



# ORKGEx: Leveraging Language and Vision Models with Knowledge Graphs for Research Contribution Annotation

Hassan Hussein , Fahad Ahmed , Allard Oelen , Ralph Ewerth , Sören Auer

Hassan Hussein

TIB – Leibniz Information Centre for Science and Technology

IARIA- Web 2025, Lisbon  
13, March, 2025



# Bibliography

## 1. **Computer Information System**

Tompkins Cortland Community College Tompkins Cortland  
Community College, NY 2009

## 2. **Interne at the legal institute in Web Development Area**

Cornell University, NY 2009

## 3. **Web Applications Development Team Leader**

Telecom Egypt 2011 to 2017

## 4. **M.Sc. in Human Computer Interaction**

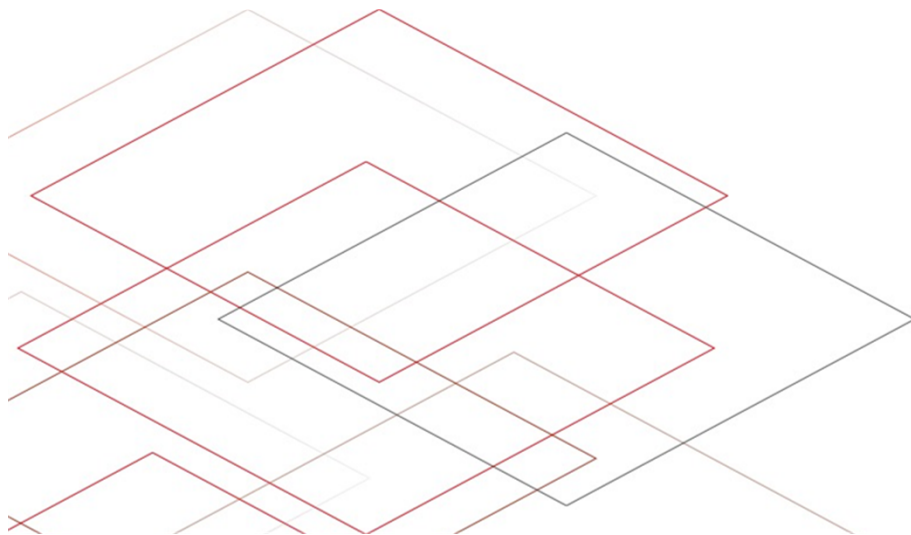
Siegen University, Germany 2021

## 5. **PhD Student in User Interface for Semantic Web**

Leibniz University, Germany



# 1. Introduction



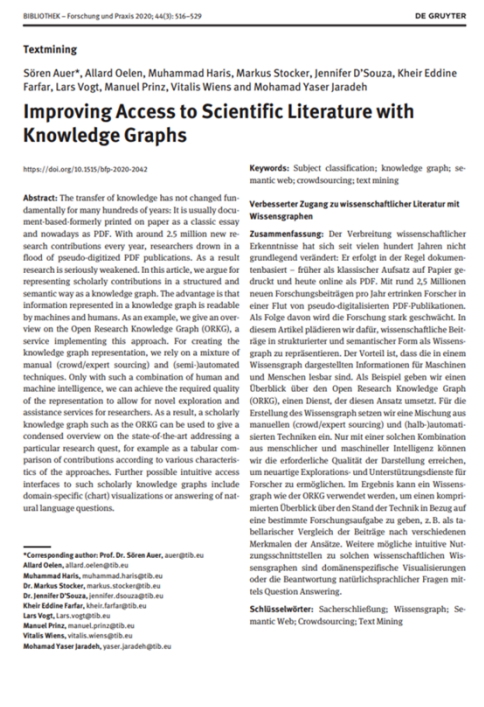
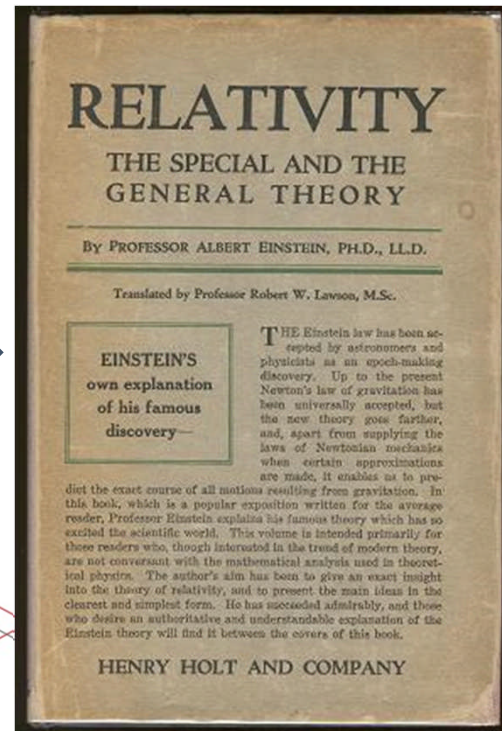
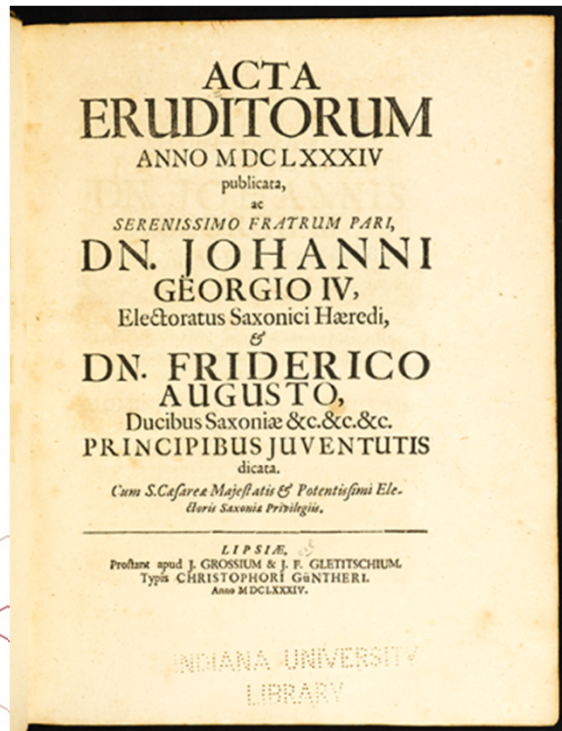
# Scholarly Communication Over Time

Over 300 years ago

100 years ago

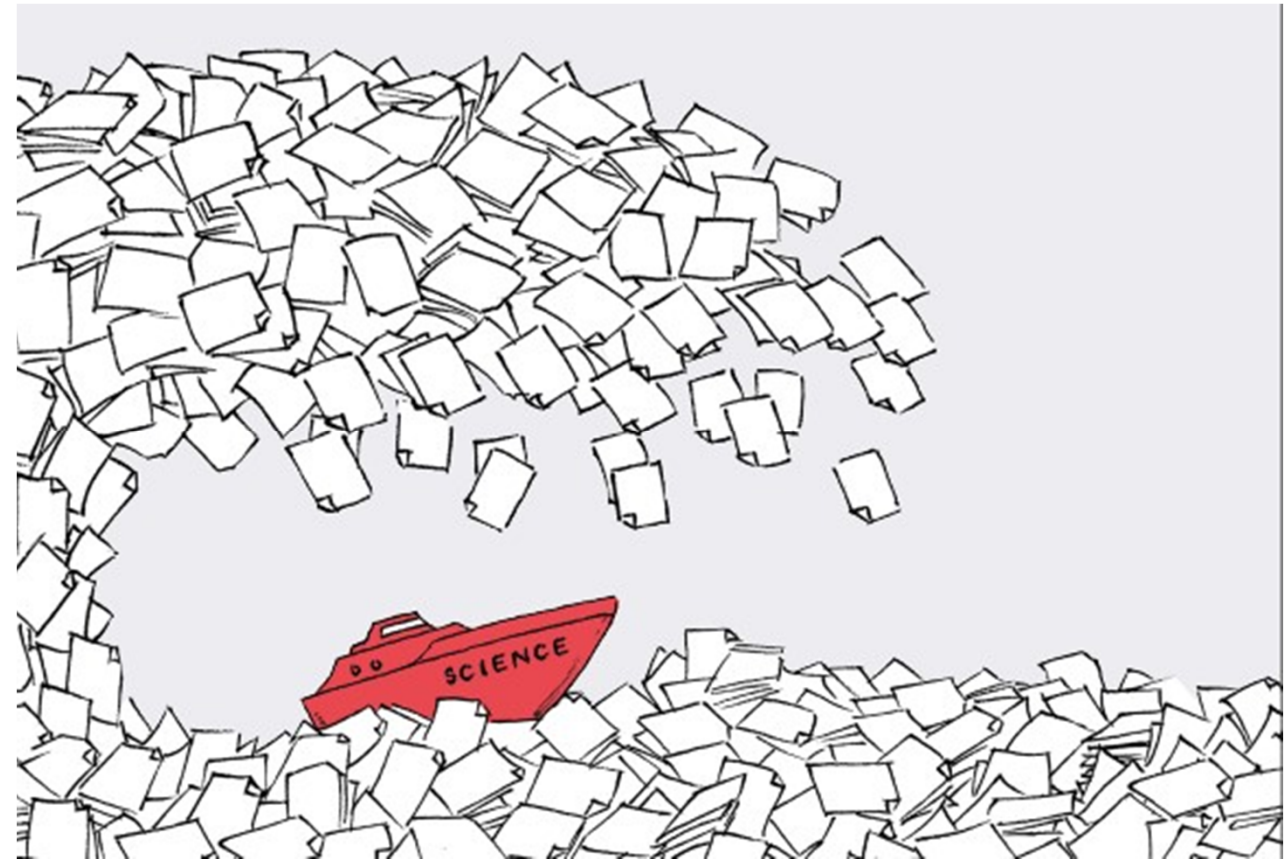
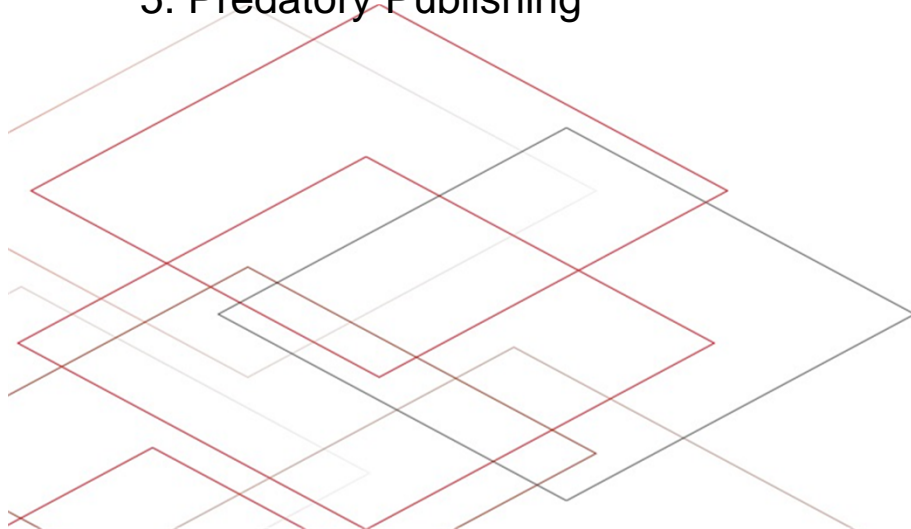
20 years ago

Today



# Reproducibility Crisis

1. ~ 2.5 million new publications per year
2. Globally ~ \$1.7 trillion spent on research
3. Monopolization of commercial actors
4. Deficiency of Peer-Review
5. Predatory Publishing



# The Data Swamp Problem

## 1. Semantic Description of Research Contributions

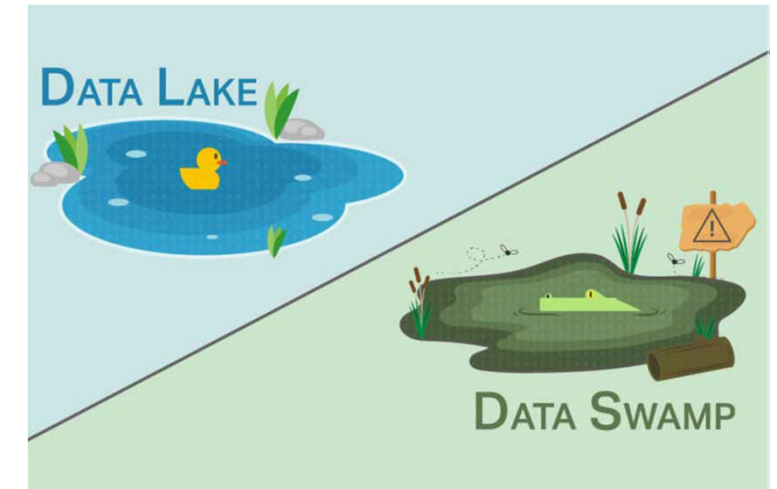
- A. Researchers often struggle to clearly and accessibly convey their work.
- B. The annotation process is time consuming and cumbersome

## 2. Information Overload

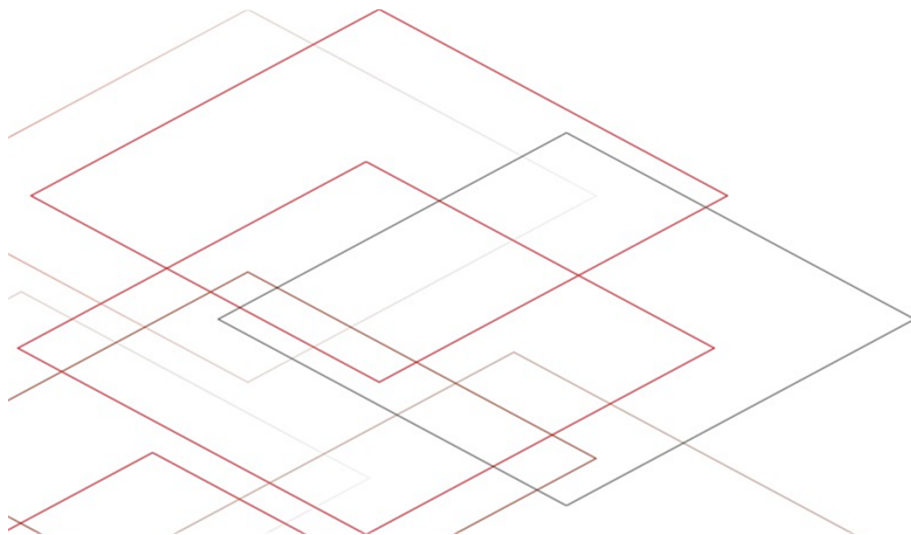
- A. The exponential growth of scientific publications has led to information overload
- B. Insufficiently automatized and lack user integration

## 3. Lack of Standardization

- A. There is a lack of standardization in how research contributions are annotated and shared.
- B. This inconsistency fragments knowledge and hinders effective meta-analyses.



# 2. Lighthouse in the Flood



# Knowledge Graphs (KGs)

**Knowledge Graphs (KGs):** Data structures that represent knowledge in a graph format, where nodes represent entities (e.g., people, places, things) and edges represent relationships between these entities.



Source: Wikidata

**Symbolic Representation:** KGs use formal knowledge representation languages (such as RDF and OWL) to encode facts, making the information machine-readable and understandable.



# KGs: Accuracy & Integrity

## 1. Accuracy & Reliability

A. Designed to store and retrieve factual information with high accuracy.

## 2. Structured Data

A. Uses a graph structure for efficient organization and retrieval of interrelated data.

## 3. Knowledge Graphs have Factual Information

**A. Enhanced Search and Querying:** Enables more precise searches by understanding relationships.

**B. Knowledge Discovery:** Links related information to uncover new insights.

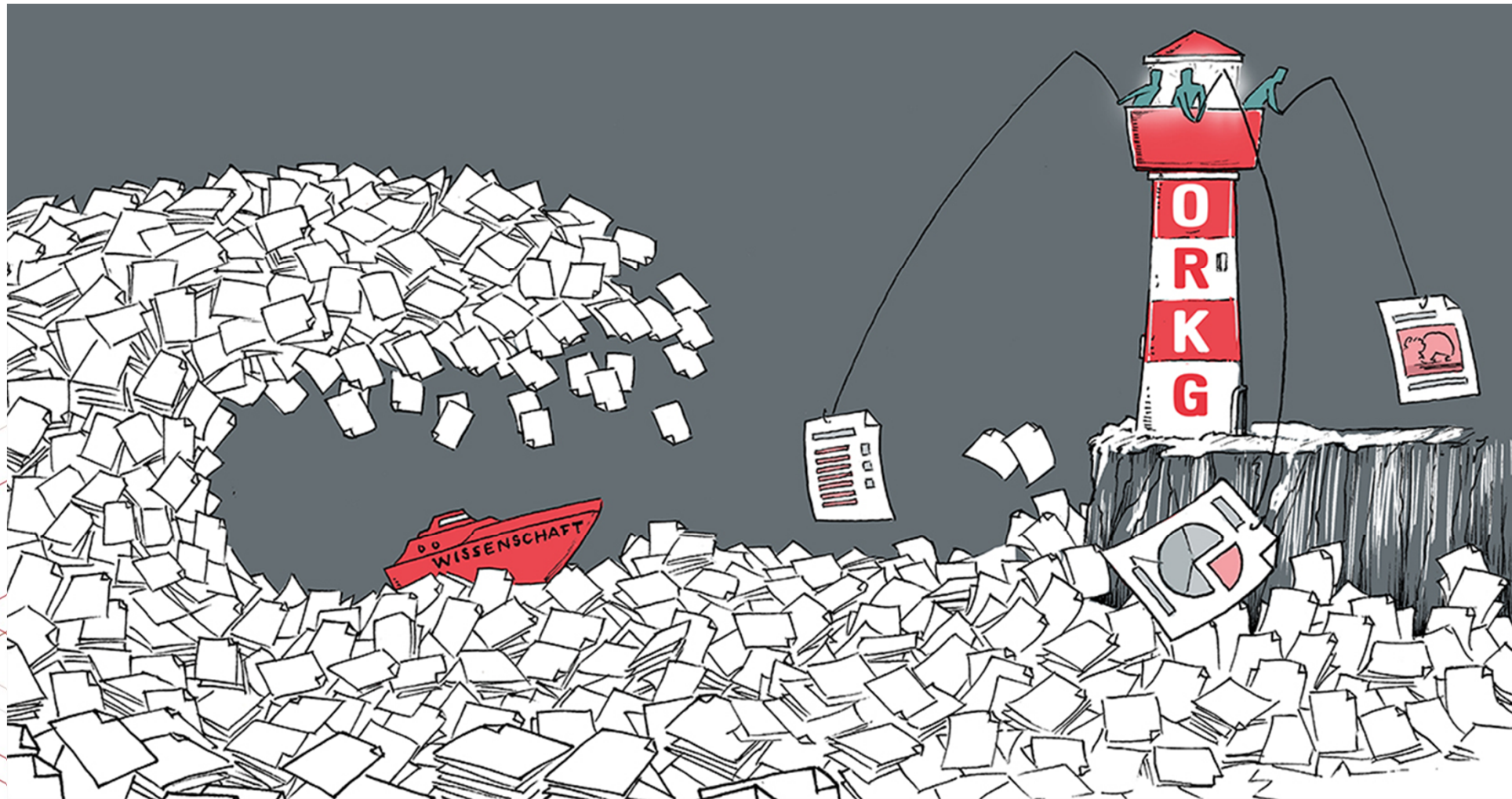
**C. Contextual Understanding:** Provides broader context for better comprehension.

**D. Symbolic Representation:** Uses symbols and formal languages to represent structured knowledge

**E. Human and Machine Interpretability:** Ensures both humans and machines can process and understand the data.

**F. Interoperability:** Supports data integration using standardized formats

# Open Research Knowledge Graph (ORKG)



# ORKG- Paper View


Integrating analysis of customers' processes into roadmapping: The value-creation perspective



 August 2011
  7 citations
  Software Engineering
  Marko Komssi
  Marjo Kauppinen
  Harri Tohonen
  Laura Lehtola
  Alan M. Davis

Published in: 2011 IEEE 19th International Requirements Engineering Conference

DOI: <https://doi.org/10.1109/re.2011.6051662>

Research Practices


 Preferences

Data analysis	<a href="#">analysis</a>
data collection method	<a href="#">case study</a> <hr/> <a href="#">workshop</a>
research question	<a href="#">How can these problems be solved?</a> <hr/> <a href="#">What kind of problems do software product companies encounter during roadmapping?</a>
research paradigm	<a href="#">exploratory</a> 
research problem	<a href="#">empirical research in requirements engineering</a> 
research question answer	<a href="#">hidden in text</a>
Threat to validity	<a href="#">mentioned</a>

Add to comparison


**Provenance** Timeline

**Belongs to observatory**  
Empirical Software Engineering



Leibniz  
Universität  
Hannover

**Added on**  
18 Nov 2022

**Added by**  
 Felix Wernlein

**Contributors**  
Felix Wernlein

# Publishing State-of-the-Art comparisons

The screenshot shows a comparison page on ORKG. On the left, four callout boxes point to specific features: 'Acknowledgement of creators' points to the authors and date; 'Citable DOI' points to the DOI link; 'Created visualizations' points to a row of six bar charts; and 'Interactive comparison with filtering' points to a 'Properties' sidebar with a 'Has dataset' filter.

**Acknowledgement of creators** → This overview shows the classification results of approaches that use the machine learning algorithms Naïve Bayes, Support Vector Machines, and Decision Trees C4.5 in combination with the machine learning features Bag of Words or Term Frequency - Inverse Document Frequency to classify user feedback as feature request.

**Citable DOI** → DOI: [10.48366/r112387](https://doi.org/10.48366/r112387)

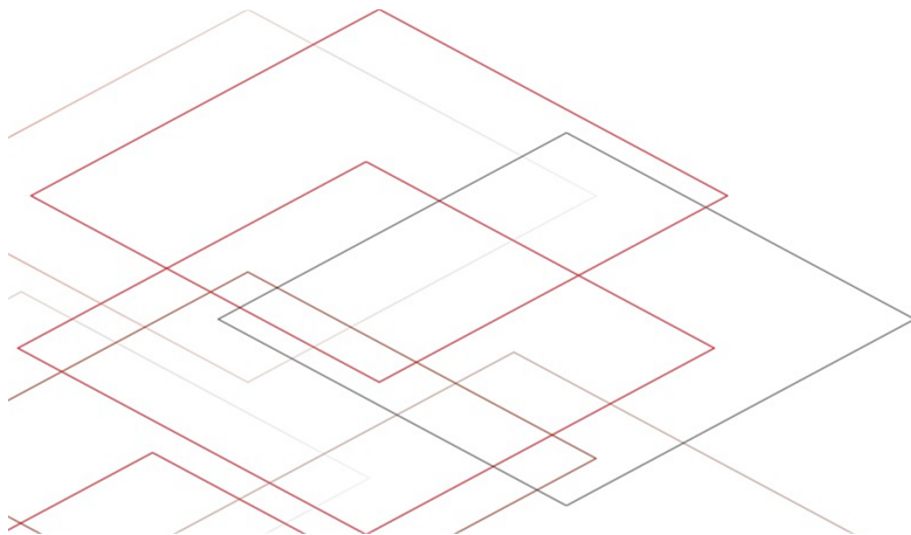
**Created visualizations** → Visualizations

**Interactive comparison with filtering** → Properties: Has dataset

Approach	Year	Dataset
Software Feature Request Detection in Issue Tracking Systems	2016 - User Feedback Classification	<a href="https://zenodo.org/record/56907#.YKT_NudCRPY">https://zenodo.org/record/56907#.YKT_NudCRPY</a>
Mining User Requirements from Application Store Reviews Using Frame Semantics	2017 - User Feedback Classification	<a href="https://mast.informatik.uni-hamburg.de/wp-content/uploads/2014/03/REJ_data.zip">https://mast.informatik.uni-hamburg.de/wp-content/uploads/2014/03/REJ_data.zip</a>
Mining Twitter Feeds for Software User Requirements	2017 - User Feedback Classification	<a href="https://seel.cse.lsu.edu/data/re17.zip">seel.cse.lsu.edu/data/re17.zip</a>
Automatic Classification of Non-Functional Requirements from Augmented Application Reviews	2017 - User Feedback Classification	Not available

<https://orkg.org/comparison/R112387/>

# 3. Problem



# ORKG Helps but Challenges Remain

1. Extensive Editing Required

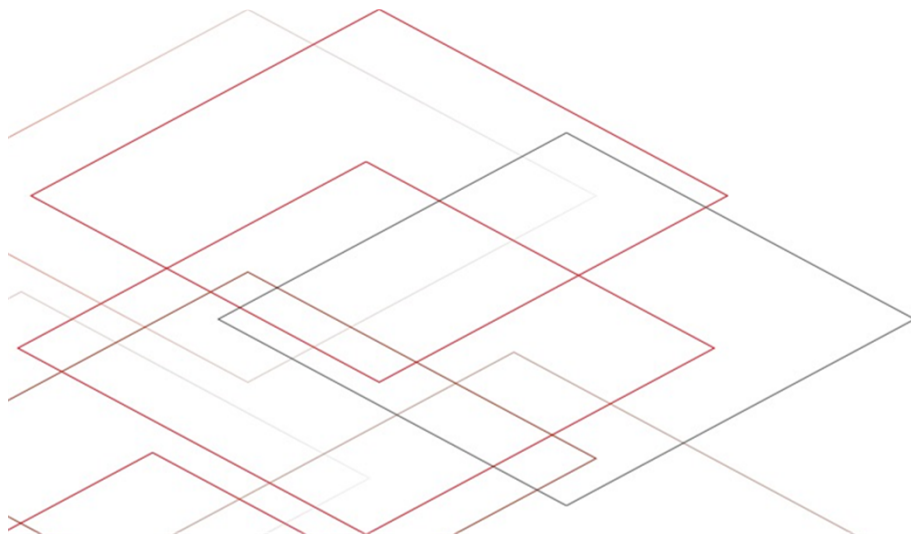
2. Property Selection Struggles

3. Semantic Descriptions Hard to Find

4. Time-Consuming Annotation

5. Limited Paper Representation (only text)

6. Lack of Motivation



# The Rise of Generative AI

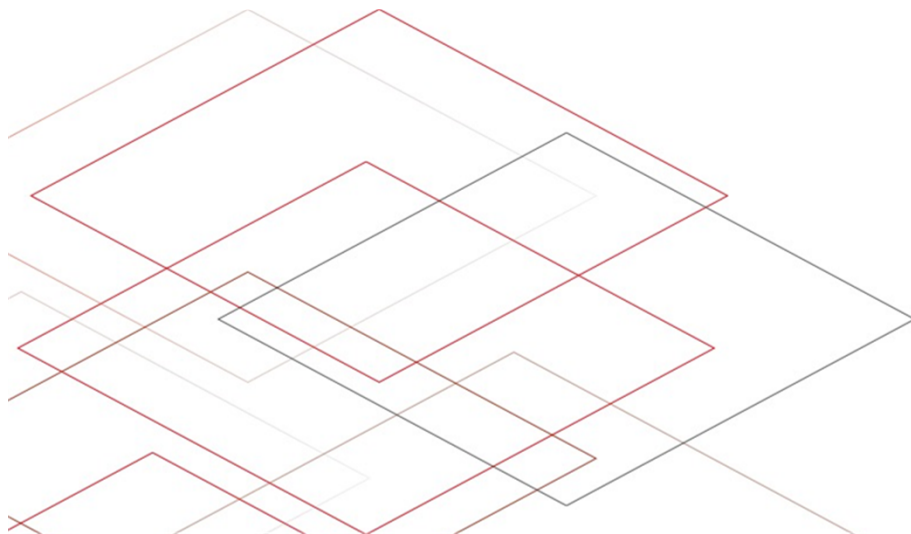
## 1. Transforming Knowledge Processing

A. AI models can automate knowledge extraction

B. Promise of reducing manual effort in annotation

C. Potential for better semantic understanding

BUT.... new challenges emerged!



# Challenges with Neural Models

## 1. Non-Deterministic Behavior

A. LLMs can generate different outputs for the same input, making consistency a challenge

## 2. Opaqueness (Lack of Transparency)

A. Users cannot see or understand how decisions are made.

## 3. Trust and Adoption Issues:

A. Users may hesitate to trust AI systems they don't understand

## 4. Tendency to Confabulate:

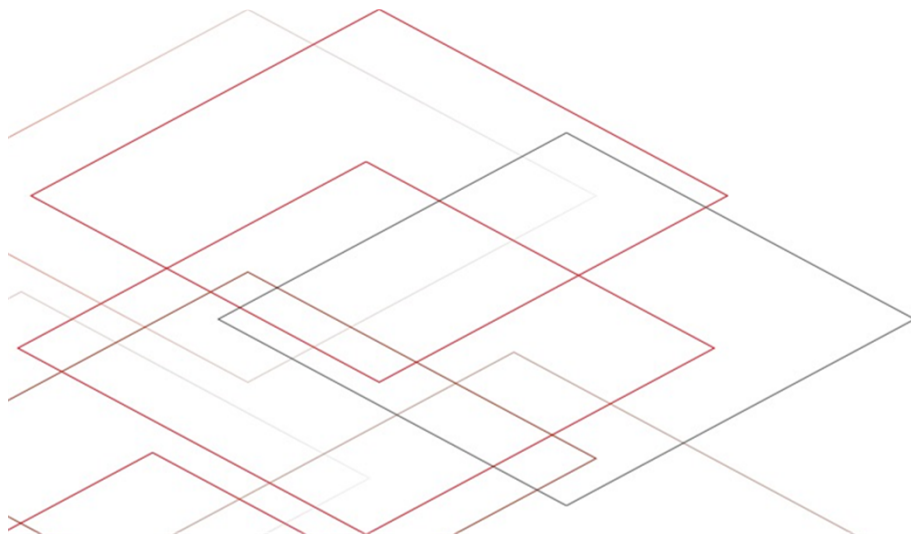
A. LLMs can generate plausible but incorrect or nonsensical information ("hallucinations").

B. Persistent errors reduce confidence.

C. Risk of spreading false information.



# 4. Goal



# Minimal invasive Interaction

## 1. We can achieve that by:

- A. Integrating the annotation process into the researchers ecosystem
- B. Automatically extract Metadata and relevant information

## 2. Leverageing the AI Techniques to:

- A. Minimize humans efforts
- B. Save the time

## 3. Seamless Integration to:

- A. Harness both human intelligence and advanced neural and symbolic AI techniques
- B. Integrate user contributions in a structured manner



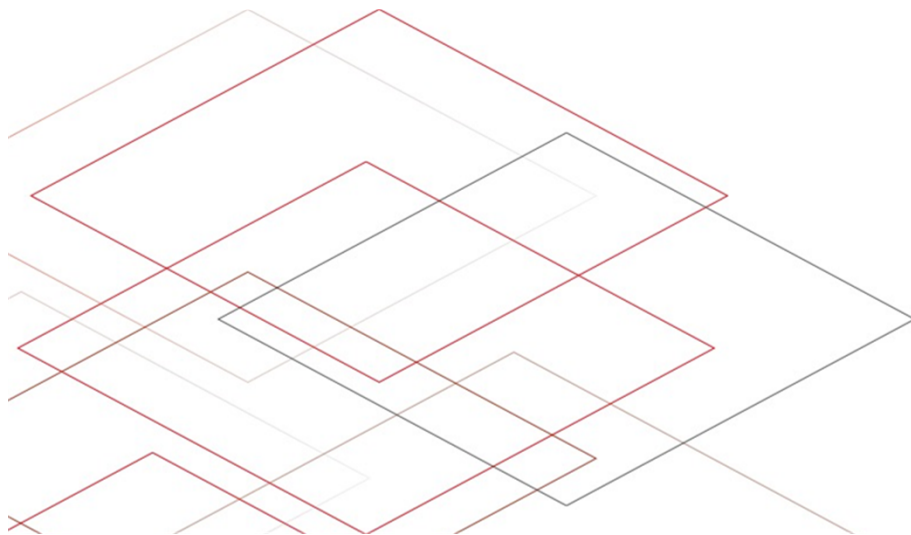
Thankfully, we can recommend a minimally invasive procedure.



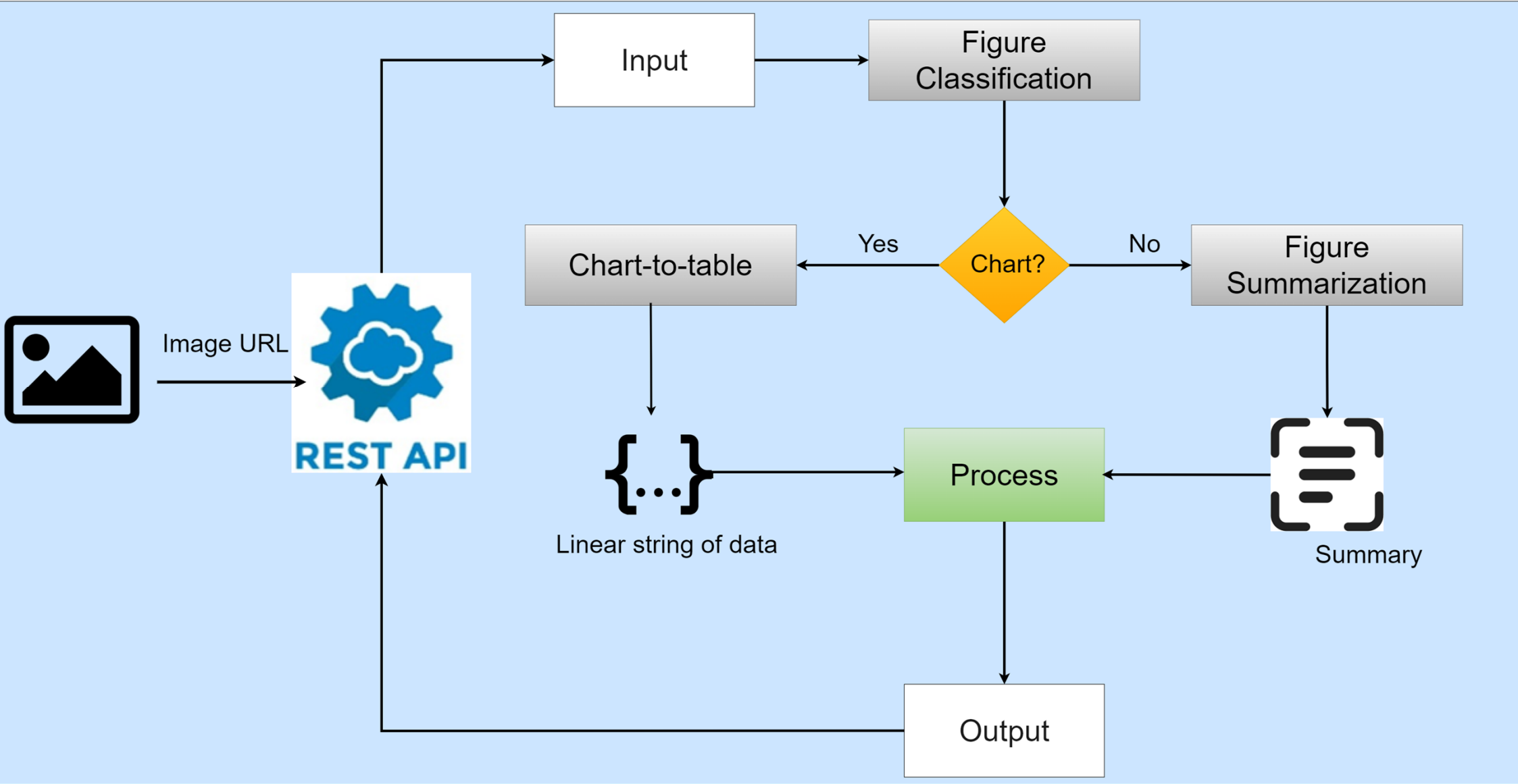
The incision will be tiny. Just big enough to let the camera and robot in.

Source: [Greg Borenstein](#)

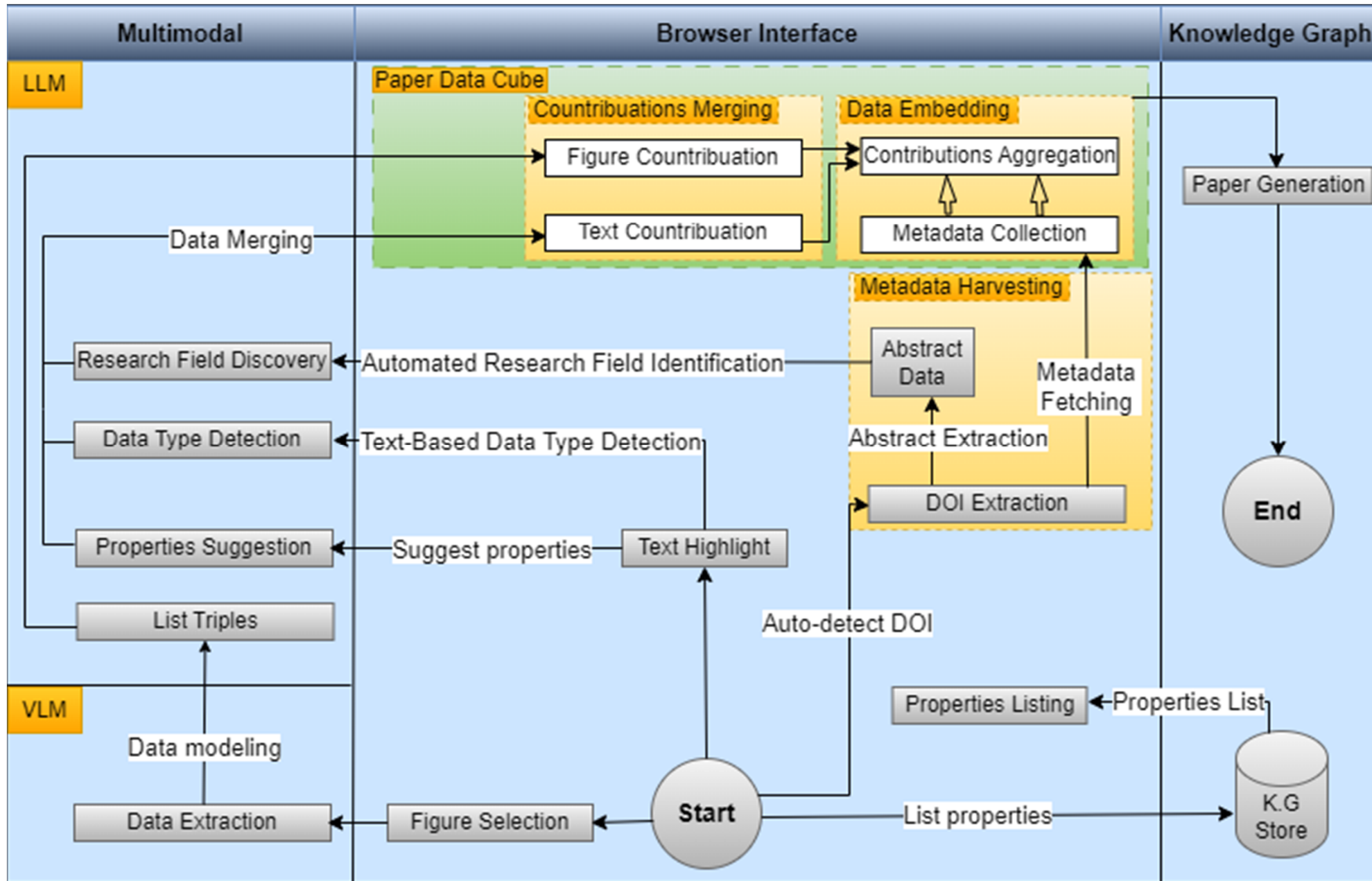
# 5. Approach



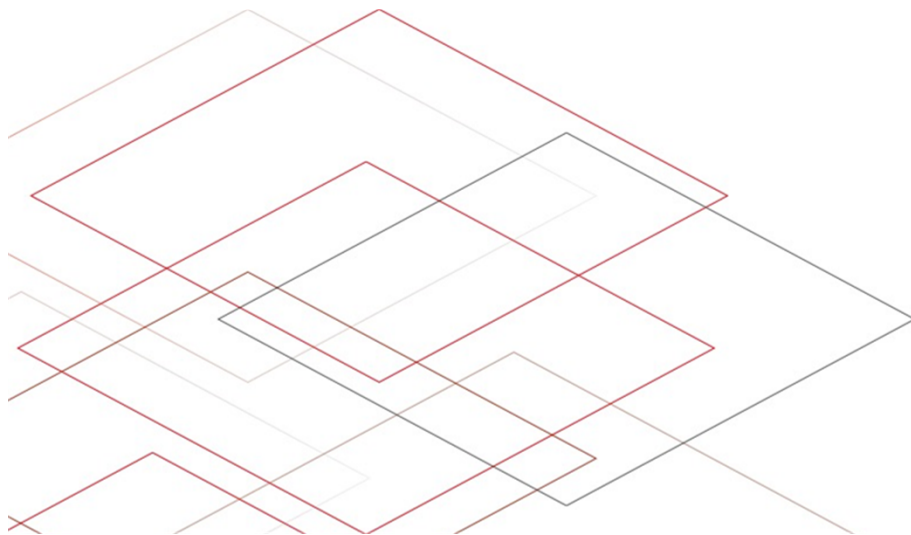
# Figure Data Extraction Pipeline



# Human-Centric Multi-Modal AI Annotation Pipeline



# 5. Evaluation



# User Study and Evaluation

1. **Participants:** 11 professionals (Postdocs, PhDs, Developers)
2. **82% had prior ORKG experience:** Provided informed feedback
3. **Key Findings:**

Feature	Mean $\pm$ SD	95% CI	Key Insight
Figure Triples Extraction	4.27 $\pm$ 0.65	(3.83, 4.71)	Highly efficient
Property Suggestions	3.73 $\pm$ 1.14	(2.97, 4.49)	Variable performance
Overall Speed	4.82 $\pm$ 0.39	(4.56, 5.08)	Significant gain

## 4. Reliability and Performance Analysis:

Metric	Mean $\pm$ SD	Distribution	95% CI
Data Type Detection	4.09 $\pm$ 0.67	5★: 27.3%, 4★: 54.5%, 3★: 18.2%	(3.64, 4.54)
Research Field Classification	4.00 $\pm$ 0.74	5★: 27.3%, 4★: 45.5%, 3★: 27.3%	(3.50, 4.50)
Metadata Extraction	4.27 $\pm$ 0.86	5★: 54.5%, 4★: 18.2%, 3★: 27.3%	(3.69, 4.85)

# User Study and Evaluation

## 5. User Feedback Highlights

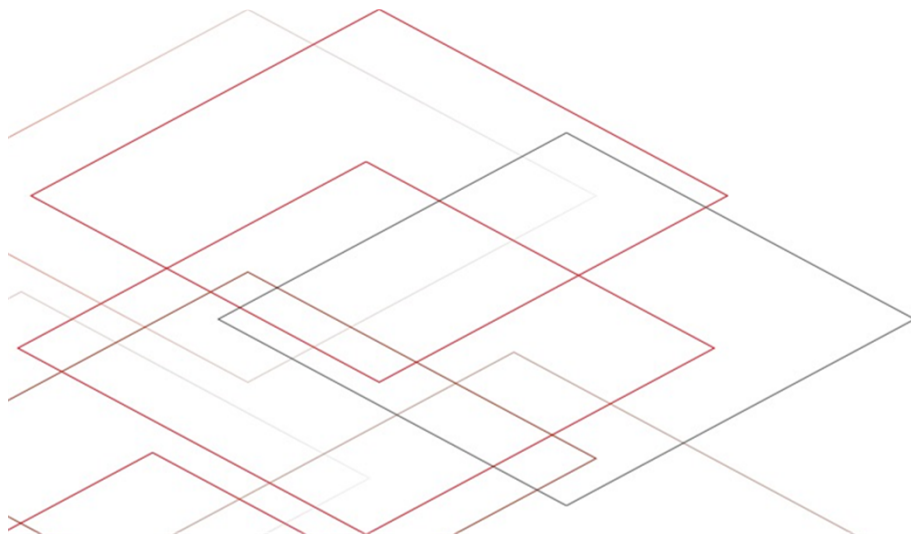
- A. **82%** reported **faster annotation** than traditional interfaces
- B. **90% effectiveness** in **figure-based triple extraction**
- C. **82% trust** in AI-generated content, with **73% accuracy perception**
- D. **High satisfaction (Mean:  $4.18 \pm 0.75$ )**
- E. **Strong AI-assisted performance**: metadata extraction ( $4.27 \pm 0.86$ ), data type detection ( $4.09 \pm 0.67$ )

## 6. Areas for Improvement

- A. AI-generated **property suggestions** need more **contextual awareness**
- B. Tooltips should have **better visibility** (larger fonts, noticeable colors)



# 6. Limitaion



# Limitations Identified:

## 1. Performance Measurement Challenges:

- A. User-reported speed improvements ( $4.82 \pm 0.39$ ), but no absolute baselines due to
  - 1. Annotator expertise and familiarity
  - 2. Paper complexity (length, structure, content)
  - 3. Number and complexity of figures

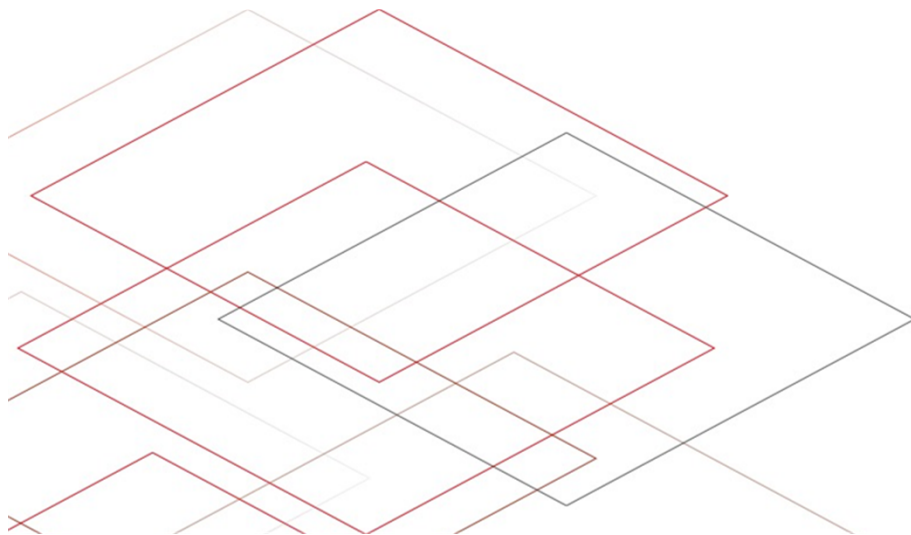
## 2. System Evaluation Challenges:

- A. The need for Larger-scale comparison (manual vs. automated annotations)
- B. Controlled environment for quantitative time measurements
- C. Standardized test sets with varying complexity

## 3. Sample Diversity:

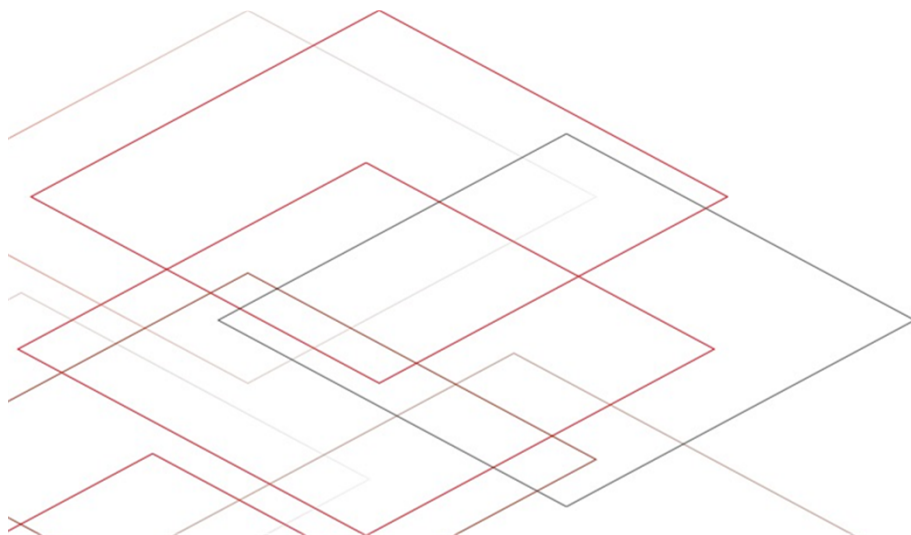
- A. Evaluation with 11 participants (82% with ORKG experience)
- B. Small sample size limits generalizability, requiring broader validation with diverse expertise levels and larger samples

# 7. Future Work



# Future Directions:

1. Explore advanced techniques in computer vision and NLP (e.g., transformer-based models for figure extraction).
2. Address **scalability challenges** for large documents and multi-user annotation synchronization.
3. Investigate **deployment challenges** (browser version consistency, complex figure processing).
4. Expand **evaluation scope** with larger, diverse research communities to mitigate biases (academic disciplines, experience levels).
5. Enhance **support for complex data types** (interactive tables) and diverse use cases.



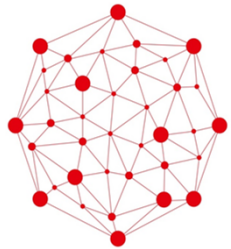
# 8. Demo

# Key Takeaways



## **Human-AI synergy enhances research capabilities:**

Curation workflows with machine assistance (LLM and VLM) and human-in-the-loop refine knowledge representations in the ORKG.



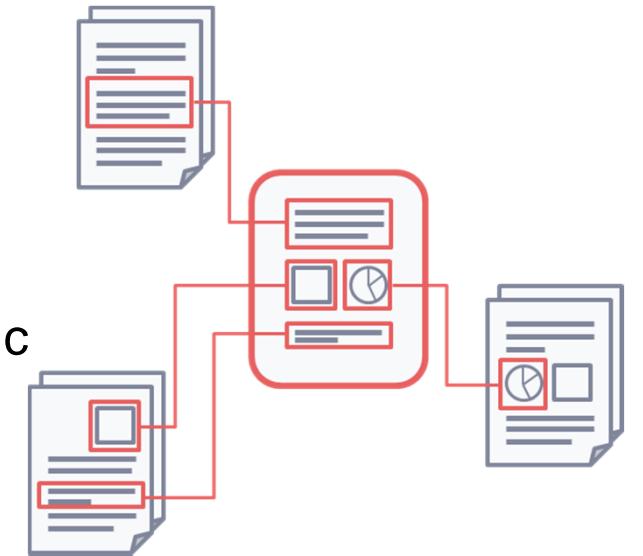
## **Clarity and consistency of Knowledge Representation:**

Knowledge graph encapsulates factual information in a symbolic form that is accessible to both humans and machines.



## **Collaborative framework fosters reproducibility:**

Transparent and accurate knowledge representation through crowd work in the KG makes it easier for other researchers to verify and reproduce study results iteratively.



# Questions