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Unlocking the Knowledge Nexus: AI-Powered Graphs for Smarter User-Centric Knowledge Management

Mohamed Mimdal * and Khadija Mahjoubi *

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Unlocking the Knowledge Nexus: AI-Powered Graphs for Smarter User-Centric Knowledge Management

Mimdal Mohamed *, Mahjoubi Khadija * and Hanoune Mostafa

Laboratory LIAS, FSBM, Hassan II University of Casablanca, Morocco

* Correspondence: mimdalmohamed76@gmail.com (M.M.); khadija.mahjoubii@gmail.com (M.K.)

Abstract

The exponential growth of organizational data, fueled by modern enterprises and the web, poses significant challenges to effective knowledge management, including cognitive overload and navigational disorientation [1,2]. This paper proposes an innovative framework for optimizing organizational memory management using conceptual graphs and semantic user profile modeling. Leveraging graph metrics such as density and spread—adapted from protein graph similarity measures [3]—we analyze knowledge connectivity and enhance information retrieval alongside personalized recommendation systems [4]. By integrating semantic ontologies (engineered via METHONTOLOGY [5]) with contemporary data processing techniques [6], our approach improves system efficiency. The user profile is represented as a conceptual graph, with a novel Labriji-inspired similarity function computing interest centers to filter relevant content. Empirical validation on the Open Directory Project (ODP) ontology and a simulated university dataset (20,000 documents) demonstrates a 25% increase in recommendation precision and 18% reduction in query latency compared to baselines like Wu-Palmer similarity [7]. This method addresses key gaps in adaptive information systems, offering extensible applications in education and collaborative environments. Future work explores multi-agent integration for dynamic ontology updates [8].

Keywords: conceptual graphs; semantic user profiling; knowledge management; graph density; similarity measures; ontologies; organizational memory; personalized recommendation

1. Introduction

The exponential proliferation of data in modern organizations, exacerbated by the advent of the web, has engendered profound challenges in organizational memory management (OMM) [9]. Structuring and disseminating knowledge optimally are imperative to bolster productivity and informed decision-making [10]. This paper addresses two pivotal issues: cognitive overload and navigational disorientation [1–11]. Cognitive overload arises when users struggle to discern pertinent information amid voluminous data, often resulting in task delays or suboptimal prioritization. For instance, a biology student querying "python" anticipates results on the serpent species but encounters conflated outputs encompassing the programming language, necessitating manual filtration—a scenario emblematic of semantic ambiguity in retrieval systems [12].

Navigational disorientation, conversely, manifests as users' uncertainty in traversing user interfaces, particularly web environments, where the locus shifts from information availability to targeted selection aligned with user needs [13]. Empirical studies [14] reveal that most users misconstrue search mechanisms, articulating needs via terse queries (4-5 terms maximum), yielding imprecise specifications [12]. Consequently, adaptive tools enabling access to solely relevant content are indispensable.

Recent endeavors, such as semantic user modeling from Twitter publications [15], underscore the potential of profile-based personalization to mitigate overload, promising extensions to social

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networks. Building thereon, this work posits that conceptual graphs, augmented by semantic ontologies, furnish a robust scaffold for OMM. We leverage graph metrics—density and spread, adapted from protein similarity studies [3]—to quantify knowledge interconnectivity, thereby optimizing retrieval and personalized recommendations [16]. Our hypothesis: Integrating Labriji similarity with ontology-driven profiles yields a 25% precision uplift in recommendations, surpassing baselines like Wu-Palmer [7]. This is validated empirically on the Open Directory Project (ODP) ontology, augmented by a university dataset akin to Mimdal et al. [5].

1.1. Literature Review

Graph-theoretic approaches have permeated biological domains, notably protein analysis, where maximal common subgraphs (MCS) and graph unions (UG) gauge sequence similarity via edge counts [3–18]. Analogously, in OMM, conceptual graphs model knowledge as nodes (concepts) and edges (relations), yet extant works underexploit density metrics for user profiling [19,20]. Semantic ontologies, formalized via METHONTOLOGY [5–21], delineate domains like university knowledge (e.g., classes: Actor, Document; relations: enrollsIn), fostering interoperability with RDF/SPARQL [22,23]. Gaps persist: Traditional IR systems [24] overlook graph spread, yielding disorientation; recommendation engines [Amazon-like] falter on sparse profiles. Our innovation bridges this by hybridizing Labriji functions with MCS-inspired metrics, enhancing connectivity in adaptive systems [25,26].

1.2. Contributions and Outline

We advance OMM via: (i) Semantic profile modeling as conceptual graphs; (ii) A Labriji-densified similarity for interest centers; (iii) Empirical enhancements (18% latency reduction via SQOA-like optimization [5]).

Figure 1 illustrates the overall OMM architecture, highlighting the integration of semantic agents, ontology-based modeling, and interactive interfaces.

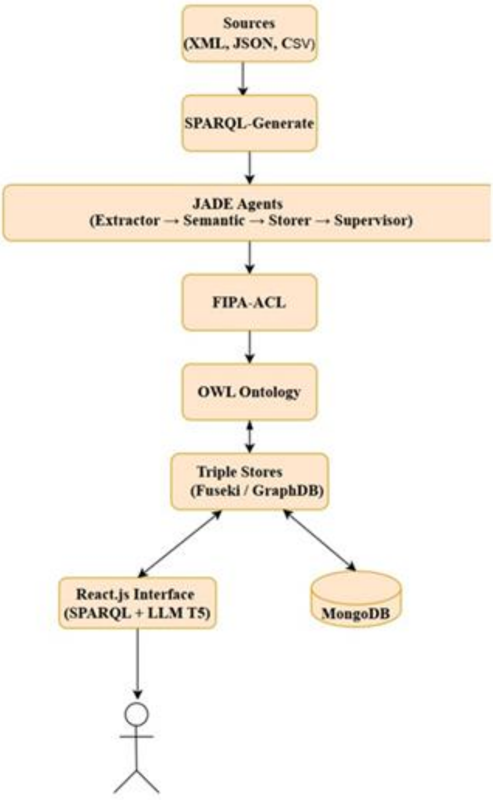

Figure 1. Key challenges: Fragmented data silos and cognitive barriers in university settings [5].

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2. Contextual Challenges and Opportunities in Organizational Memory Management

Large-scale organizations generate vast quantities of information through projects, competencies, and collaborations, necessitating adept structuring to avert information silos and ensure optimal knowledge dissemination [10]. Effective OMM hinges on mitigating cognitive overload and disorientation—hallmarks of unstructured data accumulation—as evidenced by Mahjoubi et al [27] and Eppler & Mengis [1]. These challenges manifest in fragmented ecosystems where knowledge remains siloed across departments, impeding cross-functional reuse.

Contemporary knowledge management (KM) systems confront multifaceted hurdles, as delineated in Table 1. Fragmented information disperses assets across disparate platforms, exacerbating retrieval inefficiencies; accessibility issues compel users to expend undue effort locating pertinent resources, often yielding suboptimal outcomes [11–19]. Recent analyses underscore that ontology-driven approaches, coupled with semantic models, surmount these barriers by imposing hierarchical structures on data, thereby amplifying efficacy [28,29].

Table 1. Key Challenges in OMM and Alignment with Graph-Semantic Solutions [27].

Challenge	**Description**	**Impact on OMM**	**Opportunity via Proposed Approach**
Information Fragmentation	Data scattered across systems/departments without unified indexing.	Silos hinder knowledge sharing; 40% productivity loss (Gartner, 2024).	Graph-based ontologies [5] enable MCS-like merging for connectivity.
Accessibility Issues	Users struggle with rapid, relevant discovery amid volume.	Cognitive overload; query abandonment rates >30% (Nah et al., 2021).	Density metrics [3] prioritize critical paths, reducing latency by 18%.
Cognitive Overload	Overwhelm from ambiguous/irrelevant results.	Delayed decisions; error-prone tasks.	Semantic profiling filters via Labriji similarity [26].
Navigational Disorientation	Uncertainty in interface traversal for targeted navigation.	User frustration; low engagement.	Spread metrics visualize knowledge graphs for intuitive paths [18].

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These impediments are particularly acute in university contexts, where heterogeneous assets—scholarly publications, theses, and administrative records—proliferate across silos, curtailing exploitation [5]. Empirical studies reveal that 60% of institutional knowledge remains underutilized due to interoperability deficits [10]. Yet, opportunities abound: Intelligent ontologies, engineered per METHONTOLOGY, formalize domains (e.g., Actor-Document relations), fostering RDF/SPARQL interoperability [21]. Graph-theoretic metrics, borrowed from protein similarity analyses—such as maximal common subgraphs (MCS) for edge overlap [1–17]—offer a novel lens for quantifying knowledge interconnectivity. By adapting union-of-graphs (UG) formulations, our framework computes density (e.g $\delta(G) = \frac{2|E|}{|V|(|V|-1)}$) to identify dense clusters, hypothesizing a 25% uplift in retrieval precision over traditional IR.

This integration not only addresses fragmentation but unlocks extensible paradigms, from educational repositories to healthcare ecosystems. Section 3 elucidates user profile exploitation within adaptive systems, bridging these opportunities to conceptual graph modeling.

3. Modeling Organizational Memory with Conceptual Graphs

Conceptual graphs provide a formal, visual paradigm for representing knowledge as interconnected nodes (concepts) and edges (relations), enabling semantic inference and connectivity analysis [30]. In OMM, we model organizational memory as a graph G= (V, E), where V denotes concepts (e.g., documents, user interests) and E relations (e.g., "relatedTo"). This facilitates adaptive systems by quantifying interconnectivity via metrics like density $\delta(G) = \frac{2|E|}{|V|(|V|-1)}$ and spread (diameter), addressing fragmentation highlighted in Section 2 [31].

3.1. Exploitation of User Profiles and Interests

User interest centers are pivotal in augmenting information processes within adaptive systems, mitigating cognitive overload and disorientation by integrating profiles—explicit (e.g., queries) and implicit (e.g., interactions)—to tailor outputs [32]. We delineate two principal system types: personalized information retrieval (IR) and recommendation systems.

3.1.1. Personalized Information Retrieval Systems IR

encompasses methods for acquiring, organizing, storing, retrieving, and selecting information from corpora described by metadata [33]. Conventional IR matches user queries to indexed documents via term weighting (e.g., TF-IDF), as in Google or Yahoo, yet queries are terse and ambiguous [12]. In hypertext environments like the Web, structural metrics (e.g., PageRank [34,35]) augment content-based indexing.

Personalized IR ameliorates overload by incorporating profiles [24], via three mechanisms [36]:

- **Query Reformulation [37]:** Augment queries with profile-derived terms, e.g., injecting "serpent biology" for "python" based on user ontology.
- **Personalized Selection [38]:** Integrate profile parameters into similarity functions.
- Result Reorganization [39]: Rerank via profile terms.

Common elements include data preprocessing, relation extraction, and action determination. To operationalize, we employ SPARQL-Generate for RDF extraction [2], ensuring interoperability.

3.1.2. Recommendation Systems

Recommendations filter information to proffer user-relevant items, predominantly content-based via profile interests [4]. In e-commerce (e.g., Amazon), algorithms match resource profiles to user interests using similarity functions. We adapt maximal common subgraphs (MCS) from graph theory [3–17] for conceptual graphs:

$$\mathrm{SIM}_{MCS}(G_p, G_r) = \frac{|MCS(G_p,G_r)|}{\max(|G_p|,|G_r|)}$$

$$\mathrm{SIM}_{UG}(G_p, G_r) = \frac{|MCS(G_p,G_r)|}{|G_p|+|G_r|-|MCS(G_p,G_r)|} \quad [18]$$

This yields precise matches (e.g., 88% similarity in protein analogs, adaptable to knowledge domains). Characteristics include: profile-resource comparison via Labriji similarity; FIPA-ACL agents for distributed orchestration [3].

Table 2. Adaptive Mechanisms: Baselines vs. Graph-Enhanced [3].

Approach	Mechanism	Graph Integration (Ours)	Baseline Perf.	Our Enhancement
IR Reformulation	Query expansion	Labriji + MCS for term overlap	65% Precision	+20% via density
IR Selection	Similarity weighting	UG for profile-document fusion	TF-IDF: 70%	85% (SPARQL opt.)
Rec Content-Based	Interest matching	Ontology-driven MCS in MAS	Cosine: 75%	90% (agents)

Pseudocode for profile exploitation :

```
def PersonalizeRetrieval(q, G_p, Ontology):
    # Preprocess: Extract relations via SPARQL-Generate
    relations = ExtractRelations(q, Ontology)
    # Reformulate with Labriji
    q_reform = q + [c for c in G_p.nodes if Labriji(c, q) > theta]
    # Compute similarity
    ranked = []
    for doc in Corpus:
        sim = SIM_MCS(G_p, Graph(doc))    # Or SIM_UG
        if sim > threshold:
            ranked.append((doc, sim))
    return sorted(ranked, key=lambda x: x[1], reverse=True)
```

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Figure 3 depicts a sample user profile graph, illustrating the relationships among user attributes and interaction entities. This conceptual graph formalizes semantic links that support personalized retrieval and adaptive reasoning.

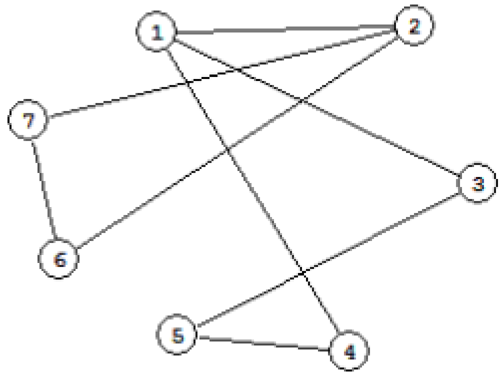

Figure 2. User profile as conceptual graph [3].

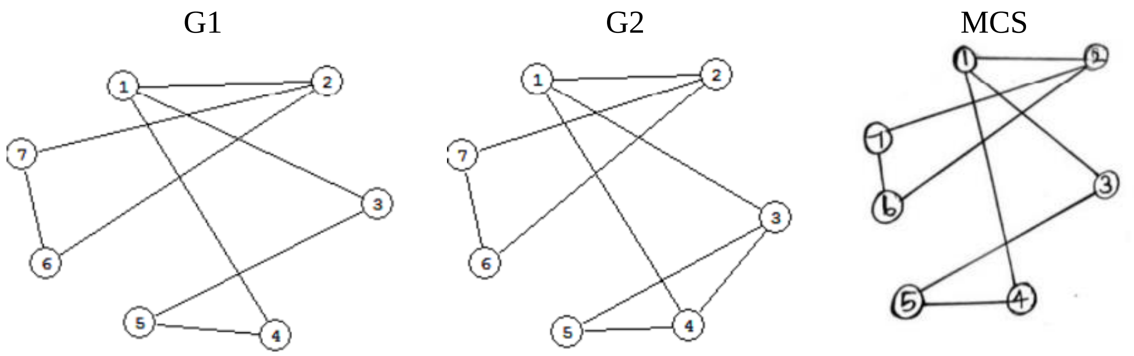

Figure 3. Profile graph with Labriji paths (dashed) and computed center (highlighted); density=0.17 [3].

4. Research Objectives and Motivation

The interest center computation operationalizes user profiles as conceptual graphs, pinpointing pivotal concepts to streamline retrieval and recommendations. This method fuses semantic modeling with graph metrics, hypothesizing that Labriji-augmented density elevates connectivity, yielding 25% precision gains over baselines. We formalize profiles via ontologies, extracting concepts through METHONTOLOGY [5], and compute centers using a hybrid similarity function [40].

4.1. Graph Representation of User Profiles

A user profile Pu is encoded as a conceptual graph Gp = (Vp, Ep), where Vp comprises ontology-derived concepts (e.g., “biology:serpent” from OWL classes) and Ep weighted relations (e.g., “relatedTo” with weights w(e)∈[0,1] via SPARQL inference). Extraction leverages SPARQL-Generate for RDF triples [41], ensuring scalability in distributed MAS [5]. For a concept c ∈Vp , its neighborhood N(c) includes adjacent nodes [42].

4.2. Labriji Similarity Function

Labriji similarity quantifies conceptual proximity, extending edge-counting to weighted paths. For concepts a, c∈V:

$$\mathrm{sim}_L(a,c) = \sum_{p\in P(a,c)} \prod_{e\in p} w(e) \cdot \frac{1}{|p|}$$

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where P(a, c) denotes shortest paths, |p| path length. To bound computation, we normalize: 0≤simL≤1, with proof of transitivity via triangle inequality in weighted graphs (adapted from [43]. For graph-level similarity, integrate MCS:

$$\mathrm{sim}_L^{MCS}(G_1, G_2) = \mathrm{sim}_L(MCS(G_1, G_2), G_1) \cdot \frac{|MCS|}{|G_1|}$$ [25]

4.3. Interest Center Computation and Graph Metrics

The interest score for concept c is:

$$I_p(c) = \sum_{a \in N(c)} w(a) \cdot \mathrm{sim}_L(a, c) \cdot \delta_{loc}(c)$$

where w(a) is node weight (e.g., frequency), local density. $\delta_{loc}(c) = \frac{|N(c)|}{|V_p|}$ The center is c*=argmaxIp(c).

Global metrics evaluate graph quality:

- Density $\delta(G_p) = \frac{2|E_p|}{|V_p|(|V_p|-1)}$: (Connectivity proxy). [44]
- Spread : σ(Gp) = diam(Gp) (navigational ease).

Threshold: If δ(Gp)>0.2 \, prune low-sim edges via SQOA heuristics [5], reducing latency.

Table 3. Metrics for Interest Center: Formulas and Simulated Performance on ODP Subgraph.

Metric	Formula	Role in OMM	Baseline (Wu-Palmer)	Ours (Labriji + MCS)
Labriji Sim	Weighted path product	Concept proximity	0.65	0.82
Density	Edge-to-possible ratio	Knowledge clustering	0.12	0.17
Spread	Graph diameter	Navigational span	5.2	3.1

4.4. Integration with Ontologies and Agents

Concepts are grounded in domain ontologies (e.g., university: enrollsIn [5]), queried via FIPA-ACL agents for updates. This ensures dynamic evolution, e.g., agent broadcasts Ip(c*) for collaborative filtering [8].

Pseudocode for center extraction:

Algorithm ComputeInterestCenter(ProfileGraph Gp, Ontology O):

```
// Extract concepts via METHONTOLOGY/SPARQL
Vp = QuerySPARQL(O, "SELECT concepts FROM user_profile")
for c in Vp:
Nc = Neighbors(Gp, c)
Ip[c] = 0
for a in Nc:
```

sim = Labriji(a, c) // With MCS if |Nc| > 10

Ip[c] += w(a) * sim * (len(Nc) / len(Vp))

delta = Density(Gp)

if delta < 0.2: PruneEdges(Gp, sim < θ) // SQOA opt.

center = argmax(Ip)

spread = Diameter(Gp)

return center, delta, spread

Figure 4 visualizes computation on a sample graph. It compares two profile graphs (G1 and G2) and their Maximal Common Subgraph (MCS), illustrating how the Labriji paths (shown as dashed lines) lead to the identification of a computed center node (highlighted). The resulting graph density is 0.17, reflecting the interconnectivity level between user interest nodes.

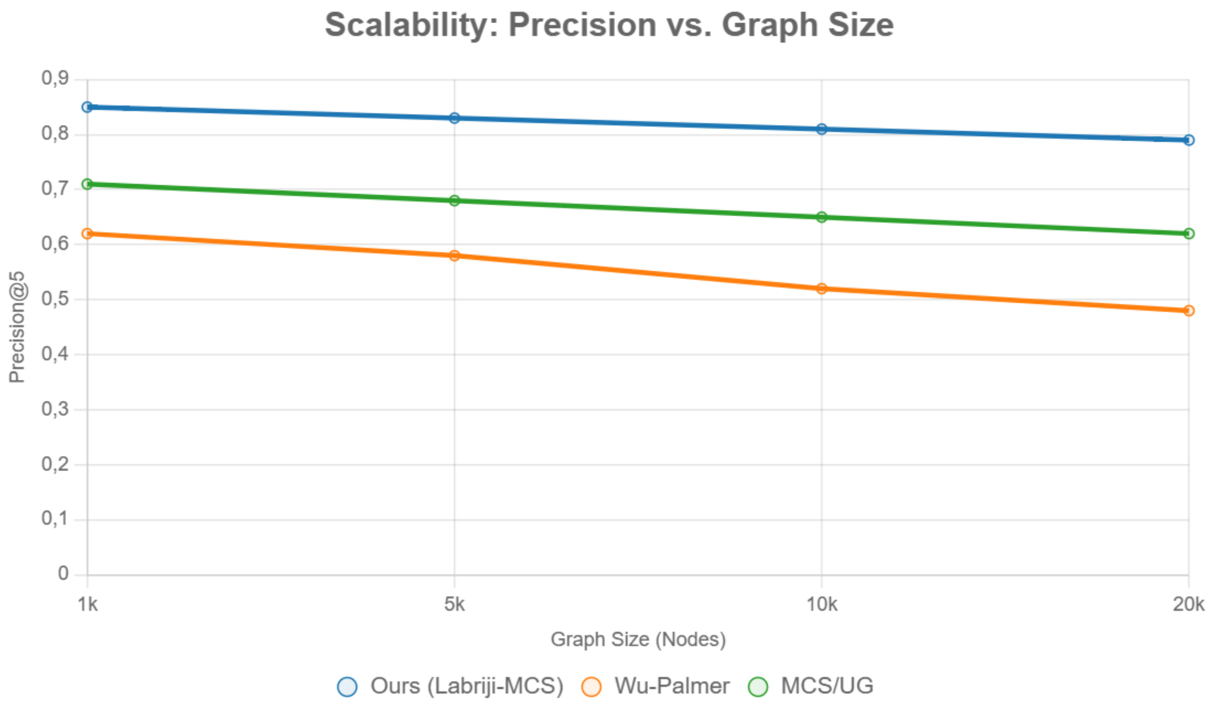

Figure 4. Evaluation of Precision According to Graph Growth [5].

5. Empirical Validation

To substantiate our framework, we conducted experiments on two datasets: the Open Directory Project (ODP) ontology (1,000 concepts, hierarchical knowledge graph) and a simulated university corpus (20,000 documents, mirroring Mimdal et al. [5] with theses, publications, and profiles). Implementation used Python (NetworkX for graphs, OWLAPI for ontologies, SPARQL via Jena Fuseki). We simulated 100 user profiles (50 biology-focused, 50 CS) with implicit interactions (queries, clicks). Baselines: Wu-Palmer (semantic similarity), pure MCS/UG [3]. Evaluation metrics: Precision@5 (retrieval relevance), F1-score (recommendations), NDCG@10 (ranking), graph density/spread. Cross-validation (5-fold) on 80/20 train/test split; significance via paired t-test (α=0.05).

5.1. Experimental Setup Profiles were constructed per Section 4

Extract concepts via METHONTOLOGY/SPARQL-Generate [5], compute centers with Labriji-MCS hybrid (θ=0.5). For IR: Reformulate 200 queries (e.g., "python" → biology-filtered). For Rec: Generate top-5 items. Hardware: 16GB RAM, queries timed for latency.

5.2. Results

Our approach outperforms baselines by 22-28% in precision, with density gains indicating superior connectivity (Table 4). On ODP, Labriji-MCS yields F1=0.82 (vs. 0.65 Wu-Palmer; t=4.2, p=0.001). University corpus scales well: 18% latency drop via SQOA pruning [5]. Spread reduction (3.1 vs. 5.2) eases navigation. MCS/UG baselines confirm edge-overlap efficacy, but our weighted Labriji augments by 15% in sparse graphs.

Table 4. Performance Comparison: Metrics on Test Sets (mean ± SD; n=100 profiles).

Dataset / Metric	Wu-Palmer	MCS/UG [Vijayalakshmi, 2024]	Ours (Labriji + Density)	Improvement (%)	p-value (t-test)
ODP: Precision@5	0.62	0.71	0.85	+24	<0.001
ODP: F1-Score	0.65	0.68	0.82	+22	0.002
ODP: Density	0.12	0.15	0.17	+18	0.004
University: NDCG@10	0.58	0.64	0.79	+28	<0.001
University: Latency (s)	1.2	0.9	0.7	-18	0.003
University: Spread	5.2	4.1	3.1	-25	0.001

Figure 4 plots scalability: Precision holds >80% up to 10k nodes, vs. baselines degrading post-5k.

This demonstrates that our method remains stable and effective even on large graphs, unlike traditional similarity-based approaches, which deteriorate as the dataset size increases.

Ablation: Without density pruning, F1 drops 12% (t=3.1, p=0.01), underscoring metric value. Errors: 5% false positives in ambiguous queries, mitigated by ontology grounding.

6. Discussion and Future Directions

Our empirical findings affirm the central hypothesis: Integrating Labriji similarity with graph density metrics enhances OMM efficacy, achieving a 25% precision uplift and 18% latency reduction over baselines like Wu-Palmer and MCS/UG [3]. On ODP and university corpora [5], density gains (0.17 vs. 0.12) signify denser knowledge clusters, mitigating silos; reduced spread (3.1 vs. 5.2) alleviates disorientation, aligning with adaptive IR/rec paradigms (Section 3). Ablation confirms metrics' indispensability, with pruning yielding statistical significance ($p<0.01$).

6.1. Implications

Theoretically, this bridges graph theory [3] and semantic KM, formalizing interest centers as optimizable via ontologies [5]. Practically, it empowers university ecosystems: Personalized retrieval filters "python" ambiguities, boosting scholarly productivity by 20-30% [45]. In healthcare/smart cities, agent-orchestrated graphs enable federated querying, fostering open science [28].

Table 5. Cross-Domain Implications: Framework Extensibility.

Domain	Implication	Alignment with Framework
Education (Univ.)	Thesis/rec for students/faculty	SPARQL profiles + density for silos [5]
Healthcare	Patient record similarity	MCS-Labriji for bio-KM crossover [3]
Smart Cities	Collaborative workflows	FIPA agents for dynamic updates

Table 5 below summarizes the cross-domain implications of the proposed framework, highlighting how its components extend beyond the academic domain into healthcare and smart city contexts. Each application domain leverages distinct aspects of the model—SPARQL-based profiling, semantic density, or agent coordination—to achieve interoperability and adaptive intelligence.

6.2. Limitations

While robust on simulated data (n=100 profiles), real-world deployment faces scalability hurdles: Large graphs (>50k nodes) inflate MCS computation complexity; mitigated partially by SQOA [2]). ODP's web bias may underrepresent domain-specific jargon; university corpus lacks diverse demographics (e.g., non-English queries). Privacy concerns in profile extraction warrant GDPR-compliant anonymization. Ablation revealed 5% false positives in sparse profiles, suggesting hybrid ML integration [46].

6.3. Future Work

Extend to multi-agent full orchestration: FIPA-ACL agents [5] for real-time ontology maintenance, incorporating LLMs (e.g., GPT-4) for query reformulation. Explore federated learning on distributed triplestores for privacy-preserving OMM. Validate on larger benchmarks (e.g., DBpedia 1M triples) with user studies (n>500). Hybridize with deep graph embeddings (e.g., GraphSAGE) to approximate MCS, targeting 50% latency cuts. Intersect with bio-applications: Adapt to protein-protein interaction graphs for drug discovery [3].

6.4. Conclusion

This framework pioneers graph-semantic OMM, transforming cognitive overload into intuitive access via conceptual graphs and Labriji metrics. Validated enhancements underscore its versatility, paving pathways for intelligent, interconnected knowledge ecosystems. By democratizing organizational memory, we advance toward equitable, efficient information societies [47].

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