Research Proposal for Dissertation: Is metadata ready for RAG?

An analysis and case study of title and abstract content as an external knowledge source in retrieval-augmented generation

This research proposal is for a monograph dissertation following the 5-chapter model.

Introduction

Abstracts from bibliographic metadata have been shown to be a viable external knowledge source in retrieval-augmented generation (RAG) architecture, which is subset of natural language processing (NLP) and artificial intelligence (AI). While previously used for discovery or analysis, these open sources of metadata can be used to ground RAG applications to provide answers using current, verifiable, and citable sources. Metadata is used in discovery and retrieval systems in academic libraries and past research has evaluated metadata quality for presence and coverage. Current systems such as Concensus or ProQuest Research Assistant used in academic environments are likely using the principles of RAG to bring in external knowledge. Yet RAG has been shown to be affected by irrelevant or incorrect content, such as spelling errors, known as “noise”, in text provided as external knowledge. It is unknown what noisiness exists in abstract content, which databases have it, and what the effects are on RAG. The purpose of this research is to investigate what textual characteristics, errors, or noisiness exists in abstracts and titles from bibliographic metadata, how metadata sources may contribute to these characteristics, and explore the effect on RAG.

Problem statement

There are no studies on the content of title and abstract metadata for characteristics that may be noise and the potential harmful or beneficial effects on RAG applications (Wu et al., 2025). RAG has been used in current systems such as Concensus[1] or ProQuest Research Assistant[2] and deployed by academic libraries (Taylor et al., 2025). As there are few limits on abstract content, abstracts can be added to databases with artifacts from publishing software, web-page scraping, or full-text parsing, to name a few method (*About the Data*, n.d.). When used by RAG systems, noisiness, such as typos, irrelevant text, or formatting characters, can significantly degrade performance (Cho et al., 2024; Wu et al., 2025; J. Zhang et al., 2025).

While metadata has been used successfully as a RAG external knowledge source in past work, there are two unknowns with this approach. One concern is abstract and title content since both can be used together for their semantic content. There is a lack of characterization of the text content within the title and abstract elements from the perspective of what may be a challenge for an NLP task (gap 1). Prior research has found that typos (Cho et al., 2024), noisiness due to irrelevant information (Chen et al., 2024; F. Shi et al., 2023), formatting from scanned PDFs (J. Zhang et al., 2025), or invisible formatting characters (Stambolic et al., 2025) negatively impact language models whether they are used for embedding or generation. Understanding the breadth of characteristics, (whether they are errors, irrelevant, or noisy), and

[1] https://consensus.app/

[2] https://support.proquest.com/s/article/ProQuest-Research-Assistant-FAQs?language=en_US

their occurence has implications for text cleaning and preparation which can be important for providing the appropriate data or implementing the right NLP process.

While abstract and title elements have been investigated for accuracy, coverage, and availability, a detailed analysis to characterize their content from the perspective of an NLP task has not been performed. There may be characteristics that are due to local practices, regional or cultural publishing norms, artifacts from publishing production systems, or content introduced by inexperienced metadata creators. Prior research has investigated Crossref, OpenAlex and other databases for metadata coverage (Alperin et al., 2024; Eck & Waltman, 2022) or completeness (Delgado-Quirós & Ortega, 2024), of funder data (Kramer & de Jonge, 2022; Mugabushaka et al., 2022), license types (Schlosser, 2016), references (Culbert et al., 2024), DOI errors (Cioffi et al., 2022), changes to document types (Haupka et al., 2024; Mongeon, Hare, Krause, et al., 2025), language attributes (Céspedes et al., 2024; Mongeon, Hare, Riddle, et al., 2025; J. Shi et al., 2025), journals coverage (Mongeon & Paul-Hus, 2016), institutions (L. Zhang et al., 2024), abstracts (Delgado-Quirós & Ortega, 2024; Färber et al., 2022; Kramer & de Jonge, 2022) and varying combinations. The Eck & Waltman, (2022) study provided evidence to support selecting Crossref or OpenAlex as a source for analysis based on availability of abstracts, in addition to OpenAlex's code base being open, unlike other databases. Similar to the Cioffi et al., study (2022) which identified characters and patterns that caused DOIs to fail during their ingest process, an investigation of characters, encodings, irrelevant text, and patterns may be helpful to anticipate causes of problems when using titles and abstracts in NLP.

The second concern relates to the source of metadata as abstracts are optional and not required content deposited as part of the metadata record assigned to a DOI. But they may be added as part of an aggregation process in other databases thus introducing unintended content containing problematic characteristics or errors. Past studies have compared sources such as Crossref and OpenAlex for their coverage (Culbert et al., 2024; Delgado-Quirós & Ortega, 2024; Schares, 2024; Scheidsteger & Haunschild, 2023; L. Zhang et al., 2024) and change of element values during ingest from one schema to another (Haupka et al., 2024). Some studies have investigated the translation of journal types or topic areas (Santos et al., 2023), have identified how transformations can introduce information loss (Yasser, 2011), or introduce problems that did not exist in the original metadata deposit (Delgado-Quirós & Ortega, 2024). Despite this, Eck and Waltman showed that certain elements in Crossref metadata have improved over time, especially for journal articles (Eck and Waltman, 2022). Aggregators, such as OpenAlex, obtain data from multiple sources to complement data from the registration agency, (Crossref or DataCite) by adding data with web scraping or parsing the full text. As a result of this ingest process, more information may be introduced than from the original source (from the RA), the text may be altered, or information may be lost. At this time, selecting a source for metadata can be based on past studies for coverage or availability, but there is a lack of supporting evidence documenting any differences between the title and abstract content between metadata sources (gap 2). Knowing these differences may affect RAG configuration decisions, (such as text cleaning steps or selection of appropriate embedding models) or provide evidence of which database may be better for use in RAG.

Metadata and RAG

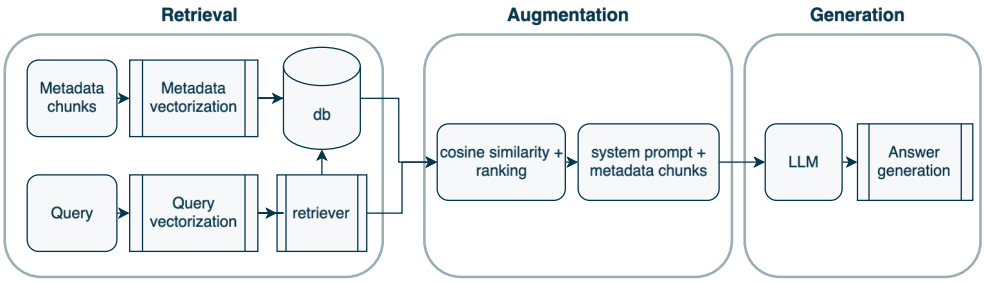

Fig 1: Diagram of a basic RAG architecture.

RAG systems leverage large language models (LLM) for embedding and response generation but augment the internal knowledge of the LLM with external knowledge addressing issues of discipline specific, proprietary, more recent, or other sources of knowledge that were out of scope of the training data for the LLM (Mazumder & Mukhopadhyay, 2024). In the context of question-and-answer or chat applications, RAG architectures have several advantages over just using LLMs in that their grounding data can be dynamically updated, be private or confidential, or be more up to date than the training data used for the LLM (Lewis et al., 2020). Additionally, RAG applications can be quickly and easily adapted to provide answers for different users by changing the grounding documents (Fan et al., 2024). In the figure above, documents that are semantically like the query are selected and combined with the user query to form the context. This augmented context is then sent to the generating LLM which creates a response based on the included documents in the context. By not relying purely on the knowledge within the generating LLM, responses should address problems of falsely constructed, out dated, or irrelevant answers to queries (Lewis et al., 2020).

The noisiness in external knowledge provided to RAG architectures has an impact on performance. Typos, truncations, or swapped letters significantly affect retrieval performance (Cho et al., 2024). Other perturbations such as punctuation insertion and phonetic and visual similarity also negatively affect RAG performance (Cho et al., 2024). Irrelevant text can negatively affect an LLM's ability to correctly answer questions (F. Shi et al., 2023). Counterfactual information from external knowledge sources also has negative effects on LLMs (Liu et al., 2023) resulting in inaccurate responses. J. Zhang et al., (2025) identify two types of noise from optical character recognition (OCR) produced texts, semantic and formatting noise, and found that semantic noise consistently affected LLMS while formatting noise affected 'specific retrievers and LLMs differently' (J. Zhang et al., 2025, p. 17449). While their investigation examined the effects of malicious intent, Stambolic et al., (2025) found that invisible characters can affect retrieval. While this research is not focused on adversarial, safety, or security risks, invisible characters can exist as formatting noise, such as from PDFs. However, noise does not always have negative effects. Wu et al., (2025) described two types, beneficial and harmful noise, and investigated ways that noise can both enhance retrieval or have negative effects on retrieval.

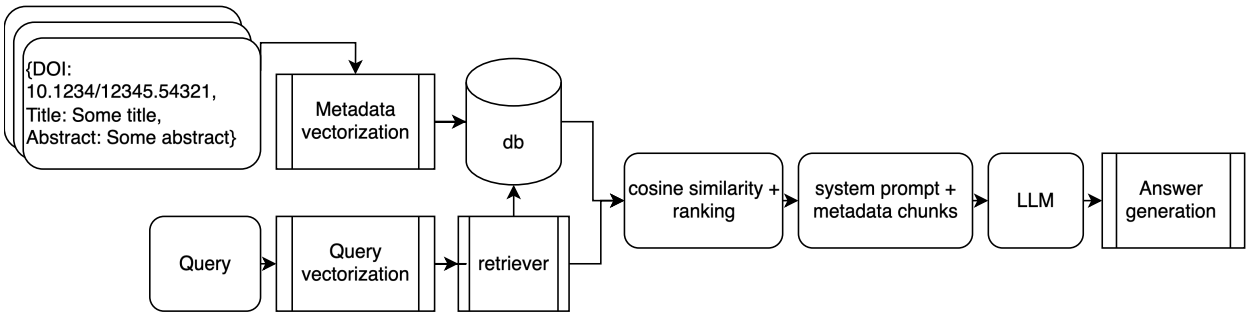

Fig 2: Where metadata elements of title, abstract, and DOI fit in a RAG pipeline.

This research is different from past work where metadata was used as a query filter (Bruni et al., 2025; Poliakov & Shvai, 2024), metadata was used as a keyword source to expand queries (Hayashi et al., 2024), metadata was used to understand outdated software in repositories (Shaik et al., 2024), or using metadata abstracts to construct expanded search queries in a RAG system developed for systematic reviews (Li et al., 2024). Past work has used bibliometric values for ranking (Li et al., 2024) though the researchers were not aware of limitations with citation metrics. Metadata has been proven as a valid external knowledge source, but in the context of proprietary metadata from corporate documents (Kang & Kim, 2023). While there are multiple RAG architectures to address various query types (Braun et al., 2024; Teixeira de Lima et al., 2025), there is a lack of case studies for the IS community that explicitly show the connection between metadata content characteristics, errors, and noise when the metadata is used as the external knowledge source.

Theoretical position

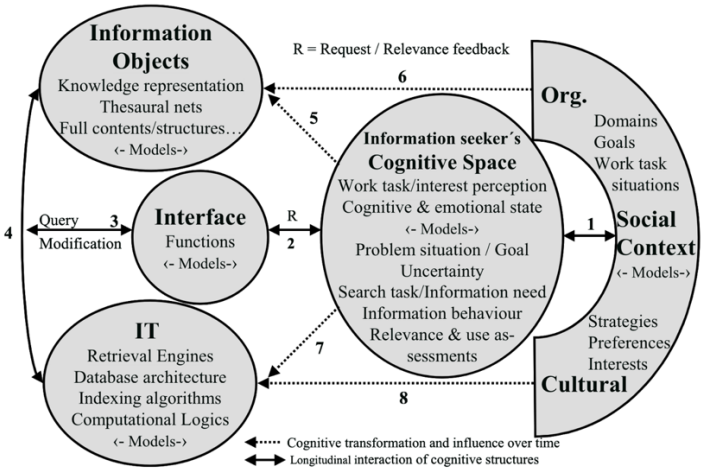

Figure 1: From Ingwersen & Järvelin (2005, p. 271), the interactive information seeking, retrieval and behavioural processes which they describe as "a generalized model of any participating cognitive actor in context".

To frame and limit this research, I use Ingwersen & Järvelin's cognitive information search and retrieval, (IS&R) model (Ingwersen, 1996; Ingwersen & Järvelin, 2005) to situate a research area within a system of components and their influences. Their IS&R model extended what was

the traditional laboratory model of information retrieval (IR) research to include the cognitive world of the user/information seeker while simultaneously acknowledging the impact that social, cultural, organization, and technological influences upon their cognitive state. "...[B]oth information seeking and information retrieval fall short regarding goals of a) theoretically understanding the phenomena of information access, b) empirically describing (predicting) these phenomena, and c) supporting the development of technology covering ...tools, systems, and social practices" (Ingwersen & Järvelin, 2005, p. 377). The IS&R model (sometimes called the integrative model of IS&R (Savolainen, 2018)) is being used for its practical usefulness in identifying and acknowledging influences, assumptions, and variables within a scenario.

The IS&R model has five main components which offer a way of illustrating the perceptions and context of the actor in their world and identifying limits on influencing links. The IS&R model's components can be used to explore detailed elements within each to "support a more structured and detailed way of investigating central issues in IS&R" (Ingwersen & Järvelin, 2005, p. 307).

There are five main components of the cognitive model of IS&R. All of these are involved in information processes at any given time and over time, but all components should not be investigated simultaneously. The arrows denote the direction of mutual interaction involving and affecting influences. Likewise, there are arrows where influence only goes in one direction, such as in the one labelled 6 above, where social, cultural, and organizational influence affects information objects. This is not a process model but can be used to understand processes that exist because of the interactions between components of the model.

Each component of the model expands into a nine-dimensional design cube, (represented as a table below). As the authors state, "One may use the 9 dimensions as a checklist for what should be taken into account when designing an investigation" (Ingwersen & Järvelin, 2005, p. 360). Each study may focus completely on one component and one dimension for a descriptive or experimental study, but it is possible to use multiple components and their dimensions to account for controlled variables or assumptions. In Table 1 below, the top row indicates the five components with some components containing more than 1 dimension. Below each dimensional heading are the individual dimensions which can be assigned as independent or dependent in the case of experimental studies, or observed variables in the case of descriptive studies, along with controlled variables.

*Table 1: Design cube of nine dimensions with main components at the top. The top row contains the component names followed by the second row where some components have more than one dimension. Type in red and marked with * indicates changes I have made to adapt the model to working with metadata and RAG applications.*

Organizational Task Component		Actor Component			Document Component	Algorithmic Component		Access and Interaction Component
Natural work tasks and organizational	**Natural search tasks (ST)**	**Actor**	**Perceived work tasks**	**Perceived search tasks**	**Document and source**	**IR methods and NLP models***	**IR interfaces**	**Access and Interaction**
WT structure	ST structure	Domain knowledge	Perceived WT structure	Perceived information need content	Document structure	Exact match models	Domain mode attributes	Interaction duration

WT strategies and practices	ST strategies and practices	IS&R knowledge	Perceived WT strategies and practices	Perceived ST structure and type	Document types	Best match models	System model features	Actors or components
WT granularity, size, and complexity	ST granularity, size, and complexity	Experience on work task	Perceived WT granularity, size, complexity	Perceived ST strategies and practices	Information type in document	Degree of document structure and context used (chunking)*	User model features	Kind of interaction and access
WT dependencies	ST dependencies	Experience on search task	Perceived WT dependencies	Perceived ST specificity and complexity	Communication function	Use of NLP for document vectorization*	System model adaptation	Strategies and tactics
WT requirements	ST requirements	Stage in WT execution	Perceived WT requirements	Perceived ST dependencies	Temporal aspects	Document metadata representation	User model building	Purpose of human communication
WT domain and context	ST domain and context	Perception of socio-organizational context	Perceived WT domain and context	Perceived ST stability	Document sign language	Use of weights in document vectorization*	Request model builder	Purpose of system communication
		Sources of difficulty		Perceived ST domain and context	Layout and style	Degree of required structure and context used	User retrieval strategy	Interaction mode
		Motivation and emotional state			Document metadata*	Use of NLP for request vectorization*	Response representation*	Least effort factors
					Document content	Request metadata representation*	Feedback generation	
					Contextual hyperlink structure	Use of weights in query vectorization*	Mapping ST history	
					Data source*	Response generation*	Explanation features	
							Transmission of messages	
							Scheduler	

From the perspective of this proposal, the Algorithmic component's dimension has been renamed to 'IR methods and NLP models' and dimensions have been indicated in red for those that have been changed to update the design cube to the needs of a study on metadata and RAG. This includes aspects of LLMs for embedding and generation and moving 'Response generation' from the 'IR interfaces' dimension to that of 'IR methods and NLP models'. These

changes are not exhaustive, but I only include changes in the Document and Algorithmic components that are relevant to this research. Similar adaptation of the IS&R model can be seen in Pawlick-Potts (2022) who made modifications to the actor, IT, and information objects components.

Purpose

As LLM-powered applications proliferate in the academic environment and become easier to deploy, an understanding of how the title and abstract may serve as an external knowledge source and how its characteristics (including errors and noise) may affect RAG performance should provide three benefits for the IS community. One, it characterizes the current state of the title and abstract element and expands the concept of metadata quality to include the concept of noisiness from the perspective of natural language processing. Two, it assesses how these elements are transformed (if at all) when moving from RA to aggregator which helps the community understand limitations in their sources of data. Three, it may provide insights into how RAG components work, their limitations, and may provide critical awareness of how data characteristics impact RAG systems which is important as the academic infrastructure is rapidly deploying such systems.

Assuming metadata elements of the DOI, title, and abstract can be used as grounding for a RAG Q&A application, the purpose of this research is to identify the characteristics in metadata content that may affect RAG configuration decisions, how metadata sources compare for these elements, and explore what this looks like in action with a case study. Three studies will be used to investigate the following using the modified IS&R dimensions for assigning independent, dependent and control variables:

1. investigate works from Crossref, characterizing metadata elements (DOI, title, abstract, language) and identify text characteristics,
2. compare the same metadata elements in shared works between Crossref and OpenAlex, to understand what characteristics may be introduced with transformations from their original source, and
3. explore the effects of metadata characteristics when using a discipline specific corpora (consisting of titles and abstracts) as external knowledge sources in a RAG Q&A application as an exploratory case study.

Research Questions

1. What is the characterization of the metadata elements from a random sample of Crossref metadata?
2. What is the type and quantity of characteristics, enhancements, or transformations when a shared corpus in Crossref and OpenAlex are compared?
3. How do metadata characteristics affect retriever performance and generated responses?

Study design

Three parts will be used in this research as shown in Figure 3. Results from Part 1 will inform Part 2, and both Part 1 and 2 will inform Part 3.

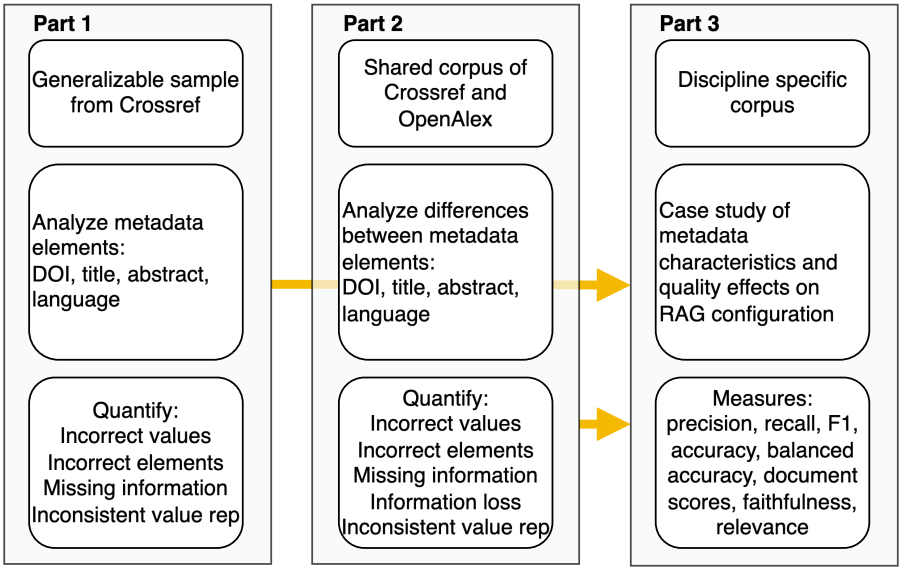

Fig 3: research framework for each part.

Part 1:

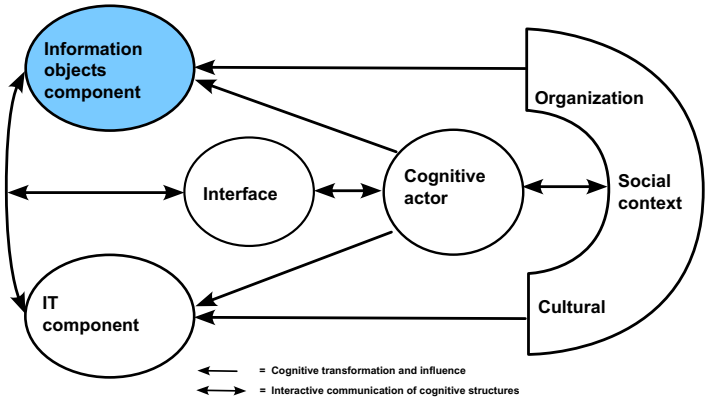

Figure 2: Adapted IS&R model for Part 1 showing the focal area for descriptive study.

Part 1 will be a descriptive study on the dimensions of the Information objects component examining the metadata as a document. A generalizable sampling of works (journal articles, book-chapters, and conference proceedings) from Crossref will be analyzed for quality by identifying incorrect values, incorrect elements, missing information, and inconsistent value representation (Yasser, 2011, p. 51) and characterize content by identifying patterns in text content. Elements to be examined will include DOI, title, abstract, and language. Their quality will be assessed by incorrect values, incorrect elements (i.e., “Title” in the article title metadata), missing information, and inconsistent value representation (i.e., using cc by, instead of CC-BY or titles in ALL CAPS). Characterization of the title and abstract will include counts of tokens, special characters, numerals, non-text elements, and non-relevant content or characters. Metadata contents will be examined with respect to the Crossref 5.4.0 metadata schema (Feeney, 2025).

Following the recommendations for study design in Ingwersen & Järvelin (2005), controlled variables will be established through data collection from the REST API and observed variables of the document sign language and content will be documented and quantified from the metadata content.

Table 2.: Design cube dimensions of the Document and source component for Part 1

Document and source

Controlled variables	Observed variables
Document structure	Document sign language
Document types	Document content
Information type in document	
Communication function	
Temporal aspects	
Layout and style	

Figure 3 shows an overview of the process for Part 1 with analysis of the full sample set and the subset. The subset will be analyzed manually for language attributes and characteristics. Patterns found from this process will be coded as regex or string patterns and applied to the full sample to measure occurrence across the whole set.

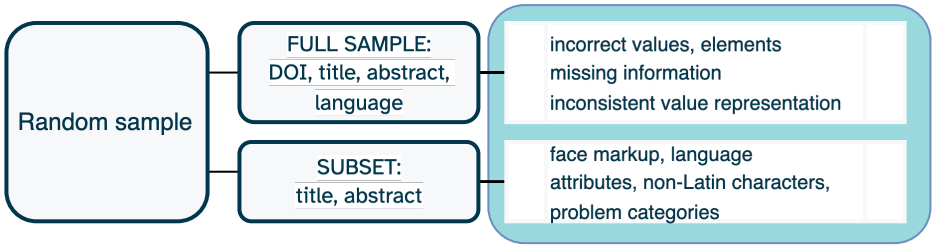

Figure 3: Part 1 process diagram for full sample (top) and subset sample (bottom).

Part 2:

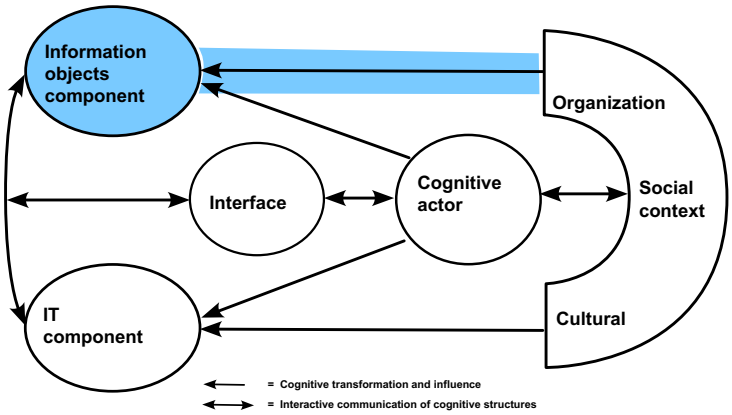

Figure 4: Adapted IS&R model for Part 2 showing focal areas of the Information object component and organizational/social/cultural influence link.

Part 2 will examine the influence of the metadata source on the content of the title and abstract. Using a shared corpus (Culbert et al., 2024) that is co-occurring in Crossref and

OpenAlex, I will identify how metadata contents compare to understand what quality problems exist with transformations from their original Crossref source. The shared corpus will be matched on their DOI, acknowledging the limitations of this method (Culbert et al., 2024). A map of the Crossref schema definitions and the aggregator's schema will be created using open-source code (*Ourresearch/OpenAlex*, 2023/2024) similar to past work on document types by (Haupka et al., 2024). The same metadata elements from Part 1 will be used to identify transformations of the publisher-deposited data (from the RA) and from the aggregator. Differences will be quantified and coded into error types (Shi et al., 2025; Yasser, 2011). Patterns identified in Part 1 will also be used on the full dataset to determine differences between the two sources.

Using the design cube to identify variables, the study focuses on the dependent variables of the content and language of the title and abstract which will be measured by changes introduced by the independent variable of the metadata source. Controlled variables extend to include the organizational component to account for the influence link of the metadata source, specifically the dependencies created by schema restrictions and ingest processes.

Table 3: Design cube variables (from Ingwersen & Järvelin) for Part 2, arranged by component and dimensions.

Organizational Task Component	**Document and source**		
Controlled variables	**Controlled variables**	**Dependent variables**	**Independent variable**
Task dependencies	Document structure	Document sign language	Data source
	Document types	Document content	
	Information type in document		
	Communication function		
	Temporal aspects		
	Layout and style		
	Document metadata		

Figure 5 below shows the process for Part 2, which is split into two sets of analysis once DOIs have been matched between the two datasets. The entire shared corpus is analysed for differences with the same quantification of the OpenAlex data as in Part 1. The subset of the shared corpus will also compare titles and abstracts that have been flagged as not exact to document differences.

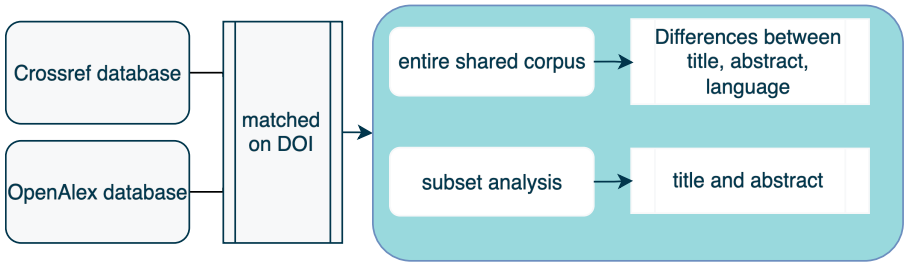

Fig 5: Part 2 process to compare metadata content from two sources.

Part 3:

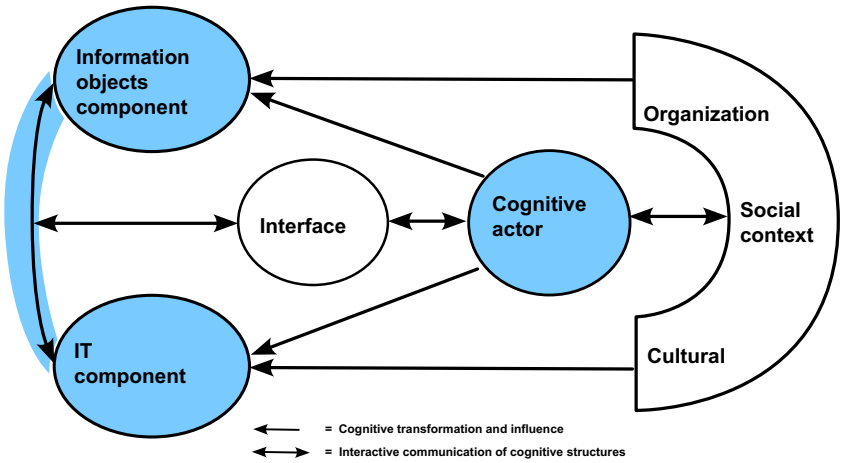

Figure 5: Adapted IS&R model for Part 3 showing the information object, IT, and actor components selected as sites of controlled, independent, or observed variables.

A case study using a constructed corpus of metadata will be used as the external knowledge source in a basic RAG application. Characteristics and errors identified in Part 1 will be used to modify a control corpus to create additional conditions, such as encodings, or multilingual text. A golden set of queries with identified true positive documents will be used on the RAG application. Analysis will examine retriever performance and generated outcomes.

Typically, RAG studies qualify outputs using a benchmark dataset, such as quac[3], SciFact[4] or SciDocs[5], which may include queries, contexts, and ground truth answers. These models were built with different purposes and do not necessarily have the full abstracts or queries as part of the data. There have been other studies that have created their own dataset and made it available as public, such as Antal & Buza's dataset of thesis abstracts (Antal & Buza, 2025), Feb4RAG which was developed based on existing datasets (Wang et al., 2024), or AMAQA (Bruni et al., 2025). PubMedQA (PQA-L) contains questions and multiple contexts extracted from scientific papers along with long and short answers (Jin et al., 2019). The problem with pre-existing datasets is that they were developed for very specific research questions or to evaluate specific RAG architectures. SciFact contains claims and queries, but not whole abstracts and each question only return one text. SciDocs only includes the title and was designed to test a specific embedding model, SPECTER, not test retrieval. Antal & Buza's dataset contains thesis abstracts but only has one query for one document and introduces the confounding variable of English syntax errors. Feb4RAG integrates subsets of many BEIR datasets, including SciFact and SciDocs, but once again, only provide one query for one document making retrieval scoring impossible. PubMedQA, specifically the PQA-L expert labelled dataset of 1000 questions, comes close as the dataset could be filtered for those questions with multiple contexts, but as it was developed for evaluating the reasoning capabilities of models, the extracted texts are short,

[3] https://huggingface.co/datasets/allenai/quac
[4] https://huggingface.co/datasets/BeIR/scifact
[5] https://github.com/allenai/scidocs

include irrelevant text, and was intended for yes/no answers to questions. This could be useful for response evaluation but not retriever evaluation. However, these previous studies provided processes for developing their own datasets including using LLM-assist for question-answer pair creation along with human curating and annotating for final evaluation. Following their processes in addition to the guidance from Teixeira de Lima et al. (2025) for dataset creation will provide the rigor necessary for creating my own dataset. They reinforce that knowing your data 'is an important step…to properly evaluate and optimize their own systems' (Teixeira de Lima et al., 2025, p. 45).

In table 3 below, the components of the IR engines/IT, Document and source, and Actor are shown with dimensions used in Part 3. Controlled variables are included for the actor due to the use of queries which assumes domain and IS&R knowledge and assumes a stage in a simulated work task. Controlled variables also are accounted for in the Document and source dimension and in the IR/IT dimension. A single independent variable, the document sets that serve as the external knowledge for the RAG, will be manipulated to observe changes in the observed variables affecting document vectorization and response generation.

Table 4: Components and Dimensions for Part 3 as controlled, independent, and observed variables.

Actor	**Document and source**		**IR engines and IT components**	
Controlled variable	**Controlled variable**	**Independent variable**	**Controlled variable**	**Observed variable**
Domain knowledge	Document structure	Document content	Best match models	Use of NLP for document vectorization
IS&R knowledge	Document types		Degree of document structure and context used (chunking)	Response generation
Stage in WT execution	Information type in document			
	Communication function		Use of weights in document vectorization	
	Temporal aspects		Degree of required structure and context used	
	Document sign language		Use of NLP for request vectorization	
			Use of weights in query vectorization	

Figure 7 below shows how the three datasets, (as the independent variable) will be sent through the RAG pipeline. Evaluation metrics precision, recall, accuracy, balanced accuracy, and document scores will measure the effect on the retriever which uses the vectorization of the documents and the query to determine a best match for similarity. The generated response will be measured for faithfulness and answer relevance.

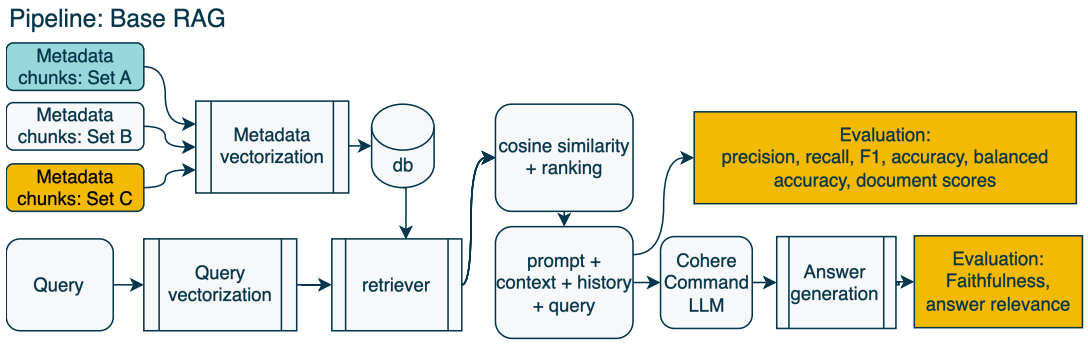

Fig 7: RAG pipeline for Part 3 showing evaluation metrics with respect to the retriever and the generation steps.

In keeping with the actor-centred intention of Ingwersen & Järvelin's IS&R model, particularly with respect to multiple influences on relevance judgements and in recognizing the limitations of existing datasets, I chose to create my own benchmark following the question taxonomy of Teixera de Lima et al., (2025) using single fact and summary question types with a simple syntax. Questions were created based on the methods by Bruni et al., (Bruni et al., 2025) with LLM-assist followed by human validation of question/answer pairs. Human annotator pairs pairs will be validated using Cohen's kappa for agreement. For LLM-assisted work in question generation, prompts from Es et al., (2024) will guide prompt development on Cohere models.

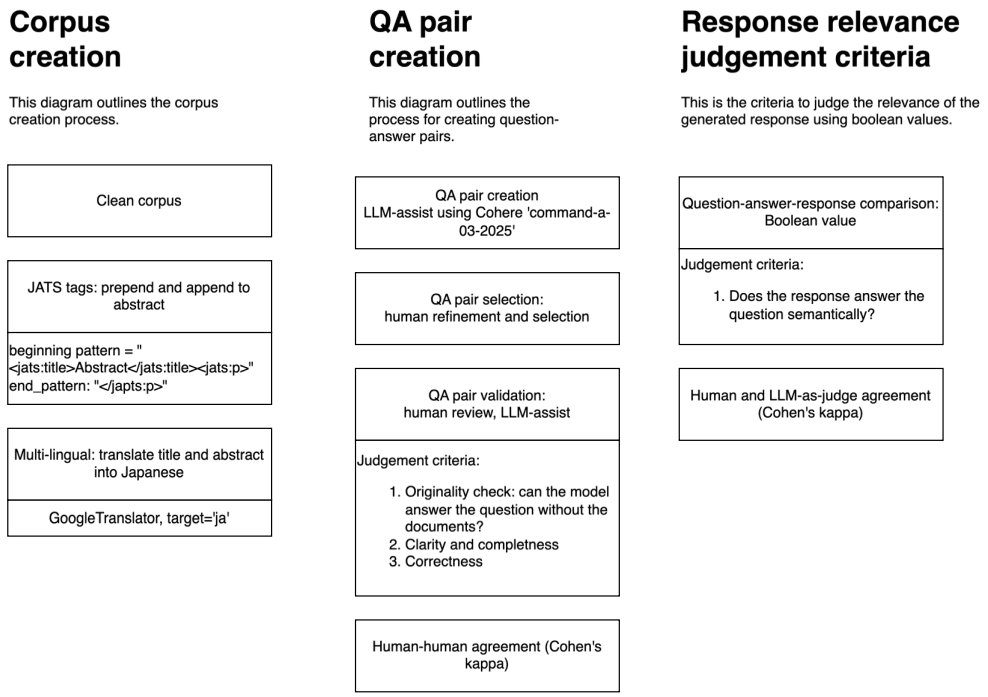

Figure 6: Processes for corpus creation, QA pair creation, and response relevance judging criteria. Where agreement will be calculated, Cohen's kappa will be used as performed in prior research (Wang et al., 2024).

Retrieval will be measured by precision, recall, F1, accuracy, and balanced accuracy scores will measure the effects of metadata characteristics or errors introduced to the dataset. Responses will be measured for faithfulness (inclusion of retrieved results in the response) and answer relevance (did the response answer the query) using a human and LLM-as-judge approach as in prior work (Antal & Buza, 2025; Wang et al., 2024).

Potential impacts of the research

In the last few years, artificial intelligence (AI) has been rapidly deployed in academic libraries (Taylor et al., 2025) as an aid for discovery (Concensus), tool for systematic review (Han et al., 2024), identifying citation contexts (Scite.ai), or to promote publisher-owned works (Scopus AI, Web of Science Research Assistant, ProQuest One, and PrimoVE Research Assistant). Large language models (LLMs) excel at generating summaries or answering questions and within academic environments, there is a need for verifiable sources. RAG architectures solve this problem by using external knowledge sources. As an open source of data, bibliographic metadata, as an open source of information, has potential to serve as a source of knowledge for these systems.

Concurrent to this research, discussions and task groups are working on what community enrichment of metadata looks like and how it might scale to be introduced in large bibliographic databases. COMET, a task group assembled by the California Digital Library[6], is currently working on enrichment projects to improve funding metadata, classification, and affiliation

[6] https://www.cometadata.org/about

parsing using community members beyond those at bibliographic databases or publishers. OpenAlex is currently having discussions about metadata enrichment, but they are interested in how they may improve metadata by aggregating it from libraries where considerable work is done to improve discoverability in local discovery systems (P. Riddle, personal communication, August 2025). Registration agencies such as Crossref and DataCite are already working towards integrating such data, with Crossref's development roadmap anticipating the need for this (Hendricks, 2025), and DataCite posting a request for comment from the community on their proposed schema (datacite, 2025). Given there are efforts to enhance metadata utilizing the public and recognizing the advantages metadata has over paywalled texts, there seems to be a timely opportunity to contribute evidence to extend metadata beyond the discover and analysis paradigm.

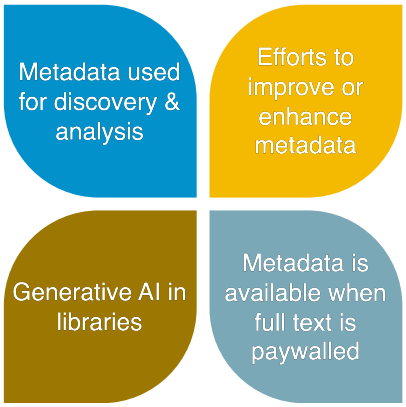

Figure 7: Four directions shaping this research proposal.

This study seeks to contribute, as novel methodological contributions, to the information science literature in the following areas. In Part 1, I identify characteristics of metadata, within the title and abstract from a registration agency source, analysing the content of the text to identify characteristics that may impact NLP processes. While analysis of the text content normally is outside the scope of scientometrics, it does pertain to local and regional publisher practices and may be further affected by proposed enrichment processes. In Part 2, I characterize the types and frequency of characteristics that may arise from transformations from source to aggregators and measure how these characteristics are different between two databases. Comparison of databases is normal within scientometrics and information science, yet the methods in this study yield empirical results that extend beyond coverage and accuracy measuring characteristics and patterns not previously studied. In Part 3, I use existing methods to create a novel dataset for the purpose of analyzing metadata content characteristics on retrieval and generation.

Empirical contributions include the quantitative results from Part 1 and 2, as well as classification of characteristics into patterns that were applied to the full dataset. These may be easily used by the community as a further practical contribution, but also as evidence of a current state of abstract and title content prior to the advent of enrichment processes. Findings from Part 3 may be of benefit to those in the RAG/IR community as empirical contributions, particularly for identification or confirmation of noise threats to embedding and generator model robustness.

As a theoretical contribution, I have refined the dimensions of the IS&R model to account for understanding the influences of RAG technology within the IT component. This research does not refine all dimensions of the IS&R components, yet I recognize that future work should investigate tasks within the organizational component and access and interaction components to adapt to RAG. While the IS&R model is intended to be media independent, the IT component has not aged as well and has been refined to work within the context of RAG applications.

Summary

In the context of how metadata may be used as an external knowledge source for RAG, the purpose of this study is to investigate characteristics of metadata elements in a generalizable sample, how sources of metadata compare for such characteristics/errors, and explore how these characteristics may impact RAG outcomes by measuring retriever performance and generated responses. Recent research showed that typos, irrelevant information, and other types of noise in the text can affect RAG outcomes. Given current conversations around metadata enrichment and bibliographic databases beginning to consider public enrichment a possibility, it is unknown what enrichment may mean for content changes within the title and abstract particularly for a new paradigm of using metadata as an external knowledge source. Knowing how characteristics or noise affect this potential new use of metadata may affect RAG developers for decisions on cleaning or source or may help database management consider improvements on metadata ingest, particularly from enrichment processes.

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