An Ontological Characterization for SBSI Research Topics

Saulo Bruno Calixto Santos
Victor Ströele
Regina Braga
Universidade Federal de Juiz de Fora (UFJF)
Juiz de Fora, MG, Brasil
saulo.calixto@estudante.ufjf.br
victor.stroele@ufjf.br
regina.braga@ufjf.br

Célia Ghedini Ralha
Universidade de Brasília (UnB)
Brasília, DF, Brasil
ghedini@unb.br
Universidade Federal da Bahia (UFBA)
Salvador, BA, Brasil
celiaralha@ufba.br

Abstract

Context: The Brazilian Information Systems (IS) community has grown in complexity involving different research topics. Characterizing the IS community research topics is vital to bringing knowledge to advance IS research maturity.
Problem: The complexity, diversity, and plurality of research topics in IS present a challenging task involving collecting adequate data, analyzing, and exploring different techniques to understand the evolution in the area.
Solution: Using research data published by the Brazilian Symposium on Information Systems (Simpósio Brasileiro de Sistemas de Informação - SBSI), we provide the NetO+ ontology to enable automated reasoning about SBSI research topics characterization.
IS Theory: This study uses the language action perspective, highlighting what people do while communicating and how they create scientific reality using language. We focus on the SBSI research topics with automatic characterization using the Large Language Model (LLM) and ontology techniques.
Method: We analyzed the technological research topics employing semantic analysis using an LLM to identify research topics with keywords related to articles' titles. Also, the ACM taxonomy CCS Concepts in the IS branch were allied to ontological inferences.
Summarization of Results: The findings with LLM to extract keywords from articles, and the ontology inference allows us to find research topics. This approach provides an overview of SBSI research, highlighting the topics' evolution and their interconnections with ACM taxonomy.
Contributions and Impacts on the IS area: This work provides IS research topics to bring knowledge enabling decision-making for sustainable community growth based on the socio-technical approach concerning excellence in IS conception, development, and maintainability.

CCS Concepts

• **Information systems → Information System Application**.

Keywords

Ontology, LLM, SBSI Research Topics

1 Introduction

The Brazilian Information Systems (IS) community completed 20 years of publication at the 2024 Brazilian Symposium on Information Systems (*Simpósio Brasileiro de Sistemas de Informação* - SBSI). Since 2004, the community has matured research, covering many different IS topics established through extensive authorship collaborations allied to national and international institutions.

There are a few studies covering collaborations and quantitative analyses of the IS community using distinct dimensions. Focusing on the SBSI ten-year history (2005-2014) of authors' publication frequency using chart bars and coauthors network graphs, the work of Araujo et al. [1] points out the need to characterize the IS community research area. Employing vertex cut measures of social network concepts, de Oliveira and Dias [7] work evaluates author collaborations of SBSI 2006 to 2011, concluding that author's collaboration from different institutions is low. A two-database approach comparative analysis of Rodrigues and Ralha [20] using SBSI ten-year editions showed that Neo4j outperforms MySQL with deep author relationship queries. Using argumentative theory shedding light on gender disparities and geographic article concentration in some federative units, the work of [16] offered an overview of 18 SBSI editions research. The work of [13] developed a two-decade temporal network visualization analysis of SBSI using structural, temporal, and evolution taxonomies to analyze communities, showing that only 12 communities publish frequently with 104 births, 20 grows, 31 contractions, and 331 deaths. A descriptive-analytical study of Carvalho et al. [2] used argumentative and critical social theories to present a multidimensional IS community panorama.

Research in IS has grown in complexity, diversity, and plurality as the SBSI evolved during the last two decades. The presented IS community works did not include characterization of research topics, offering a challenge to gain knowledge for decision-making and community growth. Thus, the central investigation of this article is to find out the main IS topics of the recent SBSI articles (last six years). This period allows us to understand the recent technological research focus of the SBSI community and whether there has been any impact on research topics due to the pandemic. In addition, the results of this investigation can bring knowledge to the IS community to advance research in the complex area of IS development in global organizations.

Ontologies with IS concepts have essential relationships enabling automated reasoning about SBSI research. Ontological studies allow implementation in semantic graph databases schemata of the plurality and complexity of research topics characterization to help understand the IS community evolution through different years.

To achieve the goal of research topic characterization, we used the ACM taxonomy, specifically the IS branch. The areas and areas path of the taxonomy were used to build the NetO+. The keywords were extracted from the articles' titles published from 2018 to 2023 in SBSI using an LLM model and prompt engineering [11]. The results were stored in the NetO+, making it possible to identify the main research interest in the IS community. Once the data was in the ontology, inference rules were implemented to analyze the evolution of the topics. In this direction, we have analyzed the NetO+ contents and identified the last 6 years as most relevant, considering the intersection of Artificial Intelligence (AI) and IS applications to present our results.

The main contribution of this work is the use of LLM enhanced with prompt engineering to populate the NetO+ ontology to analyze SBSI research topics automatically. The rest of the manuscript includes in Section 2 the related work with the proposed ontology in Section 3 used with the SBSI information on the experiments of Section 4, and conclusions on Section 6.

2 Related Work

Topic-based ontology integrated into IS significantly enhances the effectiveness of retrieval processes by providing a structured and semantically rich framework for data representation and retrieval. Ontologies facilitate the standardization and disambiguation of terms and improve search results precision, enabling personalized and context-aware information retrieval.

Ontologies provide a structured knowledge representation linking entities to concepts, improving the semantic understanding of IS. Table 1 presents ontology-based works. For instance, using ontologies to enhance information retrieval models in the biomedical domain allows for the normalization of named entities, improving information retrieval precision by linking text to standardized concepts [12].

Ontology-based models address the limitations of traditional keyword-based retrieval systems by incorporating semantic information to improve the accuracy and relevance of retrieved documents in various domains [22], including recommendation of articles to reviewers by aligning topics with user profiles [5]. Ontologies are instrumental in conversational recommender systems to guide the process by ensuring semantic coherence and relevance in user interactions, incorporating topic threads that facilitate natural conversations, leading to more effective recommendations [23].

Using semantic topic modeling frameworks demonstrates the ability of ontologies to improve document representation and classification, supporting more effective information retrieval systems [21]. In word sense disambiguation, topic-based models integrated with ontologies can utilize the entire document as context, improving disambiguation accuracy and enhancing the retrieval of relevant information [3]. In expert retrieval systems, ontologies map topics to experts by capturing semantic representations, improving relevant expertise retrieval without labeled data [14].

Also, ontologies have been suggested to map relationships between tags, enabling the discovery of implicit knowledge and semantic classification of tags related to developers [10]. Consequently, ontologies play a crucial role in automating the mapping of unstructured data into structured formats. This automation enhances the efficiency of information retrieval and ensures the completeness and accuracy of the extracted data [17].

The use of ontology is present in various SBSI editions as Table 1 indicates [6, 9, 15, 18, 19]. Confort et al. [6] present a work to automatically specify ontology concepts based on people's tacit knowledge in a storytelling business processes group at the Universidade Federal do Estado do Rio de Janeiro (UNIRIO). Helfer et al. [9] present Tellus-Onto ontology to classify Brazilian soils according to organic and textural composition with axioms and rules to allow queries and inferences on the instantiated base with 98 soil samples with classifications inferred accurately and automatically.

Martins et al. [15] propose E-OntoUML, a UML profile for process modeling using activity diagrams to capture important distinctions and make the language more expressive based on the Unified Foundational Ontology (UFO) [8]. Oliveira et al. [18] present a domain and a task ontology in an integrative Outer-Tuning framework to support the (semi) automatic fine-tuning of database IS. Finally, Queiroz et al. [19] presents a domain ontology for semantic unification of anonymization terms and interoperability between tools allied to privacy preservation in the Brazilian government-published data to comply with the precepts of the Access to Information Law (Lei de Acesso à Informação - LAI). However, the presented ontology-based works at SBSI do not focus on the IS research topics characterization challenge, presenting a research gap filled with NetO+ ontology.

Table 1: Related work overview.

Reference	Ontology Use	Application Context
Martins et al., 2011 [15]	E-OntoUML	business process modeling
Confort et al., 2015 [6]	ontology specification	business process
Oliveira et al., 2015 [18]	Outer-Tuning framework	database fine-tunning for IS
Queiroz et al., 2016 [19]	semantic unification of anonymization terms	Lei Brasileira de Acesso à Informação (LAI)
Viegas et al.,2018 [21]	topic-based ontology	document representation and classification
Chaplot & Salakhutdinov, 2018 [3]	topic-based ontology	word sense disambiguation
Liang, 2019 [14]	topic-mapping ontology	expert retrieval systems
Karadeniz & Özgür, 2019 [12]	normalization of named entities	biomedical
Oliva et al.,2019 [17]	ontology-based computational system	medical reports automation
Chughtail et al., 2019 [5]	topic-based ontology	recommendation systems
Yu, 2019 [22]	ontology-based	information retrieval
Zhou et al., 2020 [23]	ontology topic-guided	conversational recommender systems
Helfer et al., 2021 [9]	Tellus-Onto	Brazilian soil classification
Horta et al., 2022 [10]	topic-based ontology	software development in social networks
This work	NetO+	IS research topics characterization

3 Proposal

Given the complexity and growth of the concepts discussed in the IS area, an ontology can help organize them. This makes exploring the area's evolution and understanding the relationships between these concepts possible. To fill the gaps highlighted in the Related Work section, we propose a topic-based ontology to organize these concepts and their relationships.

3.1 Method

This section presents the workflow adopted to identify the main research topics addressed in the articles published at SBSI as presented in Figure 1. The first step is to extract the articles published at the Brazilian Symposium on IS data and the Association for Computing Machinery (ACM) taxonomy. Extracting data from SBSI articles involves collecting relevant information such as titles, authors, and year of publication. These data were consolidated manually in spreadsheet format (CSV). The ACM taxonomy organizes knowledge into specific computing areas. We accessed the ACM website taxonomy to identify the terms and categories relevant to IS and extracted paths related only to the broad area of IS. We downloaded the XML file from the ACM website and developed a Python script to generate a new XML file with only the IS paths. The ACM taxonomy terms were associated with the articles' title keywords using LLM. Thus, the keywords were enriched by using an ontology-based approach.

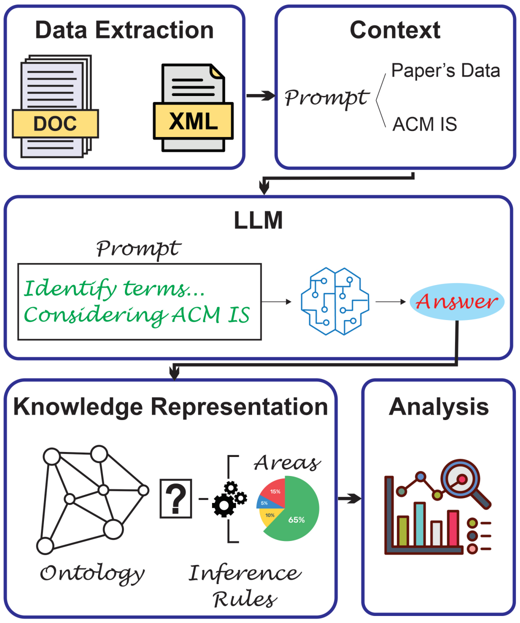

Figure 1: Workflow developed for extracting research topics from the SBSI.

Generative AI models are trained on vast amounts of data. In this sense, these models' answers can be broad and outside the context to which the question refers [4]. Integrating in-context examples and pre-answers into prompts has been shown to enhance model accuracy significantly [11].

To answer the questions and optimize the performance of LLM models, it is necessary to define the context in which the model must be based. In other words, it is mandatory to specify the scope of the application [4]. Prompt engineering consists of creating and optimizing specific instructions to guide LLM models in generating accurate and relevant answers [11]. This technique is necessary to maximize the effectiveness of interactions with AI models such as GPT-4.0. The quality of the prompt can significantly influence the quality of the response generated by the AI. Therefore, in the context phase, the prompt model is defined and used to ask questions of the LLM model. In the prompt, we limited the ACM taxonomy, defining only topics related to the IS area as the search context. Figure 2 presents the excerpt code.

With the context defined, the LLM is asked to identify the main terms of the article titles and relate them to the ACM taxonomy paths in the IS branch. This involves analyzing the titles semantically and matching them with the terms in the taxonomy. The use of prompts ensures that the LLM is based only on the information presented at the time of the question, preventing data relating to a broader scope from being used in the answer [11].

Based on the answers given by the LLM model, the terms identified for each article and their paths in the taxonomy are instantiated in the NetO+ ontology. Finally, inference rules are applied to the ontology to identify the main research topics of SBSI research over the years. The data returned by the queries in the ontology are analyzed to understand the state of the art of the SBSI.

3.2 NetO+ Ontology

The NetO ontology proposed by [10] was chosen as a starting point for this work. This ontology aims to detect semantic communities based on discussion topics, considering a topic partitioning strategy for analyzing data extracted from question-and-answer forums. Although NetO was proposed for another context, the ontology already has a structure that makes it possible to organize the concepts and the relationship between them, being publicly available on GitHub[1]. The NetO ontology was built using Protégé[2] and includes Classes, Data Properties, Object Properties, and ontological rules. In this work, we propose NetO+, an extension of this ontology to the problem of SBSI research topics characterization.

In the NetO ontology, the class hierarchy includes five categories: Tag, Node, Subject, Topic, and CombinedTopic. The Node class represents the posts automatically extracted and instantiated from the social objects, containing information about tags and people involved in the discussion. The Tag class represents the tags in raw format and is automatically extracted and instantiated from the social objects. The objects of the Tag class contain a Data Property, which can be extracted automatically from the objects. Although it is possible to detect many tags, not all are relevant to the addressed problem. For this purpose, NetO introduced the Subject class. While tags can contain spelling mistakes, unnecessary granularity, or irrelevant information, a subject acts as a filter for tags. It represents only the relevant subjects addressed by each individual. Subjects need to be predefined by the user, as they are part of the application's domain knowledge.

The Subject class in the NetO can have one or more Data Properties, predefined by the user to match the names of Tag objects, resolving spelling errors and synonyms. The Topic class refers to topics of interest predefined in the ontology as domain knowledge. The topics' definitions depend on the context in which the ontology is being applied. Once defined, the topic can be inferred using inference rules.

NetO also includes the CombinedTopic class that represents an issue simultaneously associated with several related topics. For example, articles' titles with the keywords *education* and *information system* can be related to different topics of interest, such as education in IS, challenges of IS applied to the educational domain, or perspectives and trends of IS in the educational domain. Given the predefined CombinedTopics, such as *education-in-is*, *information-systems-and-ai*, *information-systems-challenges-domains*, and *perspectives-trends-is*, the ontology can automatically infer the issue context with different research topics. Thus, a broader semantic understanding of published works is possible.

However, some components had to be added to the NetO ontology to enable a broader analysis of the SBSI data. Thus, based

[1]https://github.com/authoranonimized-ontology
[2]https://protege.stanford.edu/

```python
question = 'What are the subjects of the ID=' + str(i) + ' and title: "' + row['title']
question = question + '" and how are they related to the given hierarchy of terms? ' \
    'Give me the title, the ID, the subject identified, the term to which it relates, ' \
    'and the hierarchical path with the terms name. Answer in s cvs format. ' \
    'I DO NOT WANTO YOU TO ANALYSE ACM TAXONOMY, USE ONLY THE HIERARCHICAL TERMS GIVEN PREVIOUSLY.'

client = OpenAI()
messages = [
        {"role": "system", "content": ACM_Taxonomy_IS}
    ]
messages.append({"role": "system", "content": "The answer must be given " \
                    "in a format that makes it easy to read by a python program."})
messages.append({"role": "system", "content": "In the hierarchical path " \
                    "change the number by the term name and the point by '-'."})
messages.append({"role": "user", "content": question})

stream = client.chat.completions.create(
    model = "gpt-4o",
    messages = messages,
    stream = True,
)
```

Figure 2: Python code extract implemented to create Prompts and submit questions to the LLM model.

on this previously created ontological model, the NetO+ extended ontology was developed, defining the competence question:

(1) What are relevant research topics in IS?
(2) What subject has the main research topics over the years?
(3) What are the main research topics considering ACM areas?

Table 2 summarizes the role of each class and its relations through the object properties. Figure 3 presents the extended NetO+ ontology. The *Area* class and *AreaPath* components were inserted. The *Author* has the object properties of *hasArea* and *hasAuthor*. The *Affiliation*, *Author*, *PublicationYear* and *Submission_Id data* properties were inserted. The *Area* class aims to represent the ACM's areas of study of each article specifically. It is represented by the last term of interest indicated by the ACM taxonomy, which was used to extract search/research terms from each article. The *AreaPath* class is a subclass of *Area* since it has a location path following the ACM taxonomy, from where the search tags (keywords) for each work are extracted. The *Tag* class represents the paper's keywords extracted in this extension. The *Author* class represents the authors of the work. As the name suggests, the object properties *hasArea* and *hasAreaPath* indicate that a given individual has an ACM's research area with a respective path to that area. The *hasAuthor* object property links articles to their specific authors.

Once the domain knowledge is specified, titles from *Node* class, keywords from *Tag* class, ACM areas from *Area* class, and ACM area path from *AreaPath* class can be automatically extracted from the LLM answers. The *Subject* class uses the *Data Property* name to detect synonyms and misspellings. To extract the topics of interest of each title of the *Node* class, we defined ontological rules specified in Semantic Web Rule Language (SWRL)[3]. Rules 1 to 11 identify

Table 2: NetO+ classes details.

Class	Description	Instantiated by	Related by
Tag/keyword	"Tag/keyword" class represents the Keywords in raw format and is extracted and instantiated automatically from the titles.	Automatic extraction process.	- Subject through "hasSubject"
Node	The "Node" class represents the titles, which are automatically extracted.	Automatic extraction process.	- Tag through "hasTag"
Subject	While tags can contain problems such as spelling mistakes, a subject acts as a filter for tags.	Predefined in ontology.	- Topic through "hasSubject"
Topic	The Topic class refers to topics of interest. It is predefined in the ontology as domain knowledge.	Predefined in ontology.	- Topic through "hasTopic"
CombinedTopic	The CombinedTopic class represents when a article is simultaneously related to several topics.	Predefined in ontology.	- CombinedTopic through "hasCombinedTopic"
Area	The "Area" class represents each work's areas of study, represented by the last term of interest indicated in the path delivered by the ACM taxonomy.	Automatic extraction process and instance.	- Area through "hasArea"
AreaPath	The "AreaPath" class is a subclass of "Area" since each Area has a location path following the ACM taxonomy, from which the search keywords for each article are extracted.	Automatic extraction process and instance.	- AreaPath through "hasAreaPath"

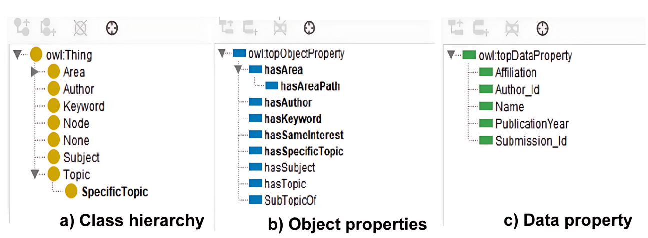

Figure 3: Classes and object property extensions of the NetO+ ontology.

[3]https://www.w3.org/Submission/SWRL

articles using keywords related to AI, and Rules 12 to 14 to combined topics, as presented in the sequence.

R1: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "Machine Learning"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R2: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "YOLOv5 (Deep learning models"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R3: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "Automatic detection"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R4: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "YOLOv5"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R5: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "Chatbot Development"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R6: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "Dialog Systems"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R7: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "Semi-Automatic"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R8: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "Classify"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R9: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "Predicting Software Design Problems"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R10: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "Data Science"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

R11: Node(?n) ∧ hasKeyword(?n, ?k) ∧ Keyword(?k) ∧ *Name*(?k, "Big Data"∧∧rdf:PlainLiteral) → *UsesIA*(?n, true)

Rules 12 and 13 were defined to identify works focused on more specific research topics using the *CombinedTopic* class. Rule 12 identifies works on education in IS. Rule 13 focuses on IS and AI. In role 14, if *Node n* has two topics, *t1* and *t2*, and these two topics together form a *CombinedTopic st*, then *st* is assigned as a *CombinedTopic* of *n*. This way, we can find other combined topics.

R12: Node(?n) ∧ hasTopic(?n, ?t1) ∧ hasTopic(?n, ?t2) ∧ *Name*(?t1, "Education"∧∧rdf:PlainLiteral) ∧ *Name*(?t2, "Information Systems Applications"∧∧rdf:PlainLiteral) → hasCombinedTopic(?n, "education-in-is")

R13: Node(?n) ∧ hasTopic(?n, ?t1) ∧ hasTopic(?n, ?t2) ∧ *Name*(?t1, "Artificial Intelligence"∧∧rdf:PlainLiteral) ∧ *Name*(?t2, "Information Systems Applications"∧∧rdf:PlainLiteral) → hasCombinedTopic(?n, "information-systems-and-ai")

R14: Node(?n) ∧ hasTopic(?n, ?t1) ∧ hasTopic(?n, ?t2) ∧ hasCombinedTopic(?t1, ?st) ∧ hasCombinedTopic(?t2, ?st) ∧ differentFrom(?t1, ?t2) → hasCombinedTopic(?n, ?st)

3.3 NetO+ Instantiation

After defining the NetO+ ontology domain knowledge, we input the titles and terms for the enrichment process of finding topics, combined topics, ACM areas, and ACM area paths. This result was achieved through an automatic process using a Python script to instantiate article titles and topics in the ontology and run the inference machine using the defined rules.

To demonstrate how the topic extraction process works using SBSI article data, we selected the one titled **A method based on machine learning to predict meal production in university restaurants**. This article has the set of keywords identified by the LLM: *machine-learning*, *forecasting*, *food production*. To illustrate the inference process using this sample article, given the way we have defined the ontology domain knowledge, the *machine-learning* keyword is relevant as an AI topic of interest used in IS. In addition, *information-systems-and-ai* is a relevant combined topic for the context since it is published in the SBSI call for articles. Table 3 shows the individuals in this sample.

Based on this sample, we can expect that when the ontology receives this article as input, it should output the object assigned with the topics *Artificial Intelligence* and *Information Systems Applications*, and the combined topic *information systems-and-ai*. When executing the inference machine with this input, the result is shown in Figure 4, and the step-by-step procedure is described as follows.

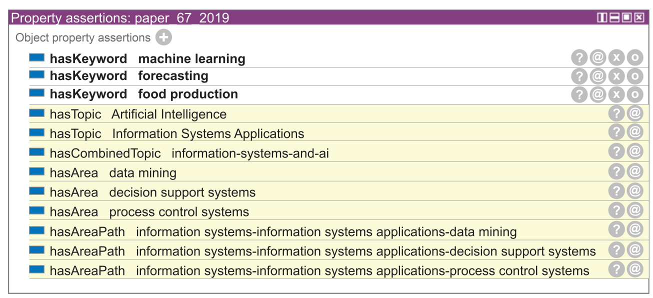

Figure 4: Inferred results achieved by the inference machine execution in the example.

First, the NetO+ ontology recognizes that the article has the keywords *machine learning*, *forecasting*, and *food production*. As *machine learning* hasArea *data mining*, given by the ACM path in the Information System branch, and it is a *subTopicOf Artificial Intelligence*, the *Artificial Intelligence* subject is assigned to the article.

Also, as *forecasting hasArea decision support system* and it is a subTopicOf *information systems applications*, the *information systems applications* subject is assigned to the article. Finally, *food production* hasArea *process control systems* and it is a *subTopicOf information systems applications*, the *information systems applications* subject is assigned again to the article, but now considering another ACM area path.

As *Artificial Intelligence* and *information systems applications* are predefined as topics in NetO+, the ontology assigns both topics to the article. As *Artificial Intelligence* and *information systems applications* topics form the combined topic *information-systems-and-ai*, the combined topic is assigned to the article.

This sample shows the role of the ontology using specific keywords to discover generic ones (machine learning → Artificial Intelligence), which is similar to solving hyponyms. The topics were assigned to the article and combined to generate a more specific topic. The NetO+ ontology output is an enriched dataset containing articles labeled with keywords, topics, combined topics, ACM areas, and ACM area paths. With this enriched dataset, we can analyze how the authors' research interest in the SBSI has evolved over the years. These analyses are detailed in Section 4.

Table 3: Individuals description of article ID 67.

Sample Individual
Node (article) name: "A method based on machine learning to predict meal production in university restaurants"^^rdf:PlainLiteral
hasKeyword: "machine learning"^^rdf:PlainLiteral (keyword1) "forecasting"^^rdf:PlainLiteral (keyword2) "food production"^^rdf:PlainLiteral (keyword3)
hasArea: "data mining"^^rdf:PlainLiteral (area1) "decision support systems"^^rdf:PlainLiteral (area2) "process control systems"^^rdf:PlainLiteral (area3)
hasAreaPath: "information systems → information systems applications → data mining"^^rdf:PlainLiteral (AreaPath1) "information systems → information systems applications → decision support systems"^^rdf:PlainLiteral (AreaPath2) "information systems → information systems applications → process control systems"^^rdf:PlainLiteral (AreaPath3)
hasTopic: "Artificial Intelligence"^^rdf:PlainLiteral (topic1) "Information Systems Applications"^^rdf:PlainLiteral (topic2)
hasCombinedTopic: "information-systems-and-ai"^^rdf:PlainLiteral (CombinedTopic1)

4 Experiments and Results

Analyzing scientific publication data is a powerful way to identify trends, patterns, and gaps related to specific research areas and study directions in a given period. This study analyzed articles published in the SBSI from 2018 to 2023 to understand the dynamics of topics and their relationship with research areas hierarchically organized in the ACM taxonomy. Our work captures articles' title keywords and explores their association with the ACM taxonomy. To this end, the keywords' temporal evolution, connection to the ontological topics, ACM areas, and ACM area paths were considered.

Using the NetO+ ontology and inference rules, we investigated how keywords have evolved, identifying trends, emerging keywords, and those in decline to reveal trends in scientific production in the IS area.

4.1 Analysis of SBSI Research Topics

Initially, to get an overview of the research areas in SBSI, we made queries in the ontology to obtain the main areas of interest to researchers. Firstly, a search was carried out using the **rdflib** library in Python, which allows querying the ontology to identify the most frequent keywords in articles published between 2018 and 2023. This query highlights the most recurrent keywords over the period investigated, pointing to *machine learning*.

After identifying the most frequent keywords, we executed a query on the ontology using a DL Query in Protégé to explore the associated research areas. Figure 5 shows the relationship between the keyword *machine learning* and its associated research areas. The query was structured using the *hasArea* property, making it possible to map the research areas directly related to this keyword, as presented in Figure 6. The query generated was fundamental to understanding how each keyword connects with different fields of study within IS in the ACM taxonomy.

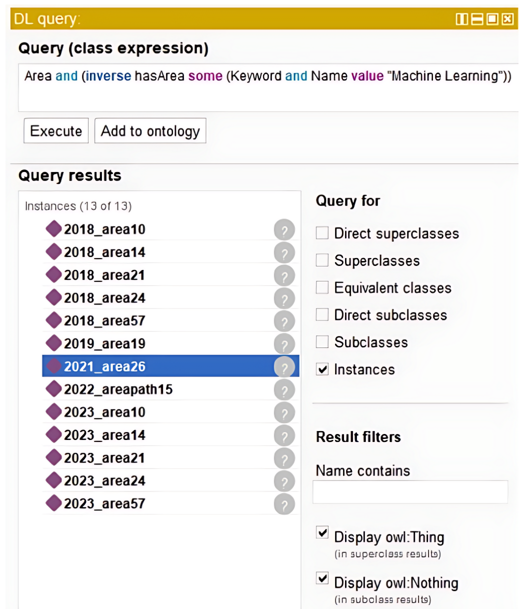

Figure 5: DL Query using *machine learning* keyword to identify the ACM area.

Based on the areas returned by the ontology, we observed in a consolidated way the key research ones:

- Data Mining - prominent, with numerous papers focusing on techniques and applications in data mining.
- Database Design and Models - significant, with research on various database design and modeling aspects.
- Information Integration - studies on integrating information from different sources are well-represented.
- Decision Support Systems - research on systems that aid decision-making processes.
- Collaborative and Social Computing Systems and Tools - includes studies on social networking and collaborative tools.
- Enterprise Information Systems - managing complex information systems in organizations.

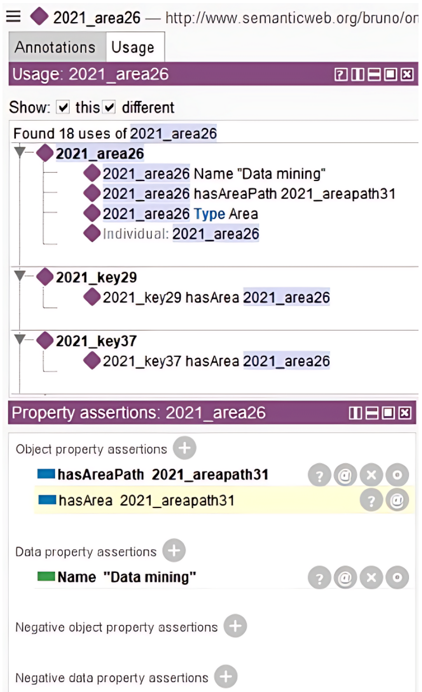

Figure 6: DL Query returned area when accessing *area26*.

In addition, we carried out an annual analysis to identify whether there is a significant variation in SBSI research topics over the years:

- 2018 - focus on data mining, database design, and decision support systems.
- 2019 - increased research into data mining, collaborative filtering, and graph-based database models.
- 2020 - emphasis on data mining, information integration, and social networks.
- 2021 - continued interest in social networking sites, data extraction (clustering), and decision support systems.
- 2022 - research in data extraction, information retrieval, and collaborative computing systems.
- 2023 - continued interest, but with emerging topics including machine learning, blockchain, and sentiment analysis.

These areas were mentioned in papers every year of the analyzed period (2018-2023), showing areas of constant interest to researchers in the IS community and remaining highly relevant in a rapidly evolving scenario. For example, data mining has emerged as a critical tool for exploring and analyzing large data volumes as data availability grows exponentially. Database design and models are essential for structuring and organizing this data efficiently. Information integration makes combining data from various sources possible, providing a more comprehensive and neat view in a scenario where data distribution has become increasingly evident. Decision support systems are essential to help make informed decisions, integrating data from different sources and advanced analysis. In addition, collaborative and social computing systems and tools reflect the growing importance of collaboration and social networks in information exchange and teamwork. Enterprise Information Systems are vital for integrating and managing complex IS in organizations, a central issue for digital transformation.

The persistence of these areas suggests that they continue to address fundamental IS challenges, receiving updates and innovations as new technologies are introduced. Therefore, it is vital to understand the researcher's focus in each area, using keywords and area paths for a more detailed analysis.

4.2 Trends Over the Years

Analyzing emerging and declining keywords is important to understand the dynamics of the topics covered at scientific events. In the context of SBSI, between 2018 and 2023, this analysis aims to identify trends of growth and decline in research topics, providing insights into emerging areas and subjects that have lost relevance.

Emerging keywords have appeared more frequently in recent years, indicating upward trends. Declining keywords are identified by the disappearance or significant reduction in their frequency in recent publications. This evaluation makes it possible to map the evolution of the scientific and technological community's interests and suggest new research directions.

The analysis was based on the annual frequency of each keyword in the articles published in SBSI, considering their first and last year of occurrence. Emerging keywords were defined as those that became more common in 2022 and 2023. Declining keywords were those that ceased to appear or significantly reduced in use after 2020.

Keywords that have gained relevance more recently but already have great potential for impact from 2019 to 2023 are:

- Blockchain,
- Ontology,
- Machine Learning,
- Sentiment analysis.

Although these keywords have a shorter lifespan than the consolidated ones, they represent topics rapidly becoming central to contemporary discussions. The growth in the use of blockchain reflects its application in data security and traceability areas. At the same time, ontology has gained prominence as a tool for semantic representation, facilitating the interoperability of systems in the areas of Enterprise IS and Information Integration. Sentiment analysis emerges in valuing qualitative data, such as analysis of opinions on social media, which was of great interest to the community between 2020 and 2022. Related to data mining, machine learning appeared in 2019 with the spread of deep learning techniques and aroused the community's interest with research boost on this subject in 2022 and 2023. The fact that these keywords have appeared consistently in recent years signals that they are moving away from experimental niches to becoming key in the field.

The analysis suggests that IS area balances its attention between well-established areas and the adoption of new technologies. The long lifespan of some topics reflects the durability of fundamental issues, while the emergence of new topics demonstrates the field's ability to adapt to contemporary demands.

It is important to note that this coexistence is not static. For example, collaborative and social computing systems may absorb emerging practices, such as using blockchain for governance on social platforms. Similarly, areas such as data mining have expanded their application by incorporating qualitative analysis based on sentiment analysis and techniques such as deep learning.

Tables 4, 5 and 6 provide a periodic quantitative breakdown of each keyword. Table 4 lists the most consistent keywords per year. Table 5 provides an overview of keywords that have already been the research subject in some papers but have not been used in recent papers. Finally, Table 6 presents a group of keywords that may indicate new trends in research carried out by the SBSI community.

Table 4: Most consistent keywords per year.

Keywords	2018	2019	2020	2021	2022	2023
Data Mining	6	10	8	4	6	6
Database Design and Models	5	2	4	0	0	2
Information Integration	4	2	5	3	2	2
Decision Support Systems	3	3	0	4	0	2
Collaborative and Social Computing Systems and Tools	6	2	2	8	4	4
Information Retrieval	2	2	2	3	6	6
Enterprise Information Systems	2	2	2	4	2	2
Web Services	2	3	3	2	4	2

Table 5: Keywords no longer in recent research.

Keywords	2018	2019	2020	2021	2022	2023
Cloud Based Storage	2	0	0	0	0	0
Distributed Storage	2	0	0	0	0	0
Usability	2	2	0	0	0	0
Web Mining	2	2	0	0	0	0

Table 6: Keywords used in recent research.

Keywords	2018	2019	2020	2021	2022	2023
AI / Machine Learning	0	2	0	2	2	8
COVID-19	0	0	2	0	2	2
Blockchain	0	1	0	0	0	3
Ontology	0	2	0	2	1	2
Sentiment Analysis	0	1	2	0	2	2

Looking at the tables, you can see two main patterns. Firstly, the persistence of consolidated keywords, such as Data Mining and Enterprise Information Systems, show constant and stable lines over the years, with little frequency alterations. This pattern reinforces the idea that these topics maintain the focus of IS and maintain a continuous presence over the years.

On the other hand, more recent keywords, such as Blockchain, Ontology, Machine Learning, and Sentiment Analysis, show a marked growth in their frequency over the period. Although COVID-19 also appears on the list, we believe this is due to the pandemic that began at the end of 2019. These words began with little or no frequency in 2018 but quickly gained prominence, indicating a growing adoption and acceleration in discussions on these topics in recent years. The analysis in turn allows us to conclude that the field of IS combines aspects of stability and innovation, with established topics continuing to play important roles, while new technologies and approaches expand the possibilities for research and application.

4.3 IS Research Trends in Data Mining

The ontology allows us to query the data to understand the evolution of the community's interest in certain areas. The results presented show areas of constant interest in the community. However, to understand the evolution of IS research, it is necessary to explore which subjects are covered within these areas.

Analyzing the numbers in the tables, we see that Data Mining is a constant interest of the community, and the keywords AI and Machine Learning appear as a trend from 2022 onwards. So, to analyze which subjects are related to the area of data mining, we queried the ontology to retrieve all the relationships between the keywords and this area, using the hasArea relationship. As a result of the query, we can see in Table 7 that the main changes in research trends in data mining based on the keywords over the years.

Table 7: Keywords used in recent research.

Year	Description
2018	**Data Mining**: Initial focus on traditional data mining techniques (clustering, classification, and association rules). **Data Analytics**: Interest in data analysis and data visualization.
2019	**Data Mining**: Continued interest in traditional techniques. **Machine Learning**: Emergence of interest in machine learning as a complementary technique to data mining. **Transfer Learning**: Introduction of transfer learning, indicating an interest in advanced machine learning techniques. **Process Mining**: Application of process mining to understand and improve business processes.
2020	**Data Mining**: Continued interest in data mining, with a greater focus on information integration and web services. **Information Integration**: Integration of data from various sources for more comprehensive analysis.
2021	**Data Mining**: Although interest in traditional techniques continues, there is a reduction in research using traditional approaches. **LSTM Neural Networks**: Introduction of LSTM neural networks for time series analysis.
2022	**Data Mining**: Continued interest in data mining, with a focus on information retrieval in large databases. **Collaborative and Social Computing Systems and Tools**: Growing importance of collaboration and social networks in data mining.
2023	**Data Science**: Focus on large volumes of data, meta-analysis, and applications in IS. **Machine Learning**: Strong increase in the use of machine learning in data mining, pointing to a trend in the use of deep learning in data analysis.

With these results, we can see the main changes in research trends in the data mining area. There is an evolution of techniques with the transition from traditional data mining techniques to machine learning and advanced neural networks. There is a growing demand for data integration and collaborative systems to support data mining. Finally, there is a focus on large volumes of data and scientific approaches to data analysis, with research into big data and data science. These changes reflect the evolution of topics of interest and the new technological trends shaping data mining research by the IS community.

5 Discussion

The results presented on the SBSI research topics from 2018 to 2023 reveal important trends and significant changes in the field of IS. The ontological analysis pointed to consolidated and emerging research areas and keywords that have gained or lost relevance over the years.

Consolidated Research Areas

Research areas such as *Data Mining*, *Database Design and Models*, *Information Integration*, *Decision Support Systems*, *Collaborative and Social Computing Systems and Tools*, and *Enterprise Information Systems* have persisted over the years. This indicates that these topics continue to be of great interest to the research community, reflecting fundamental issues and ongoing challenges in the IS area.

Emerging and Declining Research Topics

The analysis of emerging keywords, such as *Blockchain*, *Ontology*, *Machine Learning*, and *Sentiment Analysis*, shows the research community's adaptation to new technologies and contemporary demands. These keywords, which have started to appear more frequently in recent years, indicate a shift in focus towards areas that are becoming important pillars within the field.

On the other hand, keywords like *Cloud-Based Storage*, *Distributed Storage*, *Usability*, and *Web Mining* have shown a significant decline, suggesting that these topics may have lost relevance or been replaced by new approaches and technologies.

Evolution of Data Mining Techniques

The evolution of *Data Mining* techniques is particularly notable. The study shows a transition from traditional techniques to the use of *Machine Learning* and advanced neural networks. The growing demand for data integration and collaborative systems to support data mining reflects the need to handle large volumes of data and complex analyses.

The coexistence of established and emerging topics demonstrates the ability of the IS area to balance stability and innovation. While consolidated areas continue to receive updates and innovations, new technologies and approaches expand the possibilities for research and application.

Organizational and Societal Impacts

The results presented consolidated areas as *Data Mining*, *Database Design and Models*, *Information Integration*, *Decision Support Systems*, *Collaborative and Social Computing Systems and Tools*, and *Enterprise Information Systems*. However, the necessary socio-technical aspect of conceiving IS presents research gaps. The socio-technical approaches are interdisciplinary research without a well-accepted design method, challenging the IS research community to fill this gap.

The emerging research topics present collaboration opportunities among different areas. The *Blockchain*, *Ontology*, *Machine Learning*, and *Sentiment Analysis* topics are related to the AI-driven solutions involving the society and organizations. Organizational procedures for research funding decisions would benefit from the ontology results with technological advancements directed to the research community.

Nowadays, complexity is involved in the design of IS. The data manipulation focuses on big data (volume, velocity, value, variety, veracity), demanding technological advancements related to *Data Mining* and *Machine Learning* research, as presented in the evolution topics of our work. Society consumable IS demands the use of such technologies to solve real organizational problems. Organizations are very complex organisms with many interacting sub-systems that change dynamically. People in organizations enlarge their capabilities to work towards challenging goals demanding specialization in technology. Thus, integrating people and organizations into technologies is necessary to fill the socio-technical IS research gap concerning excellence in IS conception, development, and maintainability. The society sections, for instance, the industry, may use the NetO+ consolidated area results in the decision-making process of applications development, for example, using Digital Twins.

Threats to Validity

Although the article demonstrates the effectiveness of LLM, there may be inaccuracies or irrelevant outputs. Some research topics or keywords may have been classified incorrectly due to NetO+ or ACM taxonomy limitations. To minimize this threat, we conducted manual model adjustments with prompt refinements.

NetO+'s adaptability to analyze data from other conferences or journals in the IS area is promising. Even though NetO+ was structured more generically to mitigate this threat, modifications to ensure wide applicability of the ontology may be required. Nevertheless, the LLM and ontology combination advances prior technology that can integrate into different tools, enabling predictive analyses and fostering advancements in IS for sustainable community growth.

6 Conclusion

The use of ontology proves to be beneficial to semantic analysis. In this work, we presented NetO+ ontology to analyze the papers published at the SBSI between 2018 and 2023, focusing on identifying research trends, keywords, areas of study, and taxonomic paths related to research in IS. Using the ACM taxonomy as a basis, it was possible to organize data and draw up an overview of the most relevant scientific contributions within the period analyzed.

The results highlight the persistence of fundamental topics, such as Enterprise Information Systems, Data Mining, and Information Retrieval, and the progress of innovative topics, such as Blockchain and Machine Learning. The growing use of AI methods in IS reflects the field's alignment with the demands related to the digital society. At the same time, the diversity of applications reinforces the area's adaptability in dealing with complex challenges.

Despite the results, further work is necessary. The automatic extraction of titles' keywords linked to the ACM taxonomy used LLM. For this, SBSI articles were evaluated with a sample of results to check LLM hallucination. Furthermore, the analysis was restricted to SBSI articles, offering a picture of the event, but it does not capture all national IS community scientific production. These limitations do not compromise the results' relevance but point to opportunities for improvement and future exploration.

Given the results and limitations, we highlight future work:

(1) Expand the scope of the analysis, including national and international academic events and journals. This expansion allows us to compare local trends with global ones, providing a more comprehensive IS community perspective.
(2) Incorporate scientific impact analysis to keywords and research areas, exploring impact metrics such as citations and collaboration networks between authors, offering insights into the influence of published work and different institutions' role in IS research.
(3) Apply predictive models using machine learning techniques to identify emerging trends and predict research areas with high development potential. For example, keyword co-occurrence analysis can help anticipate new thematic combinations that should gain future relevance.

With these directions, we believe in overcoming this work's limitations, contributing to the continuous evolution of knowledge in IS and its integration with emerging technologies, such as Artificial Intelligence. These efforts intend to strengthen the role of academic IS research, impacting both scientific advancement and practical applications in organizations.

Acknowledgments

The authors thank Prof. José Viterbo Filho (SBC Publications Director) for providing two decades of SBSI proceedings. Profs. Victor Ströele, Regina Braga, and Célia G. Ralha, thanks the support from the Brazilian National Council for Scientific and Technological Development (CNPq) for the research productivity grant 313568/2023-5 (PQ-2), 307194/2022-1 (PQ-2), 309688/2021-3 (PQ-2), respectively.

References

[1] Renata Araujo, Célia Ralha, Alexandre Graeml, and Alexandre Cidral. 2015. A Comunidade de Pesquisa em Sistemas de Informação no Brasil na perspectiva do Simpósio Brasileiro de Sistemas de Informação. *iSys - Brazilian Journal of Information Systems* 8, 1 (Jul. 2015), 5–17. https://doi.org/10.5753/isys.2015.277
[2] Luiz Paulo Carvalho, Silas P. Lima Filho, Michele A. Brandão, Élton Carneiro Marinho, Mônica Ferreira da Silva, Jonice Oliveira, and Flávia Maria Santoro. 2024. Celebrating two decades of SBSI (2004 to 2023): A Comprehensive Descriptive and Meta-Scientific Analysis. In *Proceedings of the 20th Brazilian Symposium on Information Systems, SBSI 2024, Juiz de Fora, Brazil, May 20-23, 2024*, Ronney Moreira de Castro, José Maria N. David, Johnny Cardoso Marques, Tadeu Moreira de Classe, Victor Ströele, and Williamson Alison Freitas Silva (Eds.). ACM, Juiz de Fora, MG, Brasil, 29:1–29:10. https://doi.org/10.1145/3658271.3658300
[3] Devendra Singh Chaplot and Ruslan Salakhutdinov. 2018. Knowledge-based Word Sense Disambiguation using Topic Models. *Proceedings of the AAAI Conference on Artificial Intelligence* 32, 1 (2018), 1–8. https://doi.org/10.1609/aaai.v32i1.12027
[4] Huajun Chen. 2024. Large Knowledge Model: Perspectives and Challenges. *Data Intelligence* 6, 3 (aug 2024), 587–620. https://doi.org/10.3724/2096-7004.di.2024.0001
[5] Gohar Rehman Chughtai, Jia Lee, Mahnoor Shahzadi, Asif Kabir, and Muhammad Arshad Shehzad Hassan. 2019. An efficient ontology-based topic-specific article recommendation model for best-fit reviewers. *Scientometrics* 122, 1 (2019), 249–265. https://doi.org/10.1007/s11192-019-03261-2
[6] Valdemar Confort, Kate Revoredo, Fernanda Baião, and Flávia Santoro. 2015. Extração de Ontologias a partir de Histórias: um estudo exploratório em storytelling. In *Anais do XI Simpósio Brasileiro de Sistemas de Informação* (Goiânia). SBC, Porto Alegre, RS, Brasil, 243–250. https://doi.org/10.5753/sbsi.2015.5823
[7] Edvaldo de Oliveira and Vania Dias. 2012. Redes sociais do SBSI e o corte de vertices como base para identificar atores importantes na coesão de grupos de pesquisa. In *Anais do VIII Simpósio Brasileiro de Sistemas de Informação* (São Paulo). SBC, Porto Alegre, RS, Brasil, 204–215. https://doi.org/10.5753/sbsi.2012.14406
[8] Giancarlo Guizzardi, Alessander Bottes Benevides, Claudemir M. Fonseca, Jo ao Paulo A. Almeida, Tiago Prince Sales, and Daniele Porello. 2022. Ufo: Unified Foundational Ontology. *Applied ontology* 1, 17 (2022), 167–210. https://doi.org/10.3233/ao-210256
[9] Gilson Helfer, Adilson Costa, Rodrigo Bavaresco, and Jorge Barbosa. 2021. TellusOnto: uma ontologia para classificação e inferência de solos na agricultura de precisão. In *Anais do XVII Simpósio Brasileiro de Sistemas de Informação (SBSI)* (Uberlândia). SBC, Porto Alegre, RS, Brasil, 1–7. https://sol.sbc.org.br/index.php/sbsi/article/view/17702
[10] Vitor A.C. Horta, Victor Ströele, Jonice Oliveira, Regina Braga, José Maria N. David, and Fernanda Campos. 2022. Detecting topic-based communities in social networks: A study in a real software development network. *Journal of Web Semantics* 74 (2022), 100739. https://doi.org/10.1016/j.websem.2022.100739
[11] Zhongjian Hu, Peng Yang, Yuanshuang Jiang, and Zijian Bai. 2024. Prompting large language model with context and pre-answer for knowledge-based VQA. *Pattern Recognition* 151 (2024), 110399. https://doi.org/10.1016/j.patcog.2024.110399
[12] İlknur Karadeniz and Arzucan Özgür. 2019. Linking entities through an ontology using word embeddings and syntactic re-ranking. *BMC Bioinformatics* 20, 1 (2019), 156. https://doi.org/10.1186/s12859-019-2678-8
[13] Lucas Correa Lemos, Célia Ghedini Ralha, Daniela Barreiro Claro, Rita Suzana Pitangueira Maciel, Aline Argolo, and Claudio D. G. Linhares. 2024. A Temporal Network Visualization and Data Analysis on Two Decades of SBSI. In *Proceedings of the 20th Brazilian Symposium on Information Systems, SBSI 2024, Juiz de Fora, Brazil, May 20-23, 2024*, Ronney Moreira de Castro, José Maria N. David, Johnny Cardoso Marques, Tadeu Moreira de Classe, Victor Ströele, and Williamson Alison Freitas Silva (Eds.). ACM, Juiz de Fora, MG, Brasil, 4:1–4:11. https://doi.org/10.1145/3658271.3658275
[14] Shangsong Liang. 2019. Unsupervised Semantic Generative Adversarial Networks for Expert Retrieval. In *The World Wide Web Conference (WWW'19)*. ACM, San Francisco, CA, USA, 1039–1050. https://doi.org/10.1145/3308558.3313625
[15] Aline Martins, Ricardo Falbo, Giancarlo Guizzardi, and João A. Almeida. 2011. Uso de uma Ontologia de Fundamentação para Dirimir Ambiguidades na Modelagem de Processos de Negócio. In *Anais do VII Simpósio Brasileiro de Sistemas de Informação* (Salvador). SBC, Porto Alegre, RS, Brasil, 129–140. https://doi.org/10.5753/sbsi.2011.14571
[16] Vânia Neves, Silvana Melo, and Lina Garcés. 2023. 18+ Years of Brazilian Symposium on Information Systems: Results of a Scope Review. In *Proceedings of the XIX Brazilian Symposium on Information Systems* (Maceió, Brazil) *(SBSI '23)*. ACM, New York, NY, USA, 419–426. https://doi.org/10.1145/3592813.3592933
[17] Jefferson Tales Oliva, Huei Diana Lee, Newton Spolaôr, Weber Shoity Resende Takaki, Claudio Saddy Rodrigues Coy, João José Fagundes, and Feng Chung Wu. 2019. A computational system based on ontologies to automate the mapping process of medical reports into structured databases. *Expert Systems with Applications* 115 (2019), 37–56. https://doi.org/10.1016/j.eswa.2018.08.004
[18] Rafael Oliveira, Sérgio Lifschitz, Ana Almeida, and Edward Haeusler. 2015. Projeto e implementação do framework Outer-tuning: auto sintonia e ontologia para bancos de dados relacionais. In *Anais do XI Simpósio Brasileiro de Sistemas de Informação* (Goiânia). SBC, Porto Alegre, RS, Brasil, 171–178. https://doi.org/10.5753/sbsi.2015.5814
[19] Maria Queiroz, Natasha Lino, and Gustavo Motta. 2016. Uma Ontologia de Domínio para Preservação de Privacidade em Dados Publicados pelo Governo Brasileiro. In *Anais do XII Simpósio Brasileiro de Sistemas de Informação* (Florianópolis). SBC, Porto Alegre, RS, Brasil, 009–016. https://doi.org/10.5753/sbsi.2016.5940
[20] Natan Rodrigues and Célia Ralha. 2015. Conhecendo a Comunidade de Sistemas de Informação no Brasil: um Estudo Comparativo Utilizando Diferentes Abordagens de Banco de Dados. In *Anais do XI Simpósio Brasileiro de Sistemas de Informação* (Goiânia). SBC, Porto Alegre, RS, Brasil, 555–562. https://doi.org/10.5753/sbsi.2015.5861
[21] Felipe Viegas, Washington Luiz, Christian Gomes, Amir Khatibi, Sérgio Canuto, Fernando Mourão, Thiago Salles, Leonardo Rocha, and Marcos André Gonçalves. 2018. Semantically-Enhanced Topic Modeling. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management (CIKM'18)*. ACM, New York, NY, USA, 893–902. https://doi.org/10.1145/3269206.3271797
[22] Binbin Yu. 2019. Research on information retrieval model based on ontology. *EURASIP Journal on Wireless Communications and Networking* 2019, 1 (2019), 1–8. https://doi.org/10.1186/s13638-019-1354-z
[23] Kun Zhou, Yuanhang Zhou, Wayne Xin Zhao, Xiaoke Wang, and Ji-Rong Wen. 2020. Towards Topic-Guided Conversational Recommender System. In *Proceedings of the 28th International Conference on Computational Linguistics*. International Committee on Computational Linguistics, Barcelona, Spain (Online), 4128–4139. https://doi.org/10.18653/v1/2020.coling-main.365