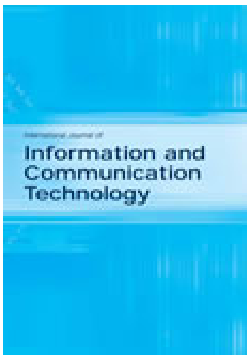


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# Knowledge graph-based analysis and intelligent recommendation of entrepreneurship course content

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# Knowledge graph-based analysis and intelligent recommendation of entrepreneurship course content

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**Abstract:** This research presents a knowledge graph-driven recommendation system for entrepreneurship courses, incorporating data collection, pre-processing, entity recognition, graph analysis, and recommendation algorithms. By combining semantic relationships with collaborative filtering, the system enhances personalisation, improving both accuracy and user satisfaction. Knowledge graphs provide a structured representation of entities and their relationships, enabling more relevant and context-aware recommendations. Leveraging this capability, the system aligns course suggestions with learners' preferences and educational goals. Prior studies highlight the effectiveness of knowledge graphs in domains such as tourism, education, and e-commerce for improving recommendation precision. The proposed workflow follows sequential stages, including data pre-processing, knowledge extraction, graph construction, analysis, and algorithm development. integrating top-down ontology design with bottom-up entity extraction, guides knowledge graph creation. Experiments on a dataset of over 6,000 educational resources achieved stable accuracy after 80 training epochs using the BERT-BiGRU-MHSA-CRF framework. User evaluations confirmed higher engagement and satisfaction compared to baseline models.

**Keywords:** knowledge graph; recommendation system; entrepreneurship education; data pre-processing; semantic analysis; collaborative filtering.

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## 1 Introduction

The data graph is a graphical representation of knowledge that describes items and the interactions between them. The area of artificial intelligence is seeing this as a promising new area of study. Through the utilisation of entities and relationships, knowledge graphs (KGs) enable the compelling depiction of intricately linked data (Huang et al., 2024a). Information extraction, knowledge integration, and processing make up the three tiers that make up the technological framework for building a KG. Knowledge processing optimises and further processes the extracted and integrated knowledge, knowledge integration resolves data conflicts and redundancy issues through processing knowledge from different sources, and information extraction extracts entities and relationships from various data sources (Deschênes, 2020). An intelligent and effective method of organising data is a KG. Numerous applications rely on it, including query answering, search engines, recommendation engines, artificial intelligence assistants, and natural language processing. Users can use it to find what they need more quickly and accurately. YAGO, Concept Net, Google KG, Wikidata, DBpedia, and Freebase are some well-known KGs (Duan et al., 2021). Given KGs' potent capabilities in knowledge representation, their coupling with recommendation systems has given a significant boost to the quick creation of intelligent teaching systems. In recent years, KGs have seen extensive use in recommendation systems. Using a sort of structured knowledge representation that incorporates both multi-dimensional features and extensive contextual Information, we may better understand user demands and make recommendations that are both correct and relevant. Using several types of supplementary data better to identify consumers' hidden interests and product attributes improves the accuracy of recommendation systems. By making complete use of the latent knowledge in graph-structured data, KG recommendation systems have recently attracted a lot of interest from researchers and businesses alike. This is because these systems have improved recommendation accuracy and made recommendation results easier to understand and work with (Huang and Chen, 2024). Prior work primarily used propagation-based techniques to integrate entity and connection representations, higher-order connection patterns, and auxiliary Information in KGs; this allowed for the generation of more personalised recommendations and full utilisation of KGs. A typical basis for the execution of this strategy is graph neural network technology. Propose the groundbreaking Ripple Net model that revolutionised KGs by integrating a method for preference propagation. It achieves this by collecting user preferences across all of the knowledge entities and then automatically expanding those preferences over the linkages in the KG (Amiri and Rahmani, 2021). One such model is KGAT, which stands for KG attention network. It depicts the KG's intrinsic higher-order connections from beginning to finish. Ongoing comprehensive evaluations of the entire line loss process are currently lacking in the power grids business.

Innovative grid technology development in these articles requires expertise in computer science, AI, and relevant application domains (Kor et al., 2024). A large amount of data must be analysed and processed before neural networks or upgraded recommendation systems can process data. Urgently needed is a thorough scientific assessment of the power grid due to urbanisation, power grid facility age, and the illogic of planning (Sabouhi and Doroudi, 2020). Examining the electrical grid's weak spots allows for more targeted upgrades, transformations, and planning efforts by revealing exactly where the system is lacking. As AI continues to make rapid strides, a new cognitive computing paradigm called the KG is starting to be used in the electric power sector. This approach effectively manages the complex knowledge structure and large-scale, multi-source, heterogeneous data associated with the power grid evaluation process by combining the knowledge of domain experts with that of technical individuals (Ji et al., 2022). KG technology sheds light on the static and dynamic properties of complex knowledge domains via data mining, information processing, knowledge assessment, and visual depiction.

It can move data from one place to another, and its cognitive computing and reasoning capabilities also make it easier to join seemingly unrelated datasets into meaningful relationships. KGs are great for issues with identifying security policy consistency. In this study, we will integrate our previous work on security policy consistency detection with state-of-the-art KG technology to provide a novel approach to recognising network security policy consistency using KGs (Hogan et al., 2021). The new approach is based on the following key points:

Given the nature of policy consistency detection as a task, we suggest a KG structure with four layers for this type of work. We offer a practical formal method for detecting policy consistency.

- Here you can find detailed instructions on how to use a KG to discover policy consistency.
- Meanwhile, the KG's intelligent computing and reasoning capabilities are put to use to provide ways for implementing certain expanded functions pertaining to policy consistency detection.

There are a total of five sections in this article. Section 1 provides an introduction to the topic and outlines the motivation for the study. Section 2 reviews related research and discusses key findings from previous studies that informed this work. Section 3 describes the proposed methodology, including the approach for building a knowledge graph (KG) capable of detecting inconsistencies in network security regulations (Duan et al., 2025). Section 4 presents the implementation process and experimental analysis used to verify the consistency of network security policies for access control instances (Li and Wang, 2024). Finally, Section 5 concludes the article with a summary of findings and recommendations for future research.

## 2 Related work

KGs have been the subject of several recent initiatives in the tourism industry, with most of these initiatives relying on data retrieved from various online sources (Bloch and Jackson, 2023). From ideation to hosting, curation, and deployment, researchers created a methodology and set of tools to help with the whole KG life cycle. Their curation strategy hinges on the accuracy and comprehensiveness of the KG. They evaluated the developed tools for the tourism sector using KGs and process models. Furthermore, they disseminated knowledge gained from applying this strategy to other use cases in both public and private sectors (Chen et al., 2024). As part of Expo Milano 2015, I created a KG example for the tourist domain. The 3cixty platform may provide a wealth of Information, including descriptions of events and activities, places and landmarks, transportation alternatives, and social events. The goal of the Tourpedia platform, which the Ope NER Project created, was to make it the de facto encyclopaedia of the travel sector (Buscaldi and Dessí, 2024). Several additional projects in the tourism sector have proven the efficacy of using KGs and semantic technology to extract data from curated private sources. The La Rioja Tourism KG and the Tyrolean Tourism KG are two prime examples. The first one combines Information from different management systems that deal with things like restaurants, vineyards, attractions, lodging, tourist routes, events, and activities. The second one solicits information technology service providers and DMOs to submit data annotated using Schema.org (Angioni et al., 2024). An additional state-of-the-art choice is the development of KGs for Chinese tourists; authors compile Information from both structured and unstructured Chinese websites.

In the linked open-data global arena, KGs like DBpedia are easy to expand and combine with other KGs. Their customisable structure allows them to hold any sort of data or metadata.

### *2.1 Background*

To improve search capabilities, Google first popularised KGs (Schöbel et al., 2024). Then, KGs were promoted as a dependable way to organise huge volumes of diverse data when large language models (LLMs) were introduced. They found applications in areas such as question answering, recommendation systems, and semantic search. KGs enhance data retrieval performance, simplify trained models, and mitigate hallucinatory effects seen with LLMs (Cadeddu et al., 2024) by depicting things as nodes and their relationships as edges. The necessity for thorough improvement and evaluation, varied data sources, and sophisticated connection learning all contribute to the difficulty of building high-quality KGs (Huang et al., 2024b). Looking upon prior research on LLM-driven hallucinations and information gaps (Du and Li, 2022), this analysis gives a summary of research on KG construction from 2022 to 2024, spanning extraction, learning, and evaluation. Insights for future innovation are offered by identifying critical difficulties and unresolved concerns in the current KG ecosystem through this exploration.

### 2.2 Recommender systems

The appropriate scientific literature has investigated recommender systems in a number of different domains. A wide variety of situations and applications make use of them, including online education, entertainment, social media, and travel. In those studies, the most popular algorithmic solutions used were hybrid approaches, content-based filtering, collaborative filtering, and machine learning (Hofer and Obraczka, 2024). One study found that ratings based on a single factor are the most common in recommender systems (overall rating). According to a study from 2020, one of the drawbacks of the popular way of constructing recommender systems, collaborative filtering, is the cold-start problem. This occurs when there is insufficient data to make inferences about people or items. Recommender systems for online classrooms are still a hotspot for innovation. In these types of systems, two critical things happen: first, the people getting recommendations are learners, and they have complex and nuanced attributes like their knowledge level. Second, the things that people get recommended to them, like learning activities, educational resources, and assessment components, can have a significant impact on how much knowledge they get (López and Alor-Hernández, 2020). The foregoing points to the apparent need for more research and development in the area of recommender systems.

#### 2.2.1 KGs for recommendations

In order to better track user preference changes and give more contextual recommendations, recommender systems have begun to incorporate KGs. The study of recommender systems based on KGs is, in fact, an active area of research (Jena et al., 2023). They find use in many different fields, such as tourism websites, online museums, e-commerce sites, film portals, and biomedical platforms. Recent meta-analyses have shown that connection-oriented techniques, embedding-based methodology, and propagation-derived methodologies are the most commonly employed ways in the literature for KG-infused recommender systems. Investigating recommender systems based on KGs, the authors of the paper presented Sem Rec, a model that takes into consideration the liked and disliked things that users have previously viewed. This approach employs a weighted meta-path to aggregate attribute values into links, which improves the representation of item linkages and user similarities.

## 3 Material and methodology

Data gathering, pre-processing, knowledge extraction, graph building, analysis, recommendation development, system deployment (Choi and Jung, 2025), and evaluation are all depicted sequentially in this workflow diagram for the entrepreneurship recommendation system.

### 3.1 Data pre-processing and knowledge acquisition

Entity recognition performance can be enhanced by including domain knowledge into the vocabulary, which in turn helps with entity recognition. The effectiveness of pre-training models like BERT that rely on raw data for entity detection in vertical domains could be diminished due to the dearth of labelled data. In order to tackle this problem, this study begins by acquiring knowledge and pre-processing raw data. Future entity recognition accuracy can be enhanced by contributing to the development of more comprehensive knowledge mining and KG. Figure 2 further shows that the entity corpus construction process is carried out using the N-LTP, a language technology platform.

**Figure 1** Workflow of a KG–driven recommendation system for entrepreneurship education, from data collection to evaluation (see online version for colours)

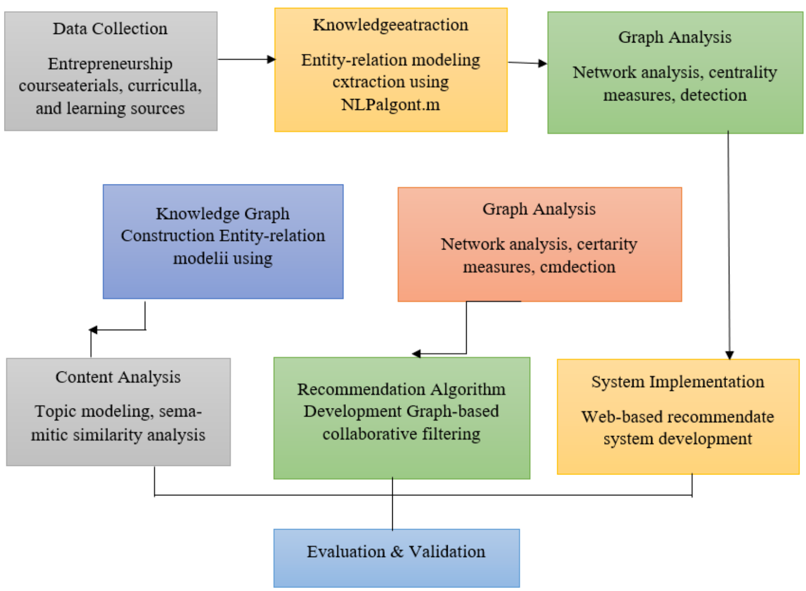
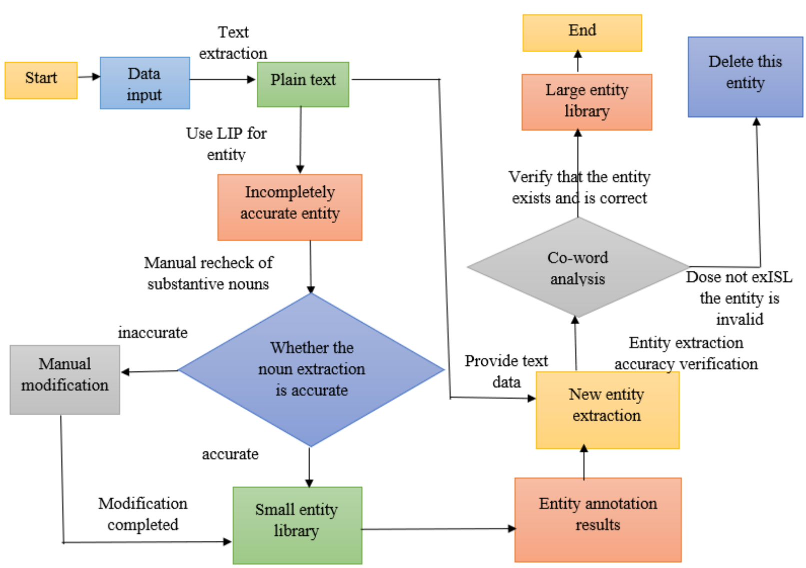



**Figure 2** Process flow diagram for extracting meaning from unstructured textual material (see online version for colours)

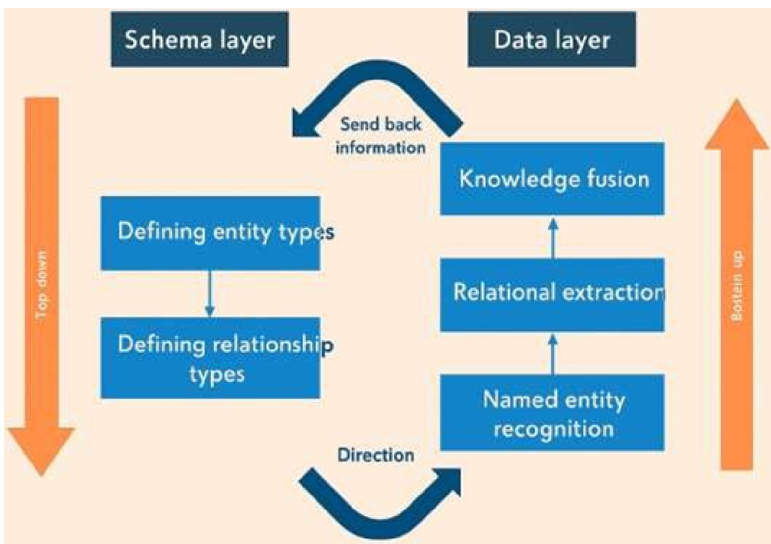


### 3.2 KG construction framework

KGs can be constructed using one of three primary methods: top-down, bottom-up, or hybrid. The bottom-up strategy prioritises knowledge extraction, whereas the top-down method begins with the definition of ontology information. The inverse is also correct:

Knowledge extraction from data comes after ontology information. The top-down approach is currently the most common for building domain KGs in the home country. The aviation health management domain is known for its many data sources and schema variances; however, this research proposes that a hybrid top-down/bottom-up design strategy would be the best approach. This approach relies on the schema layer outlining the data layer's expected entities and connections. The data layer incorporates the schema layer into its feedback loop as setup advances. In Figure 3, we can see the building process.

**Figure 3** Methodology for building KGs (see online version for colours)




### 3.3 Development of recommendation system

Building a reliable recommendation engine for business courses requires combining KG and CR data. It is possible to integrate the KG's hierarchical knowledge matching with the rest of the course material's output by using clustering algorithms tailored to both the KG and the course content. When put into action, these parts provide the system with a comprehensive picture of the interconnections among entrepreneurship's many themes, ideas, and assets. KGs map the entities using a semantic framework. Consequently, ideas are not presented in a vacuum, and pertinent connections are made between various objects. The accuracy of the results is further guaranteed by grouping related search terms. Plus, with the KG's help, the recommendation system can take advantage of similarities across materials in addition to lexical similarity and semantic context that meets the learner's request.

### *3.3.1 Recommendation algorithm design*

In order to create a reliable recommendation system for business classes, one must adhere to the principles of algorithm design. In order to provide subject- and user-specific contextualised suggestions, these algorithms take advantage of the combined KG and CR. Based on how similar a learner's activities are to other learners' interactions with the course content, collaborative filtering algorithms can suggest courses and resources to them. To ensure that the suggestions are relevant to the student's tastes and objectives, content-based filtering methods look for appropriate items using KG and CR attributes. Hybrid recommendation systems integrate content-based methods with collaborative filtering to produce more varied and high-quality suggestions. Nevertheless, machine learning techniques such as neural networks and matrix factorisation can enhance the learning environment through better prediction and a more organised list of things to learn.

### *3.3.2 User interface design*

Design: create a helpful and easy-to-use system that shows entrepreneurship course recommendations by giving significant consideration to the user interface design. An engaging, straightforward interface that facilitates rapid content browsing should be the objective of the user interface design in this instance. Users' profiles, learning objectives, and preferences should inform the presentation of tailored recommendations that prioritise their needs in the interface customisation process. Allowing users to rate the usefulness of suggested resources or express their appreciation for desirable content categories is a great way to get their input on recommendations. There should be a number of ways for the user to sort and filter suggestions in the interface, including by difficulty, topic relevance, and format (the ability to include phrases like direct quotes via text, video, or interactive modules).

Incorporating visually appealing tools such as progress trackers, charts, and graphs can further enhance the user experience by providing easily understandable data. They display the new Information regarding the plan to achieve specific objectives. In general, a better outcome is achieved when a well-designed user interface entices the user's engagement, happiness, and learning.

## 4 Result and discussion

Course Grading and Edu coder, two well-known Chinese online learning sites, provided the data used in the investigation. In particular, the studies were centred around a C programming course that utilised the cloud platform to download more than 6,000 instructional papers. We selected one hundred students at random to serve as participants for the experimental validation. Course KG was built using a variety of digital teaching materials, including electronic textbooks, courseware, exams, and syllabuses. We used the Chinese word segmentation tool Jieba to clean and prepare the textual data before training so that it would be compatible with the Chinese BERT approach. Our extraction of 6,028 Chinese characters followed an assessment of 27,042 valid phrases extracted from the training materials. In Table 1, you can see the data in its raw and processed forms.

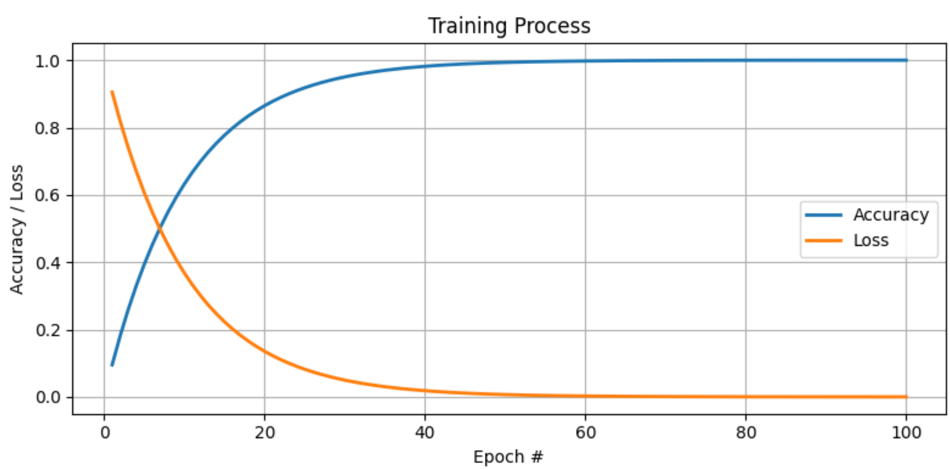
**Table 1** The datasets, both raw and cleaned

| *Raw data* | | | | *Pre-processed data* | |
|---|---|---|---|---|---|
| *# electronic textbooks* | *# syllabuses* | *# courseware* | *# tests* | *# Chinese characters* | *# sentences* |
| 100 | 20 | 20 | 20 | 6,028 | 27,042 |

Note: There are many things that the symbol # might represent.

Annotating a corpus of 6,028 Chinese words with BIOES resulted in knowledge point entity extraction using the proposed BERT-BiGRU-MHSA-CRF framework for data pre-processing. Before training the model could begin, word vectors were obtained using pre-training with the BERT module. After that, the BiLSTM module received these word vectors and trained them further. Before that, the correct label sequence for the BIOES module was anticipated by means of the CRF decoding method. All the while the model was being trained, we kept loss and accuracy in mind. Seeing the loss and accuracy curves in Figure 4 gives a visual idea of how well the model did throughout training (Troussas and Krouska, 2023). The loss curve shows the training errors, while the accuracy curve shows the model's data recognition ability. The results demonstrate that the loss and accuracy both improve with increasing epoch count. This provides more evidence that our model was learning to become more accurate. Since the model achieved consistent performance after about 80 epochs, it seems that more training cycles might not produce significant improvements. The accuracy and loss curves show that our model converged and performed well after about 80 training epochs.

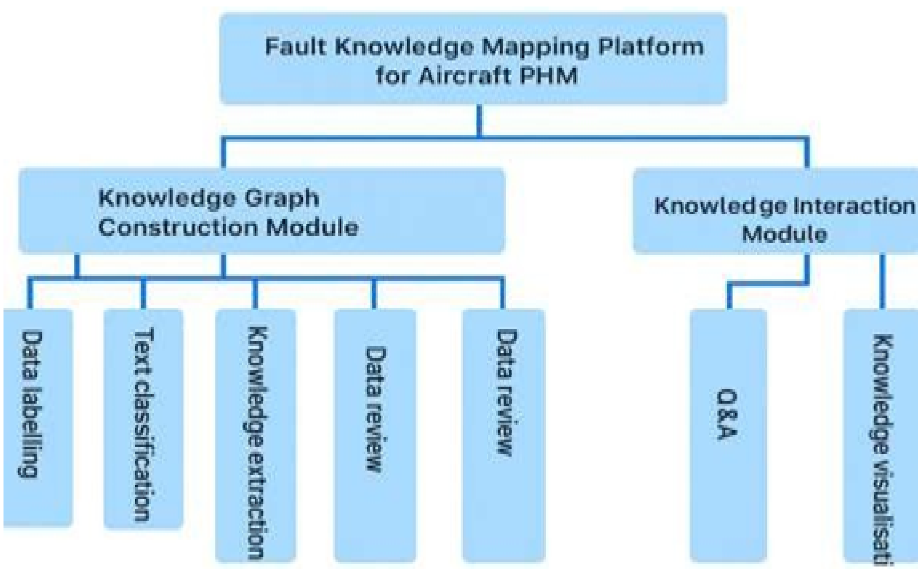
**Figure 4** Accuracy and loss curves as they pertain to training (see online version for colours)




This work presents a defect KG platform that is specifically designed for aircraft PHM. Its purpose is to simplify data administration and speed up the building of KGs that are directed toward prognostics and health management (PHM). The platform's functional modules are depicted in Figure 5, which also shows the system's architecture as a whole and the links between each module.

Figure 5 displays the knowledge mapping platform's functional modules specific to aircraft PHM concerns. A module for creating knowledge maps and another for interacting with existing knowledge are components of it (Meng et al., 2024). Using the data annotation tool, ternary data can be annotated, and training instances can be provided for the knowledge extraction technique. Sentence classification is one way the text classification function helps make knowledge extraction less affected by text-to-text semantic complexity. Through the use of the knowledge extraction tool, the types of entities and relationships are recovered from the text. You can manually audit the ternary extraction effect using the data audit tool, which lets you modify the results. Data that users submit, such as statistics on equipment failures, details about the structure of equipment, and visual representations of equipment status, are handled by the data management function. Through the use of visual representations of data and intelligent feedback on user questions, the knowledge visualisation and intelligent Q&A functions enhance human-computer interaction (Wang et al., 2025). Figure 6 shows the functional architecture of the system, which consists of three layers from top to bottom: application, interface, and data. The front-end quality assessments, data annotation, and knowledge extraction from documents are all made possible by the user-centric application layer. Knowledge visualisation and intelligent question posing and answering are further capabilities of the knowledge interaction user. At the same time, the interface layer encapsulates the implementation details and acts as the core of the system, making the system's functions actual. Finally, the Neo4j KG is mostly part of the data layer of this system. Subsections 5.3 and 5.4 provide the specifics of the functional architecture of the system.

**Figure 5** System functional module diagram (see online version for colours)




Design of a module for building KGs modules for managing data, annotating it, extracting it, classifying it, and generating KGs audit, and file and text categorisation into its design flow, as illustrated in Figure 7. In particular, algorithms run in the background to automatically classify texts and extract relevant knowledge. Thereafter, the data management, knowledge audit, and data labelling modules' implementation will take centre stage.

**Figure 6** Functional diagram of the system (see online version for colours)

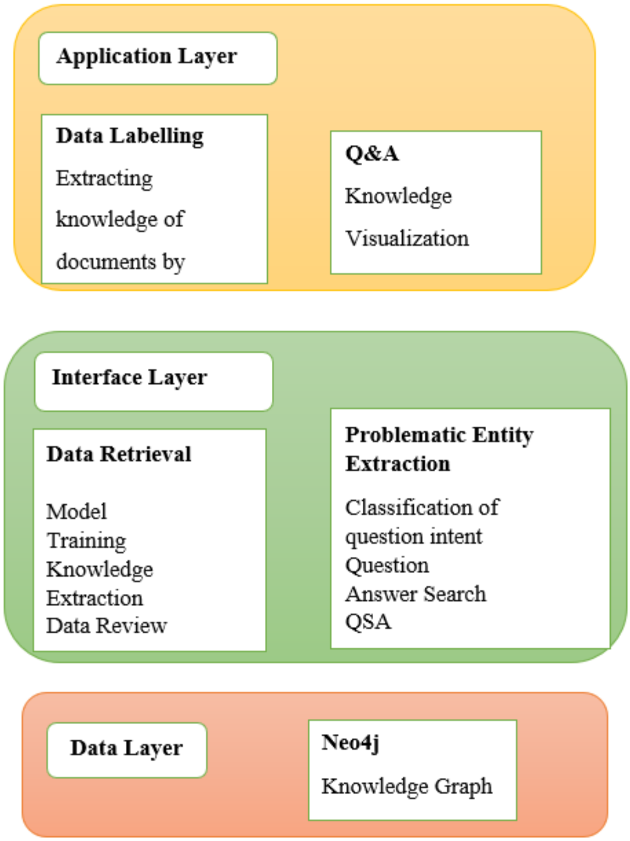
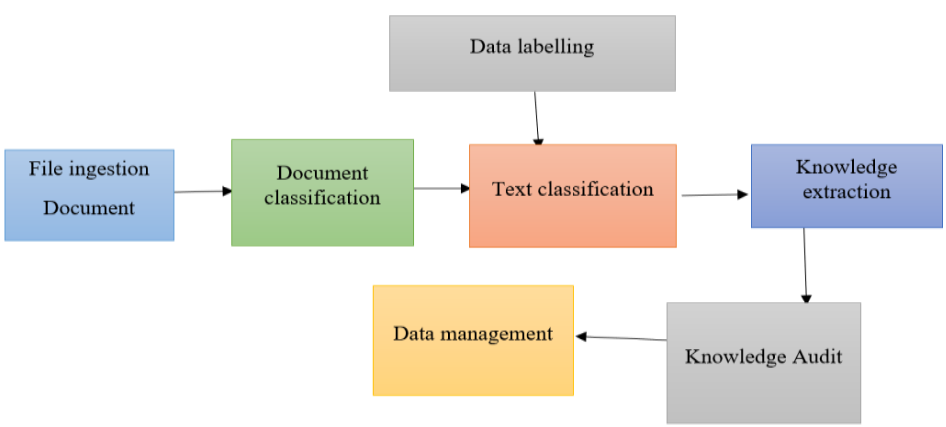



**Figure 7** KG building module design process (see online version for colours)



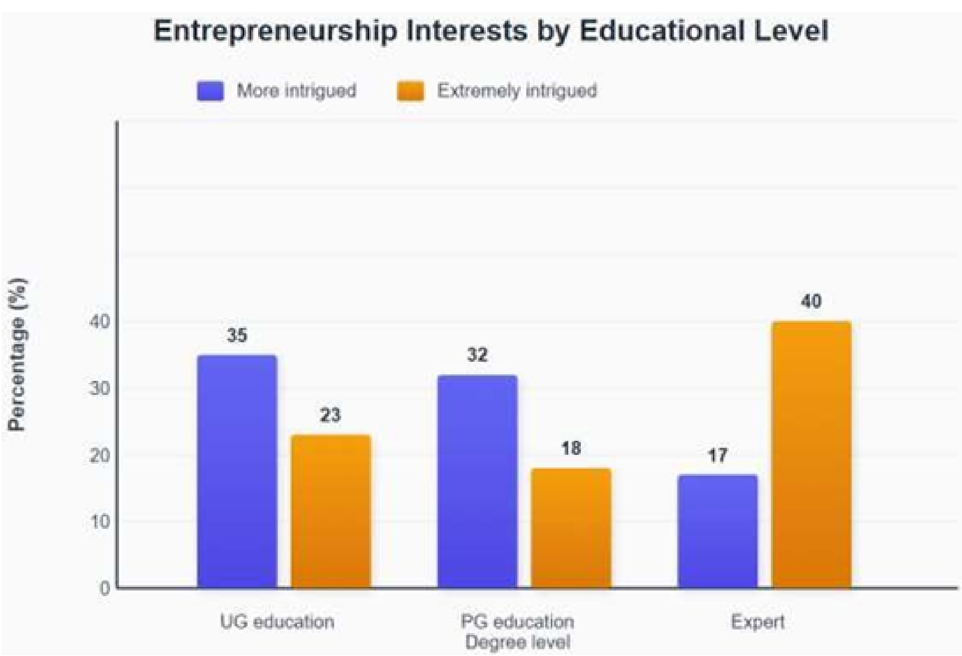
The purpose of this part is to analyse and interpret the research findings about the student entrepreneurship course recommendation system. This necessitates comparing the previously acquired re-crossing results with pre-existing benchmarks or baseline models. The system's recommendations, user input, and trends in system utilisation are all part of this research, which also includes a strengths, weaknesses, opportunities, and threats (SWOT) analysis.

**Table 2** Examination of entrepreneurial aspirations across grade levels

| *Degree level* | *More intrigued* | *Extremely intrigued* | *Overall* |
|---|---|---|---|
| UG education | 35 | 23 | 38 |
| PG education | 32 | 18 | 39 |
| Expert | 17 | 40 | 32 |
| *Map of entrepreneurial interests by education (%)* | | | |
| | *UG* | *PG* | *Expert* |
| More intrigued | 2.2 | 3.8 | 1.5 |
| Extremely intrigued | 5.5 | 8.2 | 2.6 |

To get a complete picture of the system implementation, quantitative measurements are used in conjunction with qualitative research approaches, including interviews, questionnaires, and usability studies (Li et al., 2024). The data that is streamed from the outcomes of the analysis is utilised to make incremental improvements and make the system stronger at helping people learn and unlock their full potential. In Table 2, we can see the results of an examination of entrepreneurial interest divided by educational level.

**Figure 8** Comparison of average scores between groups A and B across three categories (see online version for colours)



Based on the bar chart in Figure 8, entrepreneurship interest varies by educational level. The chart shows that while undergraduate students are more likely to be 'more intrigued' by entrepreneurship, individuals at the expert level are far more likely to be 'extremely intrigued'.

## 5 Conclusions

This study demonstrates the effectiveness of integrating KG technology with advanced recommendation algorithms to enhance entrepreneurship education. By systematically collecting, pre-processing, and extracting knowledge from diverse course materials, the proposed system constructs a robust KG that captures semantic relationships among entrepreneurial concepts, resources, and learning activities. Collaborative filtering, content-based methods, and hybrid recommendation systems all work together to give students recommendations that are specific to their needs, interests, and goals. Experimental results, supported by both qualitative and quantitative evaluations, highlight the system's capability to improve recommendation accuracy, learning engagement, and user satisfaction. The findings confirm that KG-driven recommendation systems can significantly advance adaptive learning in entrepreneurship education by offering richer semantic context, better interpretability, and more relevant learning pathways. Future research will focus on expanding domain coverage, enhancing cross-platform interoperability, and integrating real-time learner feedback to refine recommendation precision and scalability further.

## Declarations

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All authors declare that they have no conflicts of interest.

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