Fostering Scholarly Knowledge Curation with Multimodal AI: Integrating LLMs, VLMs, and Knowledge Graphs for Explainability and Trust

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1. Abstract

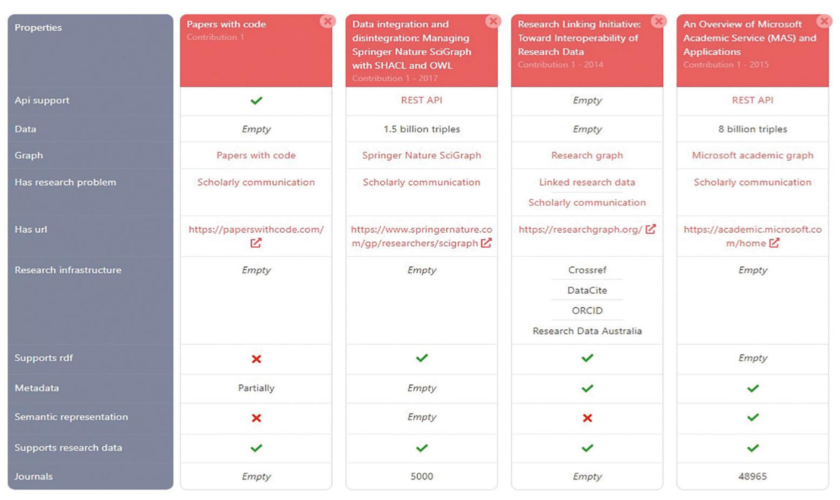
Scholarly knowledge curation faces challenges due to diverse methodologies across scientific fields. Leveraging Large Language Models (LLMs) like GPT-3.5 and visual models (VLM), we enhance AI explainability and trustworthiness in knowledge curation.

Our approaches integrates LLMs and VLMS with the Open Research Knowledge Graph (ORKG) and employs prompt engineering for accurate data extraction from academic literature.

This collaborative frameworks merges neural capabilities with symbolic knowledge graphs and human expertise, addressing practical challenges and promoting trusted, explainable AI applications in scientific research.

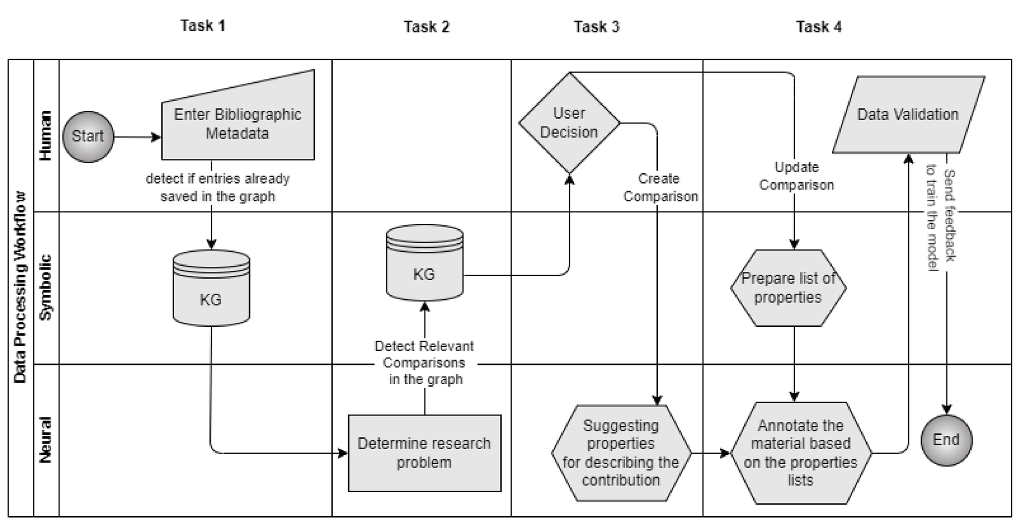
2.Introduction

Research communication faces challenges in conveying complex scientific contributions accurately. ORKG addresses this but requires significant manual effort. Our approach automates key aspects using LLMs and VLMs, while maintaining user control. This integration of AI and human intelligence streamlines the process of creating comprehensive, cross-domain research descriptions compatible with various information retrieval systems



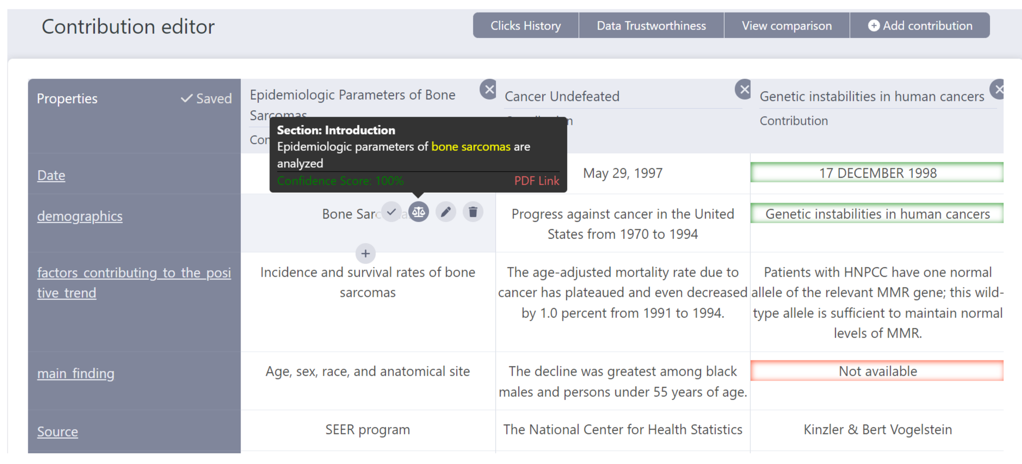
3.1 Hybrid, Neuro-symbolic Approach

We propose an approach that integrates human intelligence, LLMs, and Knowledge Graphs for the semi-automatic creation and curation of Scholarly Knowledge Graphs. The model anthropomorphizes the LLM as a human-like curator for research article annotation, fostering a collaborative framework where humans and AI work together with the Knowledge Graph as partners.



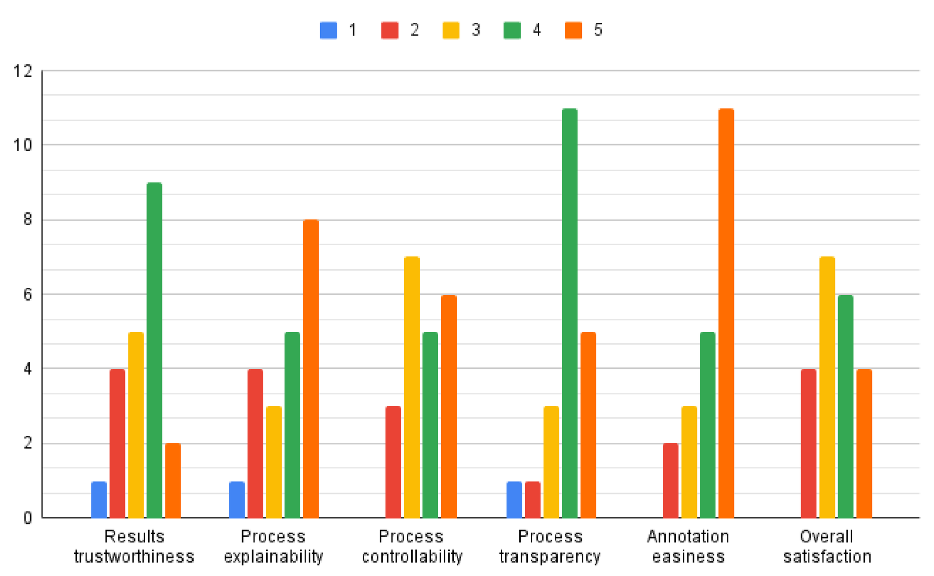
3.2 Explainable AI

We aim to enhance the trustworthiness, explainability, and transparency of AI-generated content by providing users with factual information about the generated data. To assist users in validating AI-generated properties and their values, we offer tooltip features that allow them to cross-check this information against the article's content.



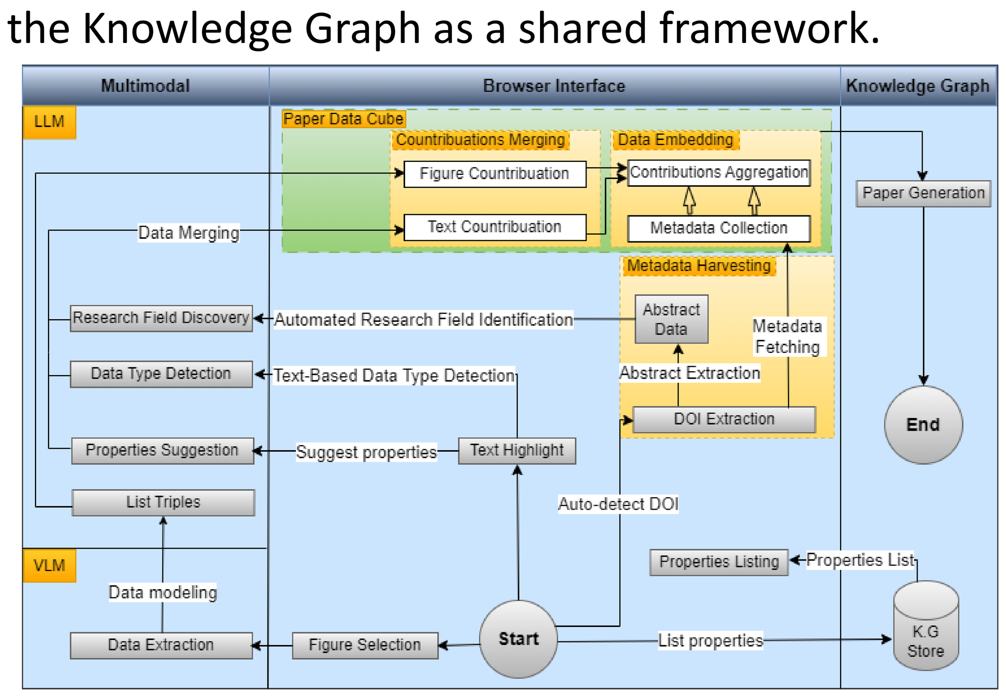
3.3 Approach Evaluation

We recruited 21 participants (71% academia, 29% industry) for our study. Academics were mostly postdocs, PhD candidates, and master's students, while industry participants held technical roles like developers and testers. To reduce bias, only 15% were regular ORKG users.

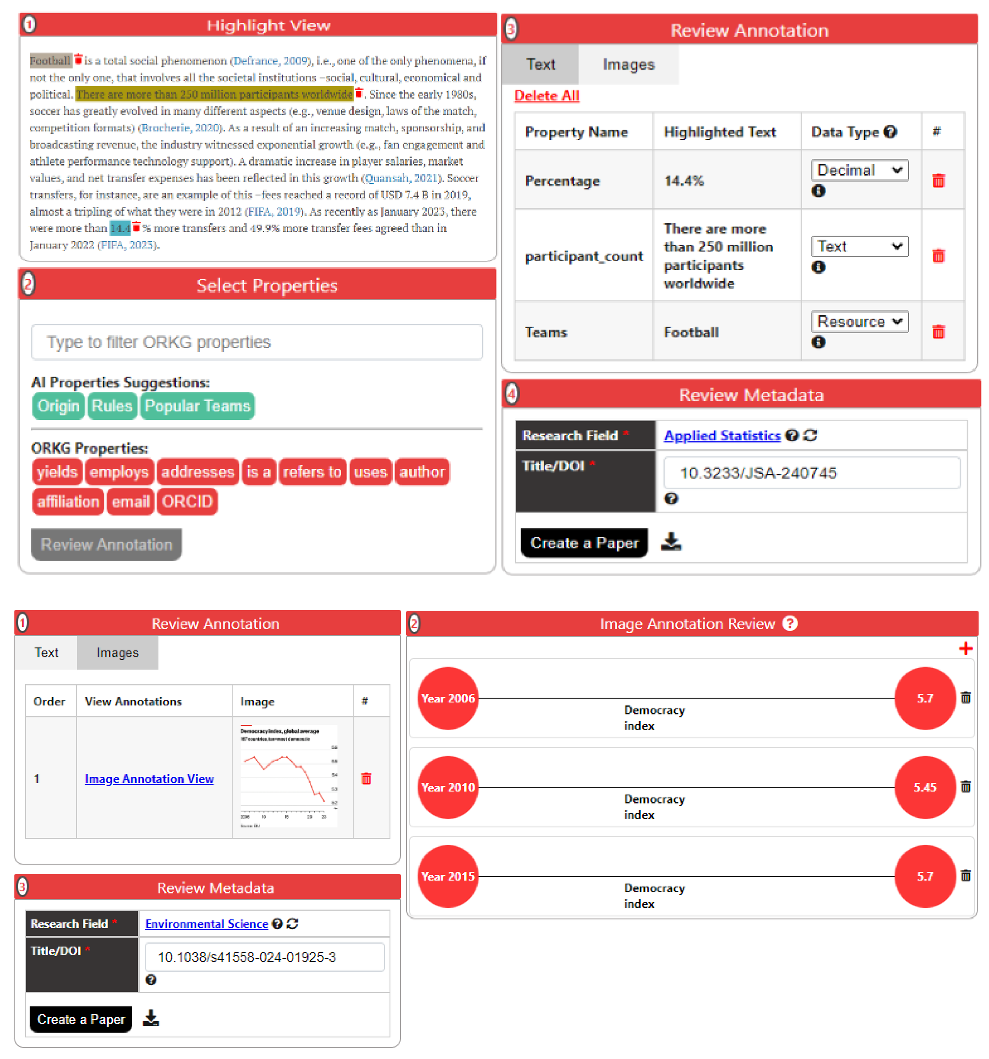


4.1 Multimodal AI Annotation Approach

We propose an approach combining human intelligence, AI techniques, and Knowledge Graphs for semi-automatic creation of Scholarly Knowledge Graphs. Our model uses an LLM, and VLM as a human-like curator for research annotation, fostering collaboration between humans and AI with the Knowledge Graph as a shared framework.

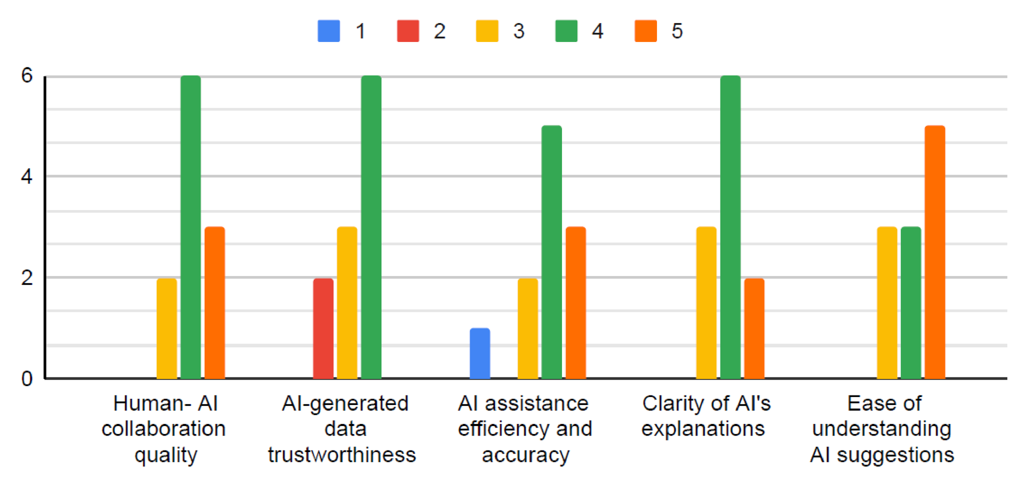


4.2 ORKGEx: Multimodal Annotaion



4.3 Extension Evaluation

We recruited 11 participants from diverse professional backgrounds, including postdoctoral researchers, PhD students, and both frontend and backend developers. Notably, 82% of participants had prior experience with ORKG, enabling them to provide insightful feedback on improving the extension based on their familiarity with ORKG's challenges.



5 Conclusion and Future Work

Our research introduces two innovative approaches to scholarly knowledge curation:

1. A hybrid neuro-symbolic method with explainable AI, enhancing transparency and trust.
2. ORKGEx: A browser-based multimodal annotation tool integrating LLMs and VLMs.

Both approaches show promising results in improving curation quality and efficiency.

For future work, we are developing an automated annotation system using LLMs and VLMs to further streamline the curation process. This system will leverage ORKG templates to extract properties related to specific research problems, focusing on continuously improving resource descriptions. This advancement aims to create a more comprehensive and dynamically updated knowledge graph.