

# Integrating Knowledge Graphs with Multi-Modal Machine Learning

## 1) Research topic and context

Building on the completed **Integrating Knowledge Graphs with Multi-Modal Machine Learning — Literature Review**, this project investigates how to fuse knowledge graphs (KGs) with multi-modal models (images, text, audio, etc.) so that systems can **retrieve, classify and explain** in open-world settings. The review identified recurring frictions: (i) loss of relational meaning when KGs are embedded as vectors, (ii) operational brittleness of single-store back ends under embedding-heavy workloads, and (iii) accuracy-only evaluation that obscures semantic fidelity, latency, robustness and interpretability. This specification translates those insights into a concrete research plan.

## 2) Research problem

Despite promising demonstrations, many KG+MMML pipelines either flatten semantics (directionality, hierarchy, cardinality), struggle to meet tail-latency and freshness targets at scale, or make claims unsupported by transparent metrics and faithful explanations.

**Problem statement:** How can we integrate KGs with multi-modal models in a way that **preserves relational semantics, meets performance budgets** at realistic scale, and **explains outputs** with path-level evidence?

## 3) Aim and measurable objectives

**Aim:** To develop and validate a **scalable, reproducible** KG–MMML integration that maintains semantic structure and provides path-level rationales, using a **hybrid** (graph as semantic spine + vector index) architecture.

### Objectives:

1. **Knowledge fidelity.** Achieve **SRS  $\geq 0.75$**  by Week 8 with **AtP  $\geq 0.95$** , **HP  $\geq 0.25$** , **AP  $\geq 0.99$** , rising from the text-only baseline.
2. **Task performance.** Demonstrate  **$\geq +3$  percentage-point micro-F1** (or equivalent retrieval metric) when adding **KG-as-features** to a TF-IDF (or single frozen encoder) baseline.
3. **Operational SLOs.** Report **p50/p95/p99 latency** at  **$N \in \{10^3, 10^4\}$**  with a reproducible harness, and discuss trade-offs.
4. **Robustness.** Under small stressors (e.g., taxonomy off / unit noise), limit relative metric drop to  **$\leq 10\%$** .
5. **Reproducibility.** Release scripts, pinned configs, seeds, and an **evaluation sheet**; document provenance and date-stamped KG snapshots.

## 4) Research questions and hypotheses

1. **Knowledge fidelity:** Do minimal, interpretable joint constraints (hierarchy, asymmetry, attribute reconstruction) raise SRS versus KG-as-features without violating accuracy/latency budgets?  
*H1: SRS increases to  $\geq 0.75$  without harming accuracy or latency materially.*
2. **Architecture choice:** Does a **hybrid** graph-vector stack beat a monolithic graph store on tail latency at scale while preserving explanations?  
*H2:  $p95 \rightarrow \geq 30\%$  at  $\geq 10^6$  entities;  $p99 \leq 2 \times p95$ ; rationale availability unchanged.*
3. **Operations:** Does a **hybrid graph-vector** stack meet **p95/p99** targets at  $10^3$ – $10^4$  scale better than monolithic approaches?  
*H3:  $\rightarrow \geq 3$  accuracy points and  $\rightarrow \geq 10$  pp rationale precision.*
4. **Honest evaluation:** Do robustness/scale tests change which configuration appears “best” compared with accuracy-only reporting?  
*H4: At least one accuracy-leading baseline is re-ranked when SRS/latency/robustness are included.*

## 5) Methodological approach (derived from the literature review)

- **Representation: Multi-resolution semantics** (types  $\rightarrow$  direct relations  $\rightarrow$  k-hop context  $\rightarrow$  paths) to prevent flattening; escalate at query time only as needed.
- **Models:** (i) baseline multi-modal model; (ii) **KG-as-features**; (iii) **joint** KG–MMML model with minimal constraints.
- **Architecture: Graph database** as semantic spine (entities, typed relations, provenance, path-level explanations) + **ANN vector index** for dense similarity; **cache** for hot subgraphs/rationales; **stream** for updates and re-index.
- **Evaluation policy:** Effectiveness (retrieval/zero-shot), **SRS, p50/p95/p99 latency** and memory, robustness (dropout/shift), **interpretability** (rationale precision + counterfactual sensitivity), reproducibility (seeds/configs/compute disclosure).
- **Ethics & governance:** Data minimisation; parity checks; time-stamped edges; change control; documented fall-backs.

## 6) Significance and potential contributions

- A portable, **measurable definition of knowledge fidelity** (SRS) that complements accuracy and can travel across domains.
- Evidence-backed **design rules** for when to use joint learning, multi-resolution semantics and a hybrid graph–vector stack.
- A transparent **evaluation sheet** and **reference implementation** (with path-level explanations and operational playbooks) that practitioners can adopt.
- Practical **decision thresholds** (e.g., “deploy only if  $SRS \geq \text{threshold}$ ”; “switch to hybrid when p95 exceeds budget”) that raise trust and reproducibility.

## 7) Scope and boundaries

**In scope:** Open-world retrieval and zero-shot classification; image–text primary, extensible to other modalities; KG integration via embeddings and joint constraints; hybrid retrieval.

**Out of scope:** Heavy-weight symbolic theorem-proving; human-subject studies.

**Assumptions:** Access to at least one permissively licensed multi-modal dataset and a KG schema with task-critical relations; compute adequate for baselines and ablations.

**Success criteria:** Meeting Objectives 1-5 plus a short demonstration video.