# 1. Research Aim and Objectives

## 1.1. Research Aim

This study aims to develop and validate a computational governance intelligence platform for systematically mapping, querying, and critically evaluating the Australian regulatory ecosystem governing building deconstruction and material salvage. Specifically, it combines large language model (LLM)-driven information extraction with knowledge graph (KG) construction and retrieval-augmented generation (RAG) to transform an unstructured corpus of federal, state, and local policy documents into a structured, auditable, and queryable **Governance Topography**. The platform enables automated identification of legislative disconnects, jurisdictional fragmentation, and governance gaps that hinder the transition from conventional demolition to a circular built environment.

## 1.2. Research Objectives

***Objective 1: Constructing a Multi-Stage Computational Pipeline for Regulatory Corpus Processing.*** To design, implement, and validate a reproducible six-stage computational pipeline that transforms heterogeneous government PDF documents (n=36) into a structured knowledge graph. This pipeline integrates multi-engine text extraction (layout-aware parsing, robust encoding resolution, and optical character recognition), semantic chunking with domain-specific keyword gating, high-dimensional vector retrieval, and LLM-based precision filtering to isolate regulatory clauses specific to structural disassembly, selective demolition, and material salvage from broader waste management narratives.

***Objective 2: Developing an Objective-Aligned Knowledge Graph Schema for Deconstruction Governance.*** To define and populate a purpose-built knowledge graph schema comprising ten entity classes (Instrument, Authority, Jurisdiction, Requirement, Practice, MaterialAsset, Stakeholder, Barrier, Enabler, OutcomeMetric) and eleven governance-mechanism relation types that reconstruct “who governs what, where, and how.” This schema supports direct traceability from every extracted statement back to its source document, page number, and verbatim evidence excerpt, enabling end-to-end auditability.

***Objective 3: Analysing Semantic and Definitional Gaps in Deconstruction Policy.*** To deploy the governance intelligence platform to critically examine the extent to which “deconstruction” and “salvage” are formally recognised as distinct regulatory activities within Australian policy. This involves quantifying the prevalence of generic “waste diversion” language (which encourages crushing and downcycling) versus specific mandates for “disassembly” and “component reuse,” and mapping the definitional boundaries across jurisdictions.

***Objective 4: Mapping the Institutional Governance Network and Jurisdictional Fragmentation.*** To use structured graph traversal queries to map the ecosystem of institutional actors—including Environmental Protection Authorities (EPAs), sustainability bodies, and local planning authorities—and to characterise the structural relationships (or absence of coordination) between agencies responsible for waste minimisation and those responsible for building standards. This includes automated jurisdictional comparison across Australia’s three tiers of government.

***Objective 5: Synthesising Governance Gaps and Regulatory Barriers Through Automated Gap Analysis.*** To systematically identify practice areas where documented barriers (conflicting permit requirements, risk-averse procurement policies, absence of certification pathways for reused materials) outweigh or entirely lack corresponding enabling instruments or policy support. The gap analysis classifies governance deficits by severity—distinguishing practices with zero institutional support from those with partial but insufficient coverage.

## 1.3. Expected Contribution

This research makes three distinct contributions. **First**, it provides the first computational regulatory analysis of **deconstruction** as a specific subset of the circular economy in Australia, moving beyond broad “waste” narratives to offer a diagnostic assessment of specific legislative gaps. **Second**, it demonstrates a replicable methodology for transforming unstructured policy corpora into structured, queryable knowledge graphs using LLM-driven extraction with full evidence provenance—an approach transferable to other regulatory domains and jurisdictions. **Third**, it delivers an operational governance intelligence backend that combines graph traversal with retrieval-augmented generation, enabling policymakers and researchers to pose structured queries against the regulatory landscape and receive grounded, source-cited answers.

# 3. Research Methods and Design

To systematically analyse the fragmented regulatory landscape governing deconstruction and material salvage in Australia, this study employed a six-stage computational pipeline leveraging Large Language Models (LLMs), optical character recognition (OCR), vector-based semantic retrieval, and knowledge graph construction. Unlike traditional manual content analysis, which is limited by volume and subject to analyst fatigue, this approach enabled rigorous processing of a heterogeneous corpus of unstructured PDF documents (n=95) sourced from government agencies and industry organisations across federal, state, and local jurisdictions. The methodology, as illustrated in Figure 1 was designed to isolate high-relevance regulatory clauses specific to structural disassembly and salvage from broader waste management narratives, and to reconstruct the governance relationships embedded within them as a structured, queryable knowledge graph. The pipeline followed a six-stage architecture: (1) Corpus Assembly and Multi-Stream Source Identification, (2) Multi-Engine Text Extraction and Semantic Segmentation, (3) High-Dimensional Vector Retrieval and LLM-Based Precision Filtering, (4) Knowledge Graph Extraction and Cleaning, (5) Governance Intelligence Backend Assembly, and (6) Retrieval-Augmented Generation. The complete pipeline was implemented in Google Colaboratory as a sequence of reproducible Jupyter notebooks.

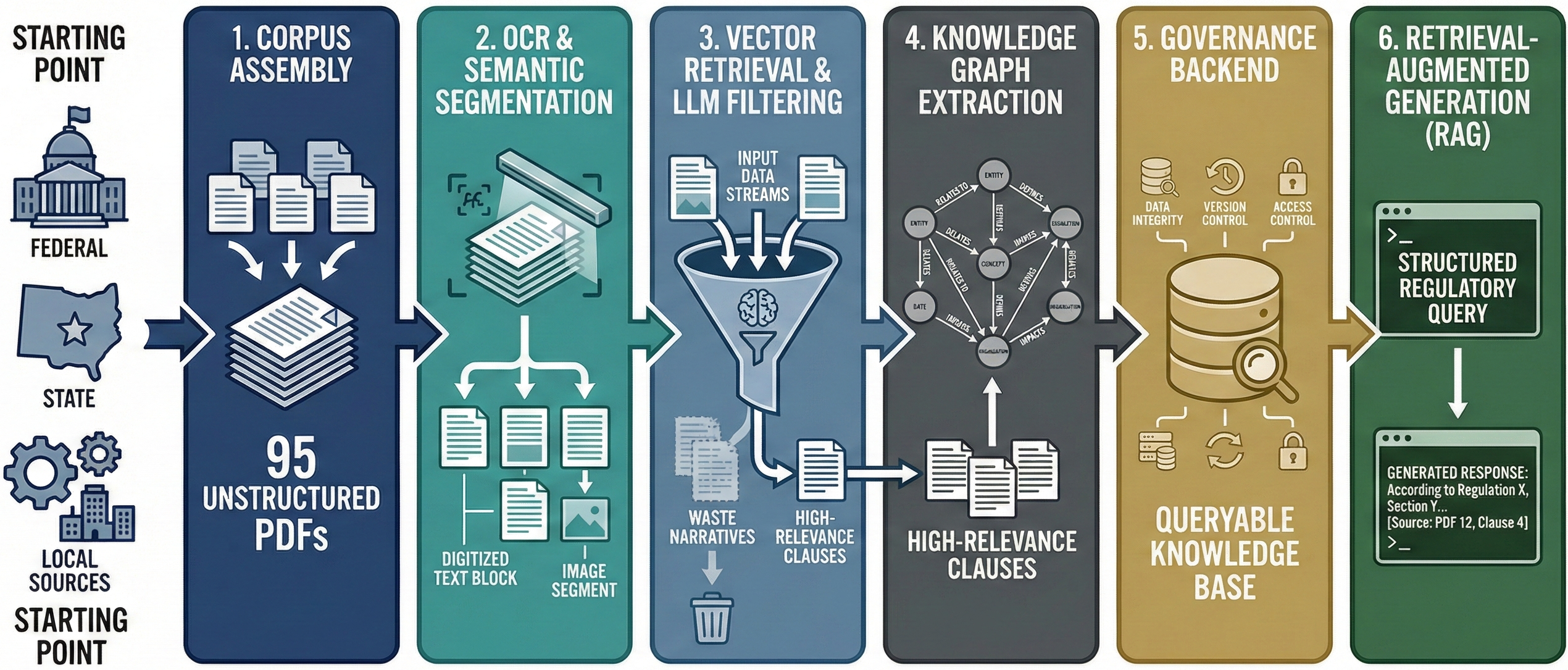


Figure . System architecture diagram showing the six-stage computational pipeline

## 3.1. Corpus Assembly and Multi-Stream Source Identification (Stage 1)

To ensure comprehensive coverage of the Australian deconstruction and material salvage landscape, this study employed a three-stream parallel search strategy targeting (i) academic peer-reviewed literature, (ii) industry and professional guidance, and (iii) government regulatory instruments. Each stream was designed to capture distinct but complementary forms of knowledge: empirical research findings, practitioner-oriented guidance, and formal legal requirements. Academic sources provided bibliographic context for synthesis and citation, while industry and regulatory documents underwent full computational processing for knowledge graph construction.

### 3.1.1. Academic Literature Search

Academic literature was retrieved through a two-stage process combining automated Scopus API queries with deterministic large language model (LLM) filtering to establish bibliographic context and identify relevant empirical research.

**Stage 1: Dual-Strategy Retrieval.** A dual-strategy Scopus search was implemented to balance precision and recall. The search employed Gemini 2.0 Pro to generate domain-specific keyword bundles from the research topic description, producing subject keywords (deconstruction, secondary materials, C&D waste, circular economy), context keywords (construction industry, built environment), and geographic keywords (Australia, Australian, state names).

Two complementary search strategies were executed:

*Strategy A (Global Search):* Broad subject-area search with mandatory geographic constraint. The query structure was TITLE-ABS-KEY((subject) AND (context) AND (geography)) with subject area limits to Engineering (ENGI), Environmental Science (ENVI), Business (BUSI), and Materials Science (MATE). This strategy prioritised geographic relevance while accepting any publication venue.

*Strategy B (Priority Journal Search):* Targeted search of 20 high-impact construction, sustainability, and waste management journals (Automation in Construction, Construction and Building Materials, Resources Conservation and Recycling, Waste Management, Journal of Cleaner Production, among others). Geographic keywords remained mandatory, but context keywords were relaxed under the assumption that journal scope provides implicit domain filtering.

Both strategies retrieved results via the Scopus API with standard view parameters (count=25, max\_results=200 per strategy). Results were deduplicated by normalised title, with strategy provenance preserved (Global, Journal Priority, or Both).

**Stage 2: Strict LLM-Based Filtering.** To eliminate false positives—particularly papers about other countries or generic waste management without deconstruction focus—all retrieved papers underwent strict LLM adjudication. Papers were submitted in batches of 20 to Gemini 2.0 Flash (temperature=0) with a deterministic inclusion rubric requiring (i) explicit focus on the Australian construction industry (case studies, Australian regulations, or Australian project data) and (ii) substantive discussion of deconstruction practices or material reuse (rejecting papers solely about waste statistics or recycled aggregate chemistry). Each paper received a binary relevance classification, a confidence score (0.0–1.0), and structured reasoning.

**Output:** The academic search produced a curated bibliography of peer-reviewed literature stored as structured metadata (DOI, title, authors, journal, year, citation count) in CSV format. These sources served as contextual references for discussion and synthesis but did not undergo full-text extraction or knowledge graph processing.

### 3.1.2. Industry and Regulatory Source Search

Non-academic sources comprising both industry guidance and government regulatory instruments were retrieved through parallel computational pipelines leveraging the Google Custom Search API and Gemini 2.5 generative models. Both searches followed similar architectures but targeted different source types and employed domain-specific credibility weighting.

**Industry Source Pipeline (Six Phases):**

*Phase 1: Dynamic Source Discovery.* To avoid researcher bias in selecting industry organisations, Gemini 2.5 Pro was prompted with the research topic and asked to recommend authoritative non-academic sources across five tiers: (i) government infrastructure and standards bodies, (ii) professional associations and green building councils, (iii) consulting firms and think tanks, (iv) trade media and industry publishers, and (v) emerging technology vendors and circular economy platforms.

*Phase 2: Organisation-Targeted Search.* For each organisation, a targeted Google Custom Search query was constructed using organisation name, domain restriction (if known), and topic-specific keywords (deconstruction, demolition, material reuse, circular economy, waste levy). Queries were rate-limited and capped at 10 calls per organisation to remain within API quotas.

*Phase 3: Domain-Targeted Search.* To capture recent publications from known authoritative domains, a second search phase restricted queries to a whitelist of verified government and professional association domains (e.g., site:gbca.org.au, site:abcb.gov.au). This phase targeted policy updates, technical guidance, and white papers published between 2020–2026.

*Phase 4: Credibility Scoring and Verification.* All retrieved sources were scored using a composite credibility metric (0.0–1.0 scale) combining source reputation (government/academic=1.0, professional body=0.9, consulting=0.7, trade media=0.6), recency (exponential decay from publication date), and topical relevance (keyword match density). Sources below a threshold of 0.60 were excluded.

**Regulatory Source Pipeline (Five Phases):**

*Phase 1: Jurisdiction-Based Regulatory Search.* Recognising Australia's federal structure and state-level variation in waste and building regulations, the search was stratified across nine jurisdictions: Commonwealth (federal), Victoria (VIC), New South Wales (NSW), Queensland (QLD), Western Australia (WA), South Australia (SA), Tasmania (TAS), Australian Capital Territory (ACT), and Northern Territory (NT). For each jurisdiction, targeted Google Custom Search queries were constructed to retrieve documents from official legislation portals, environmental protection authorities (EPAs), planning and building regulators, and work health and safety bodies. Queries prioritised document types with statutory or quasi-regulatory authority: Acts and Regulations (primary legislation), Codes of Practice (compliance instruments), EPA Guidance Notes (interpretive regulatory guidance), Practice Notes (technical regulatory guidance), and Advisory Bulletins.

The search employed jurisdiction-specific keyword combinations pairing regulatory document types with topic terms. For example, the Victoria query combined ("Code of Practice" OR "Compliance Code" OR "EPA Guidance") AND (deconstruction OR "demolition" OR "C&D waste" OR "material reuse") AND (Victoria OR VIC) with site restrictions to legislation.vic.gov.au, epa.vic.gov.au, and related domains. This approach was replicated across all nine jurisdictions with corresponding domain whitelists.

*Phase 2: Organisation-Targeted Regulatory Search.* To ensure coverage of cross-jurisdictional instruments, a second phase targeted national regulatory and standards bodies: Australian Building Codes Board (ABCB), Standards Australia, Safe Work Australia, and the Council of Australian Governments (COAG) National Waste Policy framework.

*Phase 3: Credibility Scoring and Regulatory Classification.* All retrieved documents were scored using a regulatory-specific credibility metric that weighted (i) regulatory authority tier (Acts/Regulations=1.0, Codes of Practice=0.95, EPA Guidance=0.90, Industry Guidance=0.70), (ii) government tier (Federal=1.0, State=0.95, Local=0.85), (iii) recency (documents published 2020–2026 scored higher than 2015–2019 or pre-2015), and (iv) topical precision (documents explicitly mentioning "deconstruction" or "salvage" scored higher than those only referencing generic "demolition" or "waste diversion"). Documents below a threshold of 0.60 were excluded.

To validate regulatory authority and document type, high-scoring documents were submitted to Gemini 2.5 Flash (temperature=0) for structured classification. The LLM agent verified (i) issuing authority, (ii) document type (distinguishing binding regulations from advisory guidance), and (iii) jurisdictional scope.

**Combined Output:** The industry and regulatory searches together yielded 95 documents (industry guidance and government regulatory instruments combined) that exceeded credibility thresholds and were successfully downloaded as PDF files. These 95 documents were stored in a unified corpus for subsequent processing through the computational pipeline. All 95 documents underwent full-text extraction, semantic segmentation, and precision filtering (Stages 2–3), with the final knowledge graph constructed from the subset containing substantive deconstruction content.

### 3.1.3. Final Corpus Composition

The study processed three distinct source collections through different analytical pathways:

**Academic Sources:** Bibliographic metadata only (no full-text processing). These sources provided contextual validation and were cited in discussion sections to situate findings within existing empirical research.

**Industry and Regulatory Sources:** All 95 downloaded documents (combining industry guidance and government regulatory instruments) underwent the full six-stage computational pipeline described in Sections 3.2–3.7. Following LLM-based precision filtering (Section 3.4), 36 documents were identified as containing substantive passages about deconstruction practices, salvage operations, or regulatory barriers to material reuse. The remaining 59 documents, while topically relevant to construction waste or demolition, contained only generic waste management content without specific deconstruction focus and were excluded from knowledge graph construction. The final knowledge graph was therefore constructed from 364 high-relevance text chunks extracted from these 36 documents.

This approach ensured that the knowledge graph captured only governance mechanisms and practice pathways directly relevant to building deconstruction and material salvage, while maintaining traceability to the complete search and filtering process.

## 3.2. Multi-Engine Text Extraction and Semantic Segmentation (Stage 2)

### 3.2.1. Data Pre-processing and Multi-Engine Extraction

The primary challenge in analysing government policy documents and industry reports is the inconsistency of file formats, which range from digital-native PDFs to scanned archival images. To address this, a three-tier extraction strategy was architected to maximise text fidelity across the 95-document corpus:

**Tier 1 (Layout-Aware Extraction):** Documents were first processed using pdfplumber, which excels at extracting text while preserving the structure of data tables—critical for capturing waste levy schedules and diversion targets.

**Tier 2 (Robust Parsing):** If Tier 1 yielded insufficient text (<50 characters per page), the system fell back to PyMuPDF (Fitz), which utilises a different parsing engine capable of resolving complex encoding issues and embedded fonts.

**Tier 3 (Optical Character Recognition):** For pages identified as scanned images (where previous tiers failed), the pipeline triggered Tesseract OCR (via pdf2image) to optically reconstruct text from the visual layer.

This cascading approach ensured comprehensive text recovery across heterogeneous document types while prioritising higher-fidelity extraction methods.

### 3.2.2. Semantic Segmentation and Keyword Gating

To facilitate granular analysis, the extracted text from all 95 documents was segmented into computational units using the RecursiveCharacterTextSplitter from the LangChain framework.

**Chunking Strategy:** A chunk size of 1,400 characters with an overlap of 200 characters was employed. This larger window (compared to standard NLP tasks) was empirically selected to ensure legal definitions and qualification clauses remained intact within a single semantic unit.

**Keyword Gating:** To optimise computational efficiency and reduce false positives, a "Keyword Gate" was applied prior to vector embedding. Only chunks containing high-recall regex patterns (e.g., \bdeconstruct\b, \bsalvag\b, \bcircular economy\b, \bselective demolition\b) were retained for high-dimensional analysis. This pre-filtering step reduced the computational burden while maintaining high recall for domain-relevant content.

## 3.3. High-Dimensional Vector Retrieval (Stage 2)

Retained chunks were converted into high-dimensional vector representations using OpenAI's text-embedding-3-large model.

**High-Fidelity Embedding:** Unlike smaller variants, this model projects text into a 3,072-dimensional space, providing the necessary semantic granularity to distinguish between effectively synonymous regulatory terms (e.g., distinguishing "structural deconstruction" mandates from generic "demolition" permits).

**Relevance Scoring:** The system calculated the L2 distance between query vectors and document vectors using the Facebook AI Similarity Search (FAISS) library. Based on pilot diagnostics, a strict relevance threshold of τ = 0.55 was established to filter out municipal waste management noise while retaining deconstruction-specific content.

## 3.4. LLM-Based Precision Filtering (Stage 3)

To resolve residual ambiguity between generic waste diversion and structural deconstruction, a final validation layer known as the LLM Judge was implemented. High-scoring chunks from the 95-document corpus were passed to a deterministic agent powered by GPT-4.1 (snapshot 2025-04-14).

**Model Selection:** This specific model version was selected for its enhanced instruction-following capabilities, ensuring strict adherence to the inclusion/exclusion rubric without hallucinating regulatory clauses.

**Classification Logic:** The agent evaluated each passage (Temperature = 0) to classify it into one of three categories: *Keep* (directly concerns disassembly, soft strip, or regulatory barriers to reuse), *Maybe* (contextual relevance requiring further consideration), and *Drop* (irrelevant, e.g., kerbside recycling logistics). This "Human-in-the-Loop" simulation ensured that the final dataset comprised exclusively high-fidelity, domain-specific regulatory evidence.

**Filtering Outcome:** Of the 95 documents processed, 36 contained passages classified as *Keep* or *Maybe*, yielding 364 high-relevance chunks (Keep: 152 chunks; Maybe: 212 chunks). The remaining 59 documents, while retrieved through credibility-scored searches, contained only generic waste management content without substantive discussion of deconstruction practices or salvage operations and were therefore excluded from knowledge graph construction.

## 3.5. Post-Judge Corpus Assembly (Stage 3)

Following the LLM Judge stage, all chunks labelled *Keep* and *Maybe* were retained for knowledge-graph extraction to preserve both high-certainty regulatory clauses and contextually relevant passages containing enabling conditions, institutional framing, or practice descriptions. Each chunk record preserved stable provenance metadata (source file, page number, chunk identifier, and chunk hash), enabling traceability from each graph statement back to its originating text segment and source document.

To support downstream robustness checks, the judge label was propagated into the knowledge graph as a statement-level confidence weight (Keep = 1.0; Maybe = 0.6). This enabled sensitivity analyses contrasting an evidence-grade "core" graph (Keep only) against an expanded interpretive graph (Keep + Maybe).

## 3.6. Objective-Aligned Knowledge Graph Schema (Stage 4)

To ensure the knowledge graph directly supported the study's aims—namely (i) mapping the institutional/regulatory landscape and (ii) characterising deconstruction and salvage practices—the extraction schema was intentionally compact and analysis-driven. Entity classes comprised ten types: Instrument, Authority, Jurisdiction, Requirement, Practice, MaterialAsset, Stakeholder, Barrier, Enabler, OutcomeMetric. Relation classes were restricted to eleven governance and mechanism linkages that reconstruct "who governs what, where, and how": ISSUED\_BY, APPLIES\_IN, APPLIES\_TO, REFERENCES, REQUIRES, PROHIBITS, INVOLVES, ENABLES, BARRIERS, AFFECTS, PRODUCES.

This design avoided building a broad ontology and instead targeted a reproducible representation of governance mechanisms and practice pathways relevant to regulatory deconstruction and secondary material flows. The same schema was designed for cross-jurisdictional extensibility, with identical entity and relation types applicable to United Kingdom and Canadian corpora.

[Figure 2] Entity-relationship schema diagram showing 10 entity types and 11 relation types with node counts from the Australian corpus.

## 3.7. LLM-Based Knowledge Graph Extraction with Evidence-Linked Statements (Stage 4)

Knowledge graph extraction was performed at the chunk level using a deterministic LLM configuration (temperature = 0) with structured JSON output enforcement. The extraction model was chatgpt-4o-latest (via OpenAI API). To maintain high precision and avoid over-generation, extraction was constrained by: (i) strict type control (entities and relations must match the predefined schema), and (ii) per-chunk caps (≤12 entities and ≤20 relations).

Every extracted entity and relation was required to include a verbatim evidence excerpt from the chunk. Relations were only retained when both endpoints were present as extracted entities within the same chunk, reducing the risk of speculative linking. Each relation additionally stored provenance metadata (chunk identifier and hash, source file, and page number), enabling end-to-end auditability from every knowledge graph statement back to its source document.

## 3.8. Entity Canonicalisation and Graph Cleaning (Stage 4)

Entities were canonicalised using conservative normalisation (case, whitespace, and punctuation standardisation) and assigned deterministic identifiers through hashing of (entity\_type + canonical\_name) to support deduplication across chunks and stable downstream analysis. An enhanced extraction pass was applied to resolve coverage issues identified in initial diagnostics, producing a consolidated raw graph of 1,748 unique nodes and 3,929 triples across 105 weakly connected components (90.2% of nodes in the largest component).

A dedicated graph cleaning pipeline then applied three successive operations:

**Generic Hub Pruning:** Twenty-six high-degree generic concept nodes (e.g., "Circular Economy," "Reuse," "Waste Management") were identified and removed. Despite comprising only 1.5% of nodes, these false hubs accounted for 27.5% of all edges (1,247 of 4,529), confirming they were connecting otherwise unrelated entities through semantic rather than governance relationships.

**Cross-Type Entity Resolution:** An LLM-adjudicated deduplication process resolved entities that had been extracted under different entity types across chunks (e.g., "Design for Disassembly" appearing as both a Practice and an Enabler). Using a conservative clustering approach (Jaccard similarity ≥ 0.50 on name tokens), 277 candidate entities across 79 clusters were submitted to a deterministic LLM agent, which merged 69 confirmed duplicates and corrected 192 entity type assignments.

**Post-Merge Deduplication:** A final deduplication pass resolved residual exact-match duplicates introduced when cross-type resolution changed an entity's type to match an existing node. The cleaned graph stabilised at 1,641 unique nodes and 2,788 unique triples across 219 weakly connected components (81.5% in the largest component).

## 3.9. Governance Intelligence Backend Assembly (Stage 5)

The cleaned knowledge graph was assembled into a queryable governance intelligence backend comprising three integrated components:

**Graph Store:** The cleaned node and edge tables were loaded into a NetworkX MultiDiGraph with domain-specific traversal primitives. Lookup indices (name-to-ID and type-to-ID) supported fuzzy entity matching (using token-sort ratio ≥ 70), directed neighbour retrieval with predicate and type filters, ego subgraph extraction, and jurisdiction-scoped queries. The graph store exposes traversal operations that compose into higher-level governance queries.

**Vector Store:** The 364 source chunks retained from the LLM Judge stage were embedded using all-MiniLM-L6-v2 (sentence-transformers) and indexed in a ChromaDB collection with cosine similarity and HNSW indexing. Each chunk was tagged with the entities and relations extracted from it, enabling hybrid retrieval: graph traversal identifies relevant entities, and vector search retrieves the supporting evidence passages.

**Query Engine:** A structured query engine was built atop the graph and vector stores, supporting five query types: (i) governance pathway tracing (Authority → Instrument → Requirement → Practice → Outcome, optionally scoped to a jurisdiction), (ii) jurisdictional comparison (coverage matrices of shared and unique instruments across jurisdictions), (iii) gap analysis (practices where barriers outweigh or entirely lack enabling instruments), (iv) entity explanation (comprehensive profiles with graph neighbourhood and source evidence), and (v) free-form queries answered via graph-context-enriched semantic search.

## 3.10. Retrieval-Augmented Generation for Grounded Answers (Stage 6)

To generate natural-language answers grounded in the knowledge graph and source evidence, each structured query result was passed to Claude Sonnet 4.5 (Anthropic) operating at temperature 0 with a domain-specific system prompt. The RAG system was configured to: (i) ground every claim in the provided structured data and evidence excerpts, (ii) cite specific instruments, requirements, and source documents using the format [Source: filename, p.X], (iii) explicitly acknowledge when data is insufficient, and (iv) distinguish between instruments (formal policies), requirements (specific obligations), practices (what practitioners do), and outcomes (measurable results). This architecture ensures that every answer produced by the platform is auditable back to its originating policy documents.

## 3.11. Extraction Yield and Quality Diagnostics

Across the post-judge corpus (Keep: 152 chunks; Maybe: 212 chunks; total: 364 chunks from 36 documents), knowledge graph extraction produced 2,180 initial unique nodes and 2,026 initial edges, with a mean yield of approximately 8.4 entities and 6.0 relations per chunk. An enhanced second extraction pass increased coverage to 1,748 nodes and 3,929 triples. Statement confidence (derived from judge labels) had a mean of 0.786 (Q25 = 0.6; median = 0.6; Q75 = 1.0), enabling reporting that distinguishes high-confidence evidence (Keep only) from context-supporting evidence (Keep + Maybe). After graph cleaning, the final operational graph contained 1,641 nodes and 2,788 triples with a mean node degree of 3.4.

# 4. Findings

*This section presents the results of deploying the governance intelligence platform against the Australian deconstruction policy corpus. Findings are organised around the four analytical dimensions enabled by the platform’s query engine.*

## 4.1. Regulatory Hierarchy and Corpus Composition

*➤ Report the composition of the 36-document corpus: breakdown by government tier (federal, state, local), document type (Act, Bill, Code, Standard, Strategy, Report), and temporal coverage. Present the entity type distribution from the knowledge graph.*

**[Figure 3]** *Summary statistics dashboard: (a) entity type distribution, (b) relation type distribution, (c) node degree distribution (log-scale), (d) platform metrics table.*

*➤ Discuss how the entity distribution reveals the structural emphasis of Australian governance: what entity types dominate, what is underrepresented, and what this implies about regulatory priorities.*

## 4.2. Governance Pathway Analysis: Design for Disassembly

*➤ Present the results of the governance pathway trace for Design for Disassembly (DfD) as the primary case study. Report the number of instruments, requirements, enablers, barriers, and outcomes connected to DfD in the knowledge graph. Discuss the governance chain: which authorities issued which instruments, and which jurisdictions they apply in.*

**[Figure 4]** *DfD governance pathway ego network showing instruments, requirements, barriers, and outcomes connected to Design for Disassembly practice node.*

*➤ Analyse the pathway for completeness: does the chain from Authority → Instrument → Requirement → Practice → Outcome hold, or are there broken links? Identify which jurisdictions have stronger governance chains and which have gaps.*

## 4.3. Jurisdictional Comparison

*➤ Present the jurisdictional comparison results for Victoria, New South Wales, and Queensland (and other states as available). Report the number of instruments per jurisdiction, shared instruments across all three, and unique instruments per jurisdiction. Discuss the coverage matrix.*

**[Figure 5]** *Jurisdictional coverage heatmap: (a) stacked bar chart of entity connections by jurisdiction, (b) binary heatmap of instrument applicability across jurisdictions.*

*➤ Discuss the implications of the Queensland attribution gap identified in the knowledge graph cleaning stage. Analyse whether jurisdictional fragmentation is primarily in instrument coverage, enforcement mechanisms, or both. Compare federal aspirational language versus state-level statutory reality.*

## 4.4. Gap Analysis: Barriers Without Enabling Instruments

*➤ Present the gap analysis results: total practices analysed, number of gaps identified, and number of high-severity gaps (practices with barriers but zero instruments or enablers). List the most critical gaps and their associated barriers.*

**[Figure 6]** *Gap analysis matrix: barriers versus instruments and enablers per practice, with high-severity gaps (zero support) highlighted.*

*➤ Interpret the gap analysis in the context of regulatory inertia: which barriers are legislative (conflicting permits, missing certification), which are institutional (lack of coordination between agencies), and which are market-based (risk-averse procurement)? Discuss how the severity classification (high vs. medium) maps to policy actionability.*

## 4.5. Semantic and Definitional Gaps

*➤ Present findings on how ‘deconstruction’ and ‘salvage’ are defined (or not) in the policy corpus. Report the prevalence of generic ‘waste diversion’ language versus specific ‘disassembly’ and ‘component reuse’ mandates. Use entity and relation counts from the knowledge graph to quantify definitional precision.*

*➤ Discuss the implications: if policy instruments refer only to ‘waste diversion’ without distinguishing between crushing/downcycling and selective disassembly/reuse, what are the practical consequences for deconstruction practitioners?*

## 4.6. Platform Demonstration: Query-Driven Policy Intelligence

*➤ Present the four demo queries and their Claude-synthesised answers as evidence that the platform functions as an operational governance intelligence tool. Summarise each demo: (1) DfD pathway, (2) jurisdictional comparison, (3) gap analysis, (4) material passports and deconstruction. Emphasise that every claim in the synthesised answers traces back to source documents.*

**[Figure 7]** *Demo Q&A cards: 2×2 grid showing four formatted query–answer pairs with source citations and structured data badges.*