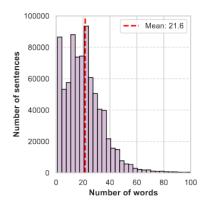
- AIMS.au: a novel dataset comprising 5,731 modern slavery statements (2019-2023), containing 800,000+ labeled sentences.
- Covers 7,270 unique entities across 20+ industry sectors including public/private companies, nonprofits, and governmentowned corporations.
- Average statement length: 10.4 pages, 141 sentences.







(b) Sentence count per statement.



(c) Word count per sentence.

Overview of the distribution of text across the 5,731 statements in our proposed dataset.





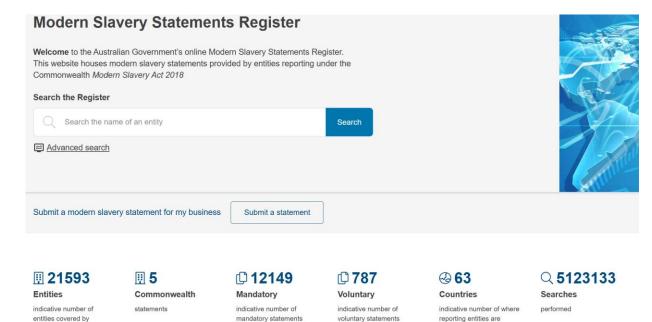




Thousands of modern slavery statements are published each year in PDF format.

## **Data Collection & Preprocessing**

- Statements sourced from the official Australian Modern Slavery Register.
- Text extraction from PDFs using PyMuPDF and ABBYY FineReader PDF, excluding scanned documents to minimize OCR errors.
- Sentence segmentation using a customized regexbased sentence splitter that handles complex punctuation and formatting.



Australian Modern Slavery Register as of March 26, 2025.





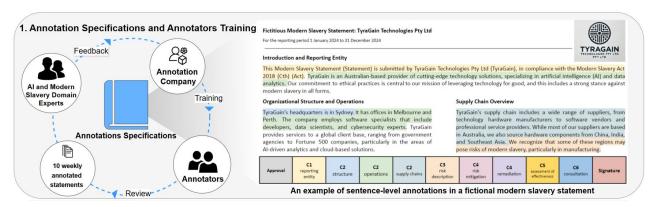




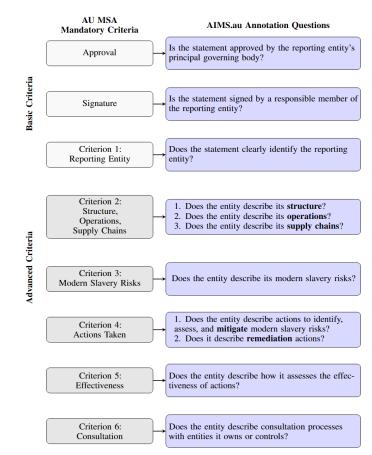
The development of high-quality annotation specifications required an interdisciplinary team.

## **Annotation Specifications and Annotators Training**

- Australian MSA's six mandatory criteria translated into 11 detailed annotation questions for sentence-level labelling.
- Annotation guidelines were iteratively refined with input from experts and stakeholders, ensuring clarity and consistency.



Overview of the annotation workflow for the AIMS.au dataset.



Correspondences between the AU MSA Mandatory Criteria and the questions designed for the annotation of the proposed AIMS.au dataset.





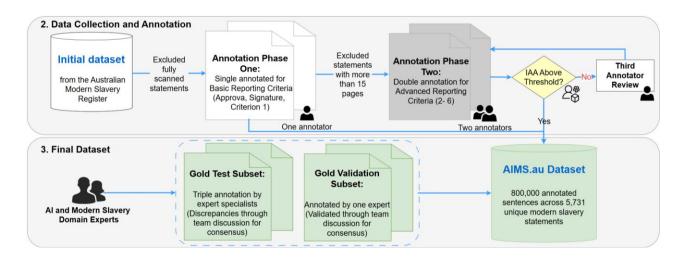




A complex annotation task that spanned one and a half years.

#### **Data Annotation Process:**

- Phase 1: Single annotation of basic criteria.
- Phase 2: Double annotation (with Inter-Annotator Agreement checks) on advanced criteria.
- Two "Gold" subsets (each comprising 50 statements), annotated by domain experts, ensuring highly reliable validation and test benchmarks.
- Rigorous quality control, including weekly checks, direct feedback loops, and corrections.



Overview of the annotation workflow for the AIMS.au dataset (continued).









# Benchmark Experiments

## **Experimental Setup and Results**

- Task: sentence-level binary classification across 11 questions.
- Evaluated Models: fine-tuned on AIMS.au (DistilBERT, BERT, Llama2 (7B), Llama3.2 (3B) and zero-shot (GPT-3.5 Turbo), GPT-4o, Llama3.2 (3B).
- Input Settings: no context classify using only the target sentence, and with context – classify using the sentence plus ±100 surrounding words.
- Key Results: fine-tuned models outperform zero-shot models and including context improves results.

| Question              | No           | context | With context |              |       |
|-----------------------|--------------|---------|--------------|--------------|-------|
|                       | GPT3.5 Turbo | GPT4o   | Llama3.2     | GPT3.5 Turbo | GPT4o |
| Approval              | 0.584        | 0.911   | 0.041        | 0.028        | 0.895 |
| C1 (reporting entity) | 0.148        | 0.378   | 0.054        | 0.031        | 0.427 |
| C2 (structure)        | 0.371        | 0.661   | 0.168        | 0.097        | 0.616 |
| C2 (operations)       | 0.268        | 0.616   | 0.172        | 0.167        | 0.601 |
| C2 (supply chains)    | 0.317        | 0.543   | 0.211        | 0.174        | 0.556 |
| C3 (risk description) | 0.337        | 0.422   | 0.182        | 0.194        | 0.512 |
| C4 (risk mitigation)  | 0.591        | 0.601   | 0.478        | 0.481        | 0.624 |
| C4 (remediation)      | 0.269        | 0.548   | 0.055        | 0.048        | 0.555 |
| C5 (effectiveness)    | 0.295        | 0.293   | 0.216        | 0.142        | 0.435 |
| C6 (consultation)     | 0.383        | 0.481   | 0.050        | 0.038        | 0.620 |
| Signature             | 0.684        | 0.480   | 0.091        | 0.030        | 0.763 |
| Overall (macro)       | 0.386        | 0.439   | 0.156        | 0.130        | 0.600 |

F1 evaluation results for zero-shot approaches.

| Question              | No context |       |        |          | With context |       |          |
|-----------------------|------------|-------|--------|----------|--------------|-------|----------|
|                       | DistilBERT | BERT  | Llama2 | Llama3.2 | DistilBERT   | BERT  | Llama3.2 |
| Approval              | 0.957      | 0.965 | 0.889  | 0.940    | 0.955        | 0.964 | 0.932    |
| C1 (reporting entity) | 0.639      | 0.605 | 0.579  | 0.643    | 0.698        | 0.728 | 0.715    |
| C2 (structure)        | 0.708      | 0.732 | 0.708  | 0.745    | 0.740        | 0.740 | 0.726    |
| C2 (operations)       | 0.741      | 0.718 | 0.672  | 0.753    | 0.769        | 0.758 | 0.773    |
| C2 (supply chains)    | 0.723      | 0.675 | 0.719  | 0.729    | 0.755        | 0.772 | 0.787    |
| C3 (risk description) | 0.653      | 0.660 | 0.650  | 0.686    | 0.705        | 0.741 | 0.752    |
| C4 (risk mitigation)  | 0.631      | 0.614 | 0.602  | 0.611    | 0.629        | 0.640 | 0.667    |
| C4 (remediation)      | 0.574      | 0.571 | 0.424  | 0.564    | 0.500        | 0.559 | 0.615    |
| C5 (effectiveness)    | 0.533      | 0.483 | 0.242  | 0.527    | 0.491        | 0.560 | 0.500    |
| C6 (consultation)     | 0.414      | 0.429 | 0.293  | 0.611    | 0.641        | 0.571 | 0.588    |
| Signature             | 0.794      | 0.859 | 0.797  | 0.830    | 0.844        | 0.866 | 0.873    |
| Overall (macro)       | 0.670      | 0.665 | 0.598  | 0.694    | 0.702        | 0.718 | 0.721    |

Figure Description: F1 evaluation results for jointly fine-tuned









## Conclusion

#### **Contributions**

- Introduced AIMS.au, the largest annotated dataset addressing a challenging sentence-level classification task—identifying mandatory disclosures in corporate modern slavery statements under the Australian MSA.
- Provided critical benchmarks using zero-shot and fine-tuned language models for sentence-level classification.
- Investigated how the addition of context affects the sentence-level classification task.

#### Limitations

- Potential annotator biases and inconsistencies despite extensive training and quality assurance.
- Inability to analyze figures and tables without OCR or vision-language models, potentially affecting context.
- No differentiation between past actions and future plans, complicating period-specific compliance evaluation.

#### **Future Work**

- Explore methods for handling noisy labels and enhancing context understanding.
- Investigate integrating Vision-Language Models (VLMs) for improved extraction from complex documents.
- Extend AIMS.au's applicability to related jurisdictions (e.g., UK and Canadian MSAs), facilitating broader research in modern slavery and corporate compliance.







## References and Resources



arXiv https://arxiv.org/abs/2502.07022



https://huggingface.co/datasets/mila-ai4h/AIMS.au



https://github.com/mila-ai4h/ai4h\_aims-au

figshare https://figshare.com/s/1b92ebfde3f2de2be0cf









# Acknowledgments

- Part of this research was supported by the National Action Plan to Combat Modern Slavery 2020-25 Grants Program, administered by the Attorney-General's Department of Australia.
- We sincerely thank Journal Ghosn for her invaluable guidance in developing the research roadmap and annotation specifications.
- We would also like to express our gratitude to Akshatha Arodi and Jordan Bannister for their support in the final stages of completing this paper.
- We also extend our thanks to Jerome Solis, Allison Cohen, and Benjamin Prud'homme for their support in establishing and overseeing the project.
- We appreciate the collaboration of the Tasq.ai and WikiRate teams in the development of the annotation specifications and dataset. Additionally, we thank ABBYY for providing a free license to use their software for text extraction from PDFs.







## Contact

## Thank you, please get in touch with any questions:

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