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Integrating Semantic Web, Artificial Intelligence, and Knowledge Management for Enhanced Accounting in SMEs

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Abstract

This study explores the integration of Semantic Web (SW), Artificial Intelligence (AI), and Knowledge Management (KM) to improve accounting practices in small and medium-sized enterprises (SMEs). Recognizing the challenges SMEs face in managing accounting knowledge due to insufficient expertise and fragmented data sources, this research proposes a conceptual model that utilizes SW technologies, such as Resource Description Framework (RDF) and Web Ontology Language (OWL), to create a unified ontology for diverse accounting information. By leveraging AI techniques, including machine learning and natural language processing, the model aims to enhance knowledge retrieval, ontology enrichment, and case-based reasoning, facilitating more efficient and accurate accounting knowledge management. The findings highlight the potential of this integrated approach to support online training, decision-making, and overall competitiveness of SMEs, addressing the limitations of traditional accounting practices. The study concludes with recommendations for further research to refine the integration of SW, AI, and KM in accounting.

Keywords: Semantic Web, artificial intelligence, knowledge management, accounting, machine learning

1. Introduction

Accounting, an essential function within any enterprise, is vital for maintaining stable operations and ensuring societal survival and success. SMEs often need more professional accounting knowledge. Studies have shown a correlation between accountants' knowledge and ability level and business performance in relation to KM (Andekina & Medeni, 2014; Trivellas, 2015). Accounting knowledge comprises explicit knowledge, such as accounting standards and tax laws, and tacit knowledge, such as attitudes and organizational culture, which are more challenging to share and express (Sellah, 2010). Over the past two decades, the global economy has transformed into a knowledge economy, emphasizing the critical role of knowledge assets. This transformation has made knowledge management (KM) a vital research area, particularly for small and medium-sized enterprises (SMEs), which must develop strong organizational capabilities in managing knowledge to remain competitive and sustainable (Metaxiotis, 2009). SMEs often face challenges due to the low professional level of accountants, unclear division of work, insufficient guidance and training, and a focus on financial accounting (Durst & Edvardsson, 2012). These characteristics highlight the need for comprehensive accounting knowledge.

Looking ahead, the emergence of the Web 3.0 era, characterized by the development of the Semantic Web (SW), offers new opportunities for KM. The SW aims to provide a framework for data sharing and reuse across various applications, enterprises, and communities. SW technologies like the Resource Description Framework (RDF) and Web Ontology Language (OWL) define data identities, formats, and logical relationships (Antoniou & Harmelen, 2008). Constructing an SW-based KM system involves stages like information extraction, knowledge representation, ontology modeling, and reasoning and usually the first three processes are integrated into ontology engineering model rather than be separated (Antoniou & Harmelen, 2008; d'Amato, 2022; Luong 2009; Rettinger, 2012; Warren, 2006). Integrating KM with the SW enhances knowledge query results by combining semantically enriched knowledge graphs (Schulze, 2022).

The importance of using the SW in KM for accounting has also been highlighted. Further, the establishment of accounting ontology — the critical technology for SW, has become a top priority for integrating KM and SW. The establishment of accounting ontology is crucial due to the development of KM, the SW, and the intellectualization of accounting information systems (Aparaschivei, 2007; Li et al., 2024). Research in this area includes ontologies in various languages and KM systems harnessing the SW for accounting (Hegazy et al., 2015; Li et al., 2024; Rachidi & Mohajir, 2016). However, they not only have regional limitations but did not involve data integration for knowledge from multiple sources to unify semantic meaning of data, eventually establishing a generalized ontology. Moreover, SMEs often struggle to connect multiple datasets or databases, negatively affecting the comprehensiveness and quality of the accounting knowledge derived from the information. By far, there is little research on linking ontologies of different accounting information sources for search and query.

The intersection between the SW and artificial intelligence (AI) offers promising advancements. The SW enables machines to understand data, while AI analyzes and drives actions, leading to optimized KM and more innovative applications (Breit, 2023; Ławrynowicz, 2020). Incorporating machine learning (ML) with SW technology is a trend and field of AI research. Today, interest in SWeML systems is proliferating, and the catalyst for this rapid growth is the increased use of ML technologies in SW. A study summarized a framework demonstrating the whole process of KM based on SWeML — reasoning and inferencing over the knowledge source, mining more knowledge from the existing knowledge base, enrichment of KB，supplementing and updating of ontology based on the available instance and schema data (Bühmann et al., 2016). These processes are implemented via automated semantic unification and ontology construction and enrichment, as well as reasoning support to derive new knowledge, such as knowledge matching and case-based reasoning (CBR) (Breit et al., 2023; Guruvayur & Suchithra 2019; Tresp et al., 2008). Matching data inferred by ML with entities in knowledge base is knowledge matching (Seeliger et al., 2019). CBR is essential in the accounting field, where know-how knowledge plays a significant role in daily practice. It consists of four stages — retrieval (e.g. similar cases and experience), reuse (e.g. previous experience and solutions applied to new cases), revise (e.g. generating new solution based on new situation) and store (e.g. new cases and newly created solutions and experience) (Berghofer et al., 2010).

To address concerns about the accuracy and validity of accounting knowledge, research has proposed using the AI knowledge engineering technique Probase, which automatically evaluates knowledge from various sources using a probabilistic method (Wu et al., 2012). Nevertheless, more research must be conducted despite its outcome to ensure greater accuracy and validity. Wang (2011) has proposed a small part of the paradigm for SMEs' accounting knowledge ontology and semantic retrieval model. However, the research does not involve any AI element in the models. There has not been research work on KM combined with AI and SW for the accounting section of SMEs by far.

This research explores the integration of SW, AI and KM, so as to study the potential solutions to effective and efficient accounting knowledge management in SMEs. A Quantitative research method survey is employed to collect data for analysis of conceptual model formation. This will be explained in Section 3 and 4. Additionally, the survey outcome and conceptual model and latent application will be described and explained in Section 3, 4 and 5.

2. Research Method

2.1 Questionnaire

Given the advantages of a survey for data collection, including originality, reliability, cost-effectiveness and generalizability of inference, this study deploys survey to collect data from a population of respondents that all are accountants in SMEs. It seeks to gather accountants' views on the application of software and AI technology in knowledge management (KM) for SMEs, aiming to explore the essential components of an integrated KM, software, and AI model.

2.1.1 Questionnaire Design

The questionnaire consists of 18 questions that cover the research's sub-themes and was conducted online. The first 12 questions aim to explore the problems resulting from lacking knowledge and knowledge sources. The remaining questions explore the potential conceptual solution via the integration of KM, SW and AI. These questions are in the form of typical five-level Likert Scale to respondents' attitudes based on the research topic. The feedback will be quantified to conduct research analysis based on variables, which will be analyzed via several approaches, including reliability and validity analysis, correlation and linear regression exploration. The variables are outlined in the following table (see Table 1).

Table 1. Variables for Data Analysis

Dependent Variable (DV)	Independent Variable 1 (IV1)	Independent Variable 2 (IV2)
A KM assembled with AI&SW that acquires and manages accounting knowledge from multiple sources can solve the work difficulties caused by lack of knowledge	Professional accounting knowledge sources	Practical accounting knowledge sources

2.2 Model

The research proposes a conceptual model of KM that leverages SW and AI to build an accounting KB for SMEs. This model facilitates knowledge capture, acquisition, processing, storage, transmission, and application. Key sources of knowledge include ERP financial data, documents, accounting standards, taxation legislations, open repositories like Wikipedia and other webpages involving accounting theoretical knowledge. AI capabilities enable knowledge processing, sharing, and application, moving beyond traditional keyword-based retrieval modes. Figure 1 provides an overview of the Knowledge Management System (KMS), illustrating the key components and processes involved. The component parts of the model include:

- ✧ A formation mechanism of ontology in OWL (RDF) format
- ✧ An intelligent SW reasoning engine harnessing ML technology
- ✧ A query capability using SPARQL

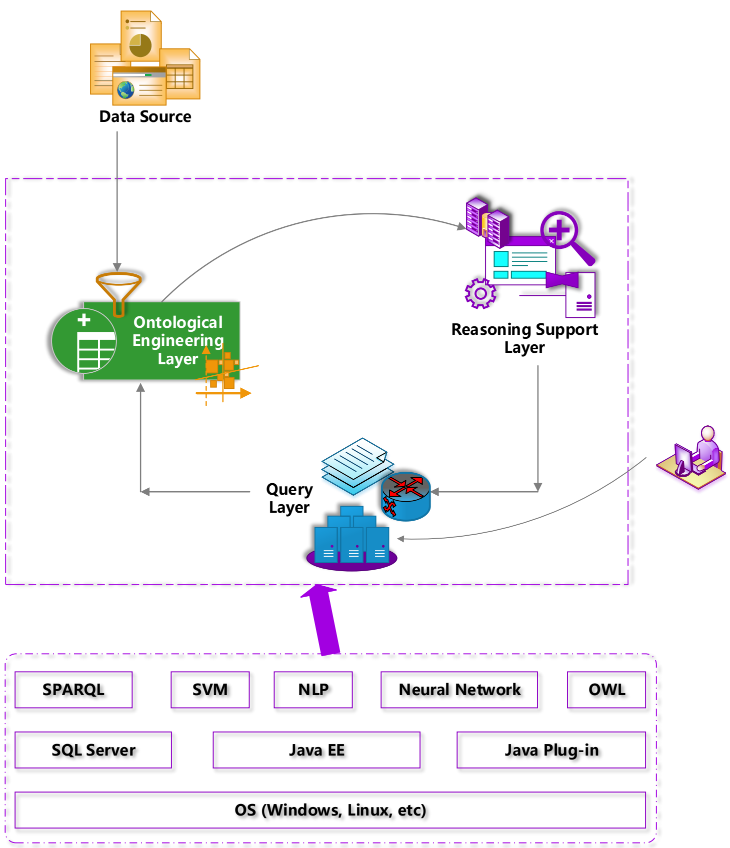


Figure 1. Overview of KM

3. Result & Analysis

3.1 Survey Result and Analysis

a) Reliability & Validity Analysis

The reliability coefficient of IVs are 0.826, 0.857, and 0.942, respectively. The standardized Cronbach's α coefficient is 0.921. Additionally, the coefficient of KMO test was 0.916, and the chi-square value of Bartlett test is 1289.037. These figures show the excellent quality and reliability of data, indicating the high reliability and validity of the questionnaire.

b) Correlation & Linear Regression Analysis

The correlation values between IVs and between each IV and DV are 0.247, 0.571 and 0.350. These data are all above 0, which indicating that the dependent and independent variables have a significant positive correlation. Further, the regression coefficient values of IV1 and IV2 are 0.503 and 0.232, implying that both IVs impact the DV significantly and positively.

These results suggest that a KM system integrated with KM & AI technology can acquire, process and manage accounting knowledge from professional knowledge and practical knowledge sources, effectively solving the work challenges caused by the lack of knowledge of accounting practitioners. In essence, our survey addresses three key research issues:

- The collaboration between SW technology and AI focuses on improving the intelligence of KM to improve effectiveness and efficiency;
- Pinpointing the source of knowledge, including the source of theoretical knowledge and practical knowledge;
- The applicability of KM conceptual model ensures that it can solve the accounting difficulties faced by SMEs.

3.2 Model

3.2.1 Ontology Engineering

In the stages involved in ontological engineering, the study harnesses an ontology learning model, which automatically supports ontology enrichment via information searching, capturing, filtering, clustering and merging data (see Figure 2). The model comprises a crawler that can browse the Internet, network and information systems to search accounting-related texts fuzzily. Then the data is processed and analyzed via an SVM-based data filter that automatically filters unrelated texts, as well as a text features evaluation method to mine, prioritize, and distinguish the features. Based on this work, the probability that these texts contain accounting information is calculated using probabilistic associations, where only those with a high probability of relevance are stored to extract information (Luong et al., 2009; Xu et al., 2012).

It is necessary to integrate these discrete ontologies into a single universal ontology as the accounting information from different sources of texts that a concept is likely to be described in other terms or vocabulary (Guruvayur & Suchithra 2019). Semantic clustering uses unsupervised learning to group data based on ontologies and instances, resulting in clusters with clearer semantic interpretation within a specific domain. The process ensures that ontologies within the same cluster are more similar to each other than to those in different clusters (Batet et al., 2010). This allows the merging of multiple ontologies within their framework. After the formation of integrated and universal ontology, a semantic embedding model assembled with Neural Network approach for OWL ontology called OWL2Vec* and an XML-RDF converter transforms the ontology and their respective instances directly into RDF triples based on OWL-RDF graph mapping, which is stored in general KB (Chen et al., 2021; Kotis et al., 2021).

Furthermore, ontological engineering also adopts the CBR model SCOOBIE to build the ontology of knowledge source of accounting cases. First, the SCOOBIE model is trained and analyzed based on the established universal OWL ontology and instances that have been formed. The analysis results are turned into a structured index. SCOOBIE then identifies the case represented by RDF with labelling approach. Each case concept is encoded and filed by the correspondent concepts name of the established universal OWL ontology. For example, concept *ADA* is encoded as *Allowance for doubtful accounts* of the OWL ontology (Berghofer et al., 2010).

The OWL ontology is of taxonomical hierarchy, the following are examples of ontology presented in OWL and the hierarchy of the ontology:

```
<owl: Class rdf: ID =“general ledger”>
    <rdfs: subClassOf rdf: resource = “#financial accounting”/>
</owl: Class>

<owl: DatatypeProperty rdf: ID =“supplementary accounting item”>
    <rdfs: domain rdf: resource = “#auxiliary accounting”/>
</owl: DatatypeProperty>
```

```
<owl: DatatypeProperty rdf: ID =“analytical dimension”>
    <owl: equivalentProperty rdf: resource = “#supplementary accounting item”/>
</owl: DatatypeProperty>
```

Financial accounting
- General ledger
  - Trial Balance
  - Auxiliary accounting
    - Department
    - Staff
    - Customer
    - Supplier
    - Project
  - Cash flow
- Inventory accounting
  - Cost calculation

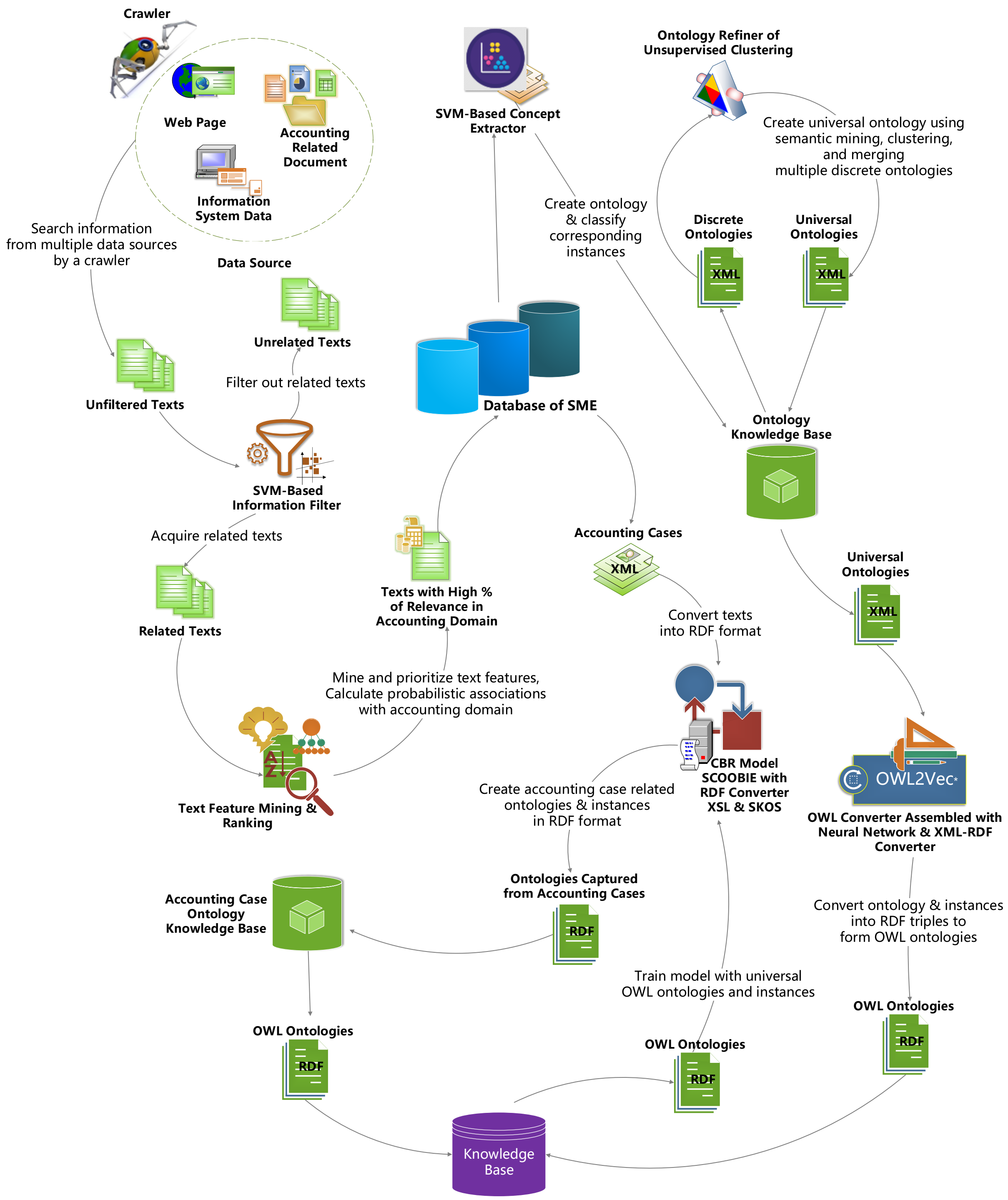


Figure 2. Ontology Engineering

3.2.2 Knowledge Inference Model

Reasoning is the core of SW and NLP has achieved semantic inference. Deep learning-based large language model (LLM) has made remarkable progress in the field of NLP. LLM is pre-trained on a large amount of text data that helps the model to learn linguistic patterns and contexts to process and generate natural language text. LLM's Transformer framework uses the "attention mechanism" approach to understand the relationship between the various parts of a sentence. Tokenizer is responsible for breaking the input text into smaller tokens for the model to learn. This mechanism effectively captures dependencies in text, enabling the model to generate contextually coherent language. This approach can greatly improve the efficiency and accuracy of text processing and reduce the reliance on large amounts of annotated data (Breit et al., 2023; Chen et al., 2021; Hu, 2020; Yang et al., 2024). Thus, the study deploys LLM to construct the ML-based knowledge inference engine of the model. The processes for the fulfillment of knowledge reasoning is as follows:

- **Pre-training**

Knowledge inference pre-training, whose process includes text feature learning and fine-tuning of the accounting domain data set. The Pre-training objectives and training models are outlined as follows:

a) Training Objective

Pre-training aims at objectively predicting the probability of text x, which optimizes the probability P(x) of the texts in the training corpus (Radford & Narasimhan 2018). It predicts the tokens of a sentence in the bidirectional sequence simultaneously under a masked language model (see Figure 3). For example, if we have a sentence "The general journal is used to record all transactions that do not fit one of the special journals", the representation of the word "journal" would be learn and predicted based on all words in the sentence. A popular alternative to the standard LLM goal is the de-noising goal, which applies noise f=noise(x) to the input sentence and then attempts to predict the original input sentence according to this noisy text P(x|≈x).

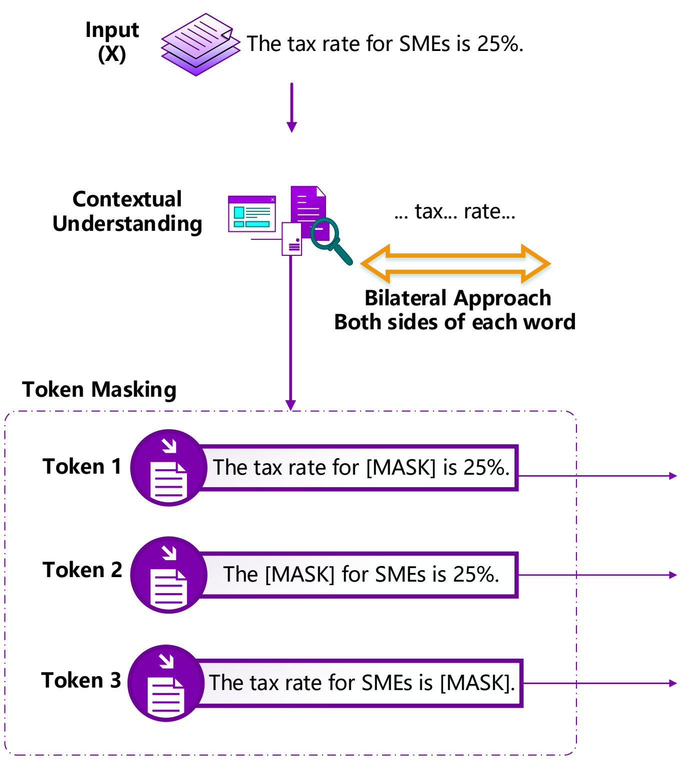


Figure 3. Masked Language Model

b) Pre-training Language Model

- **Prompt**

A promising NLP approach is prompt, which is a natural language designed to allow the pre-trained language model to "recall" what was learned and respond to the questions input by users of KM system (Wei et al., 2024). For example, when a user inputs the phrase "General ledger is", the system generates the output "The primary and controlling ledger of a business, which contains individual or controlling accounts of all assets, liabilities, net worth items, income, and expenses". Prompt engineering is the process of using prompting. As has shown in the algorithm below (1), the goal of the reasoning task is to maximize the probability of the answer A, and the probability manipulation model for prompt learning works on the input question Q, prompt T, and a parameterized probability model. a_i represents the i_{th} token of answer A, and |A| represents the length of answer A (Qiao et al., 2022).

$$p(A|T,Q) = \prod_{i=1}^{|A|} p\text{LM}\,(a_i|T,Q,a_{<i}) \tag{1}$$

An inference strategy in prompt engineering plays a critical role in improving the prompt reasoning ability of the pre-trained model. The strategy is designed to elevate the reasoning performance of LLM, and it includes cue engineering and answer engineering. Cue engineering simulates the distributed reasoning pattern of humans to enhance prompt performance. Typically, a man decomposes a complex question into simpler sub-questions to conduct reasoning process and eventually generate solutions. Similarly, prompt decomposition aims to break a task into multiple detachable sub-tasks and design specific prompt for each. This approach suits more for long texts and cross-domain texts, and increases prompt reasoning capability (Khot et al., 2022). After question decomposition, answer engineering uses an ensemble optimization approach, assembling multiple reasoning paths to learn the semantic meaning of texts and produce the final answer. It can alleviate the restriction of a single inference path by the deployment of multiple inference paths and produce the most consistent answer by majority vote. Given that a single path may cause faults when generating a wrong answer to the input question, a stepwise voting checking approach — a GPT-4 model based on DiVeRSe approach assesses and scores the accuracy of each reasoning path rather than all of the paths in a whole (Li et al., 2023; Espejel et al., 2023). Figure 4 shows the overall processes of prompt decomposition and answer engineering.

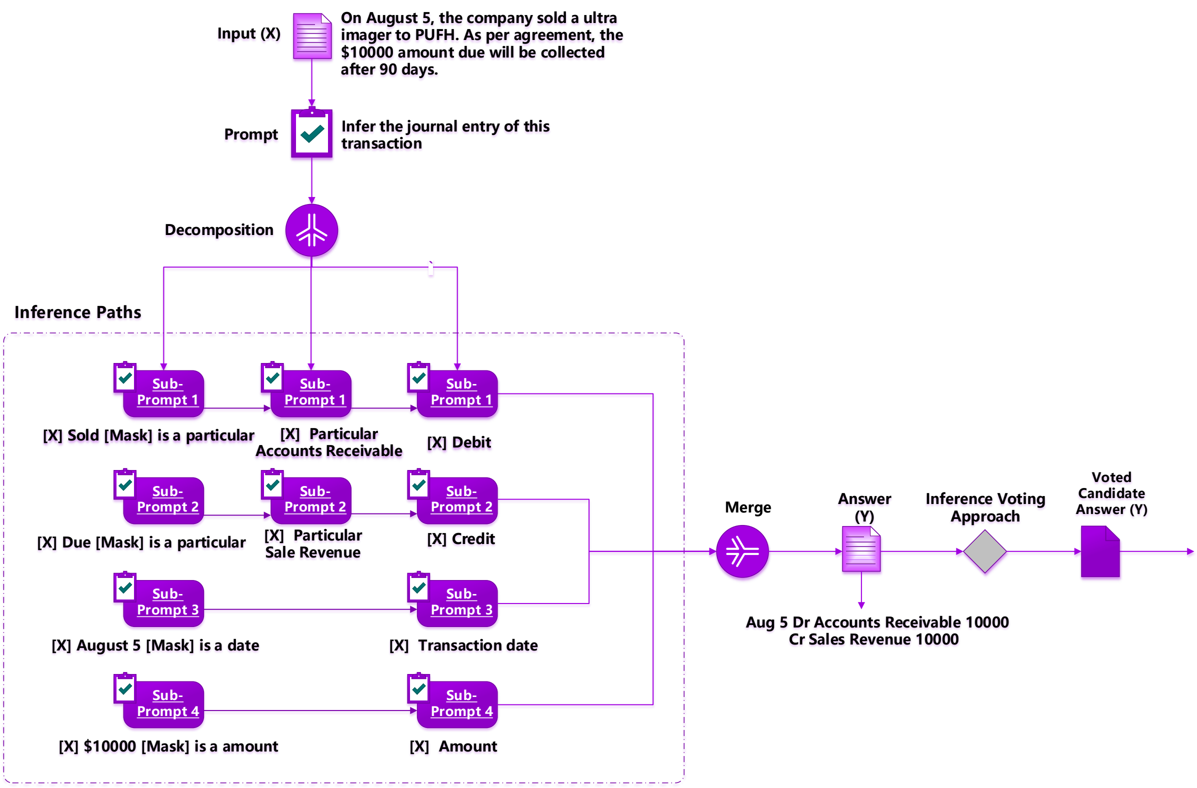


Figure 4. Prompt Decomposition of a Candidate Answer

- **CBR Model**

Due to the diverse wording of cases, it is more appropriate to perform CBR with a reasoning model designed for CBR. The model exploits the merits of deep learning, which can automatically learn the text features of cases and explain the inference steps behind each prediction of texts. Figure 5 demonstrates the composition and work processes of the model. The model's architecture is composed of encoder, decoder and a prototype layer, where unit stores a weight parameter. To begin with, the encoder learns key feature of cases, while the decoder visualizes the learning process. Then the processed data is input into the prototype layer and manipulate by the weight matrix W and compares the latent space, that is, the similarity between cases. Consequently, the distances to all the calculation results contribute to predicting and classifying the case. For example, “Account” can be difficult to distinguish from “Amount”. Thus, the training requires a data set of accounting terms, at least one of their respective similar terms.

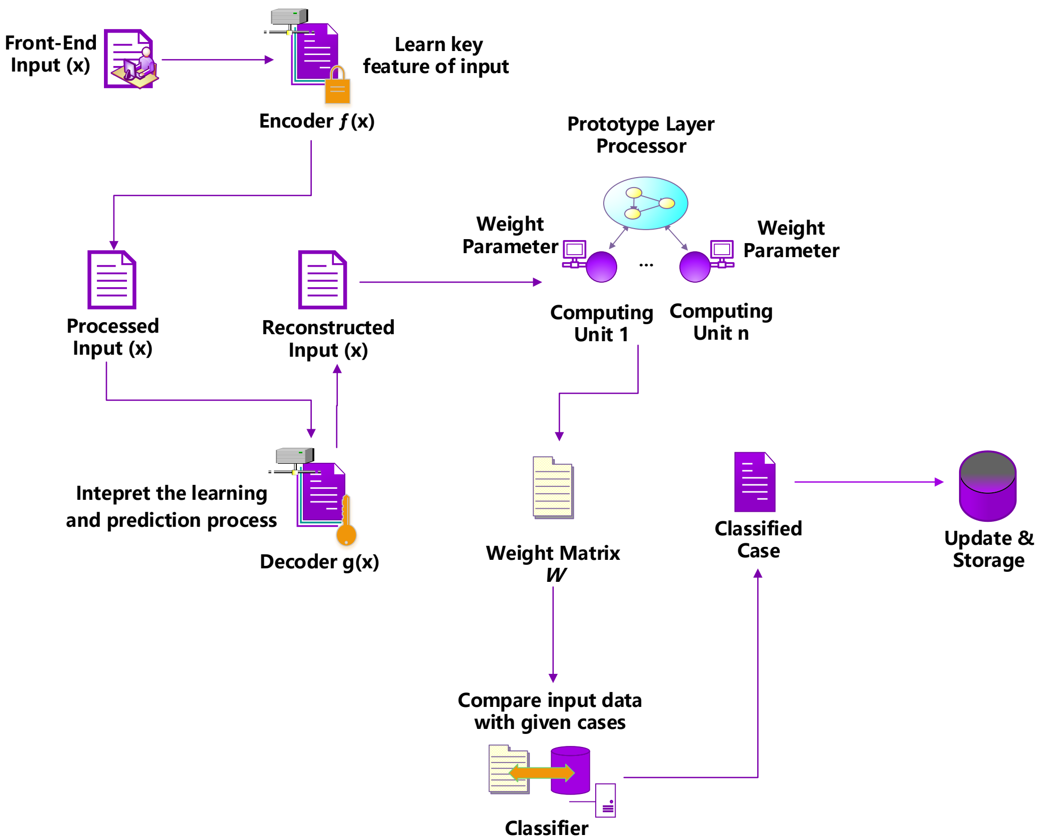


Figure 5. CBR Model Using Deep Learning

3.2.3 Query

The above research work lays the foundation of KB and KM inference ability. At the same time, query is indispensable to realize the application of KM in practical situations and its integrity. The query of the accounting KB is RQL query, which is generated through an interface consisting of search fields (e.g. key words, sort, area). Unlike traditional keyword search without application of SW, the goal of this model is combination of both traditional display of search results, each of which has the keywords that users type in, and related concepts (terms) from the hierarchy of the ontology. This enables users’ query to be ontology driven, and ultimately makes users to acknowledge how traditional information sources are presented in an innovative way. The new knowledge presentation mechanism is by the taxonomical hierarchy of ontology.

The key components and processes of the query model are shown in Figure 6. For general query, the user query model is constructed upon SPARQL collaborated with Significance Matrix Weighting (SMW) approach, which compares the predicates and the objects in the RDF triples for a query with those in the given KB using weighting algorithm for similarity score calculation. First, the query input by a user is transformed from HTML into XML files by NamLabs Tool, and then to RDF triples via XSLT (Breitling, 2009; Yang & Yan, 2018). Afterwards, the model retrieves and compares the RDF triples of the input instances and questions with the established triples in the KB, and then deduces the most appropriate RDF formatted answer, which is converted to XML and then HTML with JSON-LD and XSLT Tool respectively and return to the accountants (Chen et al., 2021; Li et al., 2024). In aspects of accounting case query, inputting texts of a case to the SCOOBIE-based query can search and retrieve solutions and experience from the newly generated base that contain a given set of cases. With the cooperation of XSL & SKOS, the query into RDF format, and then identifies RDF-represented cases. In order to match similar cases to the input texts, SCOOBIE rapidly builds a text search upon the similarity calculated by SMW method. It calculates the mapping and similarity between the query content and the cases set. Afterwards, the query model provides solutions and experience, such as a recommendation of bookkeeping for notable transactions based on the case (Berghofer et al., 2010).

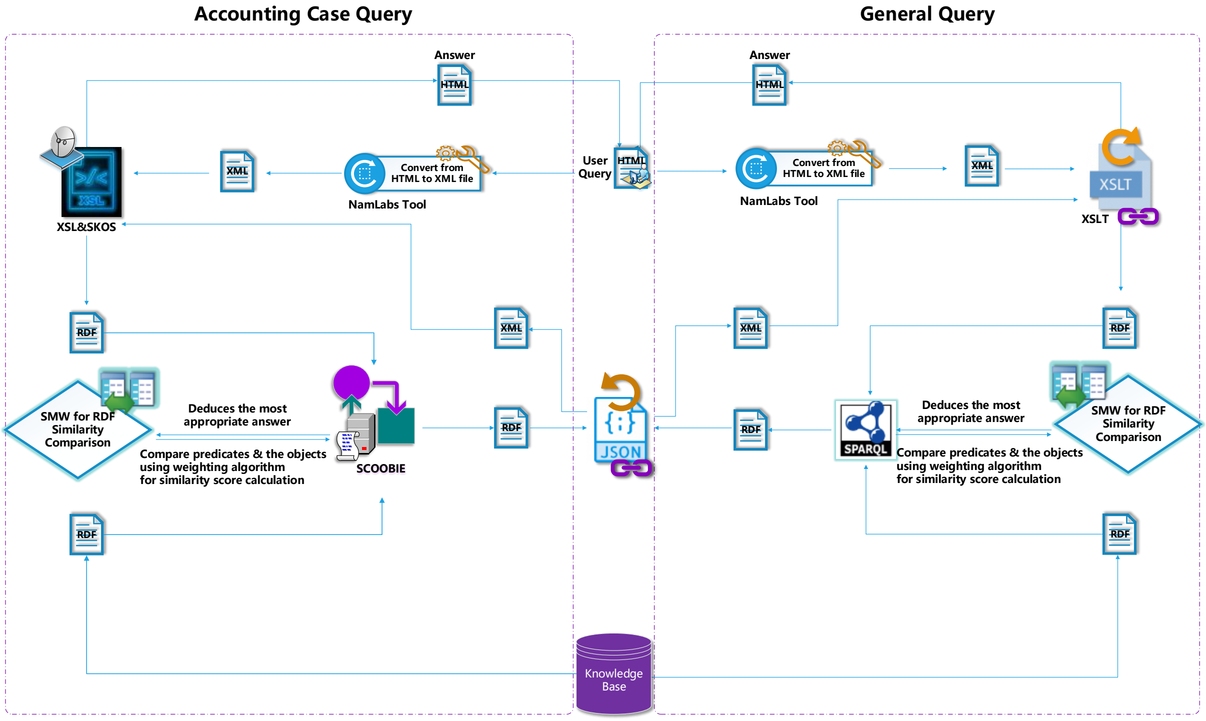


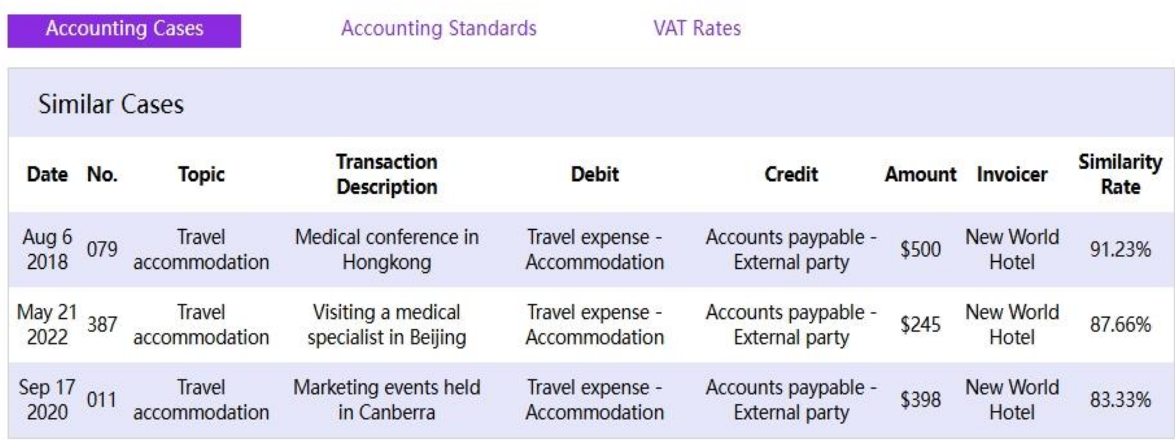
Figure 6. Query Model

4. Discussion

A practical use of the KM system integrated with SW & AI is Q&A system for online training and mentoring. Increased skills and abilities of employees plays a key role in enterprise competitiveness advancement, SMEs should personalize the at-work training to meet the needs of each employee, in order to fit them into the learning process of the daily works. It is evident that traditional learning method does not meet the requirement, whereas online training and mentoring is able to solve the problem. SW and AI provide a promising approach to meet the requirements of online training and mentoring. As a result of NLP technology, accountants can input their own questions in natural language via the query interface. The system understands the problem by mapping the question texts to the ontology in the KM system, matching the best answer among candidate answers. ML continuously improves the system's accuracy and reliability and the ability to understand the answers to complex queries. The ultimate purpose of these measures is to enrich the KB and elevate the efficiency of KM.

In the e-training environment, there is difficulty in integration of learning materials from different sources. This results from the fact that terminology of each source varies. Further, the variance in knowledge background and levels among accountants also affects search results' quality. Hence, a common ontology providing a shared interpretation mechanism is a necessary measure to help overcome the difficulty. Three categories of ontologies are developed to achieve effective interpretation mechanism in light of the characteristics of online training. First of all, content ontology describes the elementary concepts (objects) of the accounting domain for SMEs and the relations of the concepts (attributes). For example, tax exemption and reduction are part of accounting standards for SMEs. This ontology defines the concepts tax concessions and accounting standards, but also contains the relation between them — "isPartOf". Consequently, the inference engine can deduce that the knowledge on tax reduction can be found under accounting standards form SMEs. Then the pedagogy ontology classifies the training materials into theory, cases, Q&A, simulated practice, etc. At last, the structure ontology clarifies the logic relations among each training materials, which constitutes the hierarchical links, such as "hasPart", "nextLevel".

The following is an example of the Q&A system — a graphical user interface displaying information on a window (See Figure 7). The suggested entries for similar accounts are presented based on the question input by accountants. It leverages semantically rich information about the invoice issuer and the type of service to calculate the similarity between cases. Similarity indicators are weighted differently so that the invoice topic is more important than the biller, which weighs more than the service type. This results in an importance ratio of 3:2:1, where “1” indicates the service rendered. The system calculates and ranks the similarity index between the question and each similar case, the figures can also be a reference to decision support for the accountants.



Accounting Cases | Accounting Standards | VAT Rates

Similar Cases

Date	No.	Topic	Transaction Description	Debit	Credit	Amount	Invoicer	Similarity Rate
Aug 6 2018	079	Travel accommodation	Medical conference in Hongkong	Travel expense - Accommodation	Accounts paypable - External party	$500	New World Hotel	91.23%
May 21 2022	387	Travel accommodation	Visiting a medical specialist in Beijing	Travel expense - Accommodation	Accounts paypable - External party	$245	New World Hotel	87.66%
Sep 17 2020	011	Travel accommodation	Marketing events held in Canberra	Travel expense - Accommodation	Accounts paypable - External party	$398	New World Hotel	83.33%

Figure 7. Example of User Query

In summary, SW and AI realizes semantic query, conceptual navigation and decision support on the Q&A with the following characteristics: Firstly, with the common ontology that can be linked with training materials from a variety of sources, the online training becomes autonomous and self-driven by individual staff. The online training mode enables searching and acquiring training materials according concerning the context of questions, and eventually fulfill personalization of training and mentoring. Further, staff can acquire knowledge in a non-linear manner to meet their interests and needs. Lastly, the integrate-ability of knowledge is valuable for SMEs, because SW can integrate training and mentoring activities that cover all of the necessary knowledge into a unified platform.

5. Conclusion

In this study, a general technique for acquisition of ontology instances from the text of accounting domain is developed in the conceptual model. A fundamental layer of ontology is developed, which is indexed vertically by a variety of information sources. A semantic data model that adopts ontology can reasonably integrate various data sources into a single information set. Integration of different data sources can be implemented without interrupting existing application and software, via developing ontology based on data and contents sources and inserting commonly used domain knowledge. SW enables mapping of each source (e.g. records, files, documents) to this unified ontology as RDF & OWL is used as a standard semantic format for heterogeneous information sources. As a result, users in SMEs can access a wide range of knowledge through application and software. As a result, variations in how a term is represented within the accounting domain will not prevent computers from recognizing and interpreting information from different sources. The unified ontology based on predefined meaning (e.g. data semantics) provides the only integration of various data representation. Meanwhile, the conceptual model of inference engine enabled by ML technologies (e.g. NLP approach Prompt, deep learning) as well as a query model that is supported by SPARQL, SMW, SCOOBIE and RDF-related language converters is proposed to undertake knowledge derivation, ontology enrichment, CBR process and user query, improving the quality, completeness and accuracy of KB and query. In short, the SW allows machines to understand data, while AI enables them to analyze the data and drive actions, decisions, and innovations, leading to optimized KM. By leveraging this convergence, it becomes possible to power smarter applications and refine user experiences in unique ways.

Based on the experimental results, a major application of this SW & AI-capable KM in SMEs is the Q&A for online training, mentoring, and decision support. Improving the skills and abilities of employees plays a key role in enhancing the competitiveness of enterprises, and SMEs should personalize on-the-job training. It turns out that traditional learning methods can no longer meet this requirement, while online training and guidance allows Employees can acquire knowledge in a non-linear manner to suit their interests and needs. Integrating knowledge is valuable for SMEs, just as the SW and AI can integrate knowledge from different sources using a common ontology that shares interpretation mechanisms, aiding the KM to find the best answer from the candidate answers. This continuously improves the accuracy and reliability of the system, and the ability to understand complex queries and answers to them. The KM also provides a graphical user interface that embeds knowledge services with accounting work and helps with decision support using indicators to improve the user experience.

6. Limitation

It is necessary to acknowledge the limitations of this work. Firstly, the sample size is relatively small, leading to insufficient generalizability of the model. Regarding the model, OWL is limited by non-uniqueness of names for objects and knowledge inference resulted from the logic model of open-world assumption, and disallowance of composited attributes (Antoniou & Harmelen 2008). Further, the extended potential of these RDF triples, such as interfaces to more platforms (websites that are not open repositories), are yet to be developed, although the properties of accounting knowledge have been exploited in RDF constructs. This integration can further lift the explanatory depth of Q&A mechanism (Li et al., 2024). Moreover, the NLP model LLM remains limited in-depth comprehension and may lead to incorrect or meaningless output. Additionally, LLM can learn and perpetuate bias from training data, resulting in erroneous outputs. In addition, LLM is prone to errors in such tasks dealing with mathematical calculations requiring strict accuracy and logic. In other words, LLM is good at understanding ambiguity and flexibility in language (Kaddour et al., 2023; Kambhampati 2024). Much more investigation is required to determine how KM and SW may be heavily integrated with NLP technology components like ChatGPT, improving knowledge accuracy and accounting practice efficiency. Apart from that, research on mitigation or elimination for the disadvantages of RDF and OWL should be undertaken in the future.

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