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A SEMWORD based Semantic Secure Content Retrieval System in E-learning

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Abstract

Objectives: The semantic e-learning model aims to be the next generation of e-learning as it enables advanced representation, manipulation and re-use of learning materials and knowledge semantics in efficient online learning experiences. The modeling of semantic-based content retrieval for e-learning with secured content. This system will provide users with access to relevant educational resources in an easy-to-use, secure, and anonymous environment using semantic technologies. **Methods**: Semantic Web resource description format is proposed in this document by using a framework for automatically generating semantic words (SEMWORD) based on a user's keyword. **Findings**: Using SEMWORD and user queries to generate RDF (Resource Description Framework) for the query processor, this work aims to find relevant semantic content. In order to find semantic content, the semantic word is mapped. In e-learning, the tuned semantic content is built into constraints, such as B. In order to ensure security, the Learner needs to log in and enter their credentials. Students are recommended semantic-based content with relevant information based on their interests based on the retrieved semantic content. **Novelty and applications**: This e-Learning system employs semantic web in a three-fold utilization. It includes describing the semantics of learning materials by using SEMWORD, defining their learning contexts, and structuring learning materials in courses using Semantic Web technology with the security aspect of novel encryption algorithm. Multidimensional use of Semantic Web in e-Learning is innovative and can potentially improve its effectiveness.

Keywords: Semantic Web; E-learning; SEMWORD; Security; Ontology; Content Retrieval System

1 Introduction

The field of Intelligent Systems for E-learning (ISEL) has seen a proliferation of works published in recent years that demonstrate various methods for knowledge representation. Nevertheless, these methods failed to consider relevance or semantics of web content. Concepts are used in linear learning methods to teach a course. If learners don't understand the current concept, they will struggle to advance to a new one. This course ideas will need to be browsed through several times for the learner to understand its fundamental concepts in order to overcome these difficulties. In order to understand a concept, learners must be able to relate it to related concepts they have already learned. The new semantic web technologies are used in this work to propose an online learning approach guided by several ontologies based web documents.

Using an ontology based on Domain, Unit, Topic (DUT) will serve as a means of orienting learners throughout the learning cycle for a particular course. In order to comprehend concepts, it is not sufficient to learn their isolated definitions. Learners acquire knowledge by learning the DUTs addressed by the course and gaining new insights, which allows them to gradually develop a deeper understanding of the learning model. By analyzing the semantic meaning of web pages using SEM WORD (Semantic Keyword), can build an ontology for the semantic web. DUT Ontology connects semantic words to one another, making it similar to a keyword. Data Processing, Security Verification, Semantic Indexing, Mapping, Query Construction, and Content Matching are the services provided by the proposed architecture in order to achieve the following objectives.

i. Employ SEMWORD to find relevant semantic content based on its semantic structure.

ii. Convert a user request word into a semantic keyword and construct the query from it.

iii. Use a semantic Mapping & Document Resource Modeling to match the semantic query with the semantic content.

iv. Sort the results according to their relevance to the query using learner interest.

The use of searchable encryption is an effective method for securing and protecting data in the cloud. The cloud provides users with the ability to retrieve encrypted data under the premise that their own data security and privacy will be protected. Unfortunately, most of the current content-based retrieval schemes do not represent the semantic information of the article adequately[(1)]. Providing machine-understandable web data, metadata, and other information objects is the goal of the semantic web. Semantic Web technologies include the latest buzzwords, such as AI, NLP, or Natural Language Understanding. There are four parts to the paper[(2)]: Architecture of Web 3.0, Current Web Status, Challenges associated with Semantic Web, Need for Semantic Web, Semantic Web and Online Education, and Applications of Semantic Web Steganography.

The proposal[(3)] is based on features derived from deep convolutional networks for privacy-preserving image retrieval. In the first step, images are encrypted using a novel hybrid encryption technique, and then an improved DenseNet model is built using the encrypted images. Cloud servers are then used to upload the encrypted images and fine-tune the feature extractor. In the meantime, the cloud server runs secure CBIR service. COVID-19 crimes must be prevented and controlled in order to control the pandemic. The paper[(4)] describes an intelligent system for retrieving legal information on the WeChat platform during the pandemic to provide efficient and convenient services. The People's Republic of China's Supreme People's Procuratorate published a report on "typical cases of national procuratorates handling crimes against prevention and control of coronary pneumonia." A ciphertext retrieval scheme based on deep learning language training is presented in the paper[(1)]. With it, the previous schemes' limitations of low relevance scores and semantic context-free search are overcome. The attention model mechanism makes the semantic vector context-relevant, and the BERT model's mask language prediction training makes the trained vector more semantic. By using the MRSE encryption framework, we were able to retrieve outsourcing cloud ciphertext.

Recent COVID-19 pandemics have highlighted the need for personalized e-learning applications, according to H.K.M.Al-[(5)]. Educational institutions are rapidly adopting e-learning as a part of their teaching process. Using semantic web technologies, this study evaluated a previously proposed adaptive e-learning platform that supports multi-personalization parameters and standardization across multiple learning management systems. The work[(6)] addressed two issues: the generation of DL data and the generation of DL architectures. In the overall framework, the system knowledge is separated from the DL architecture generation procedure in order to support adaptability towards frequent updates and new architectural approaches. Design strategy involves creating an ontology for DL generation and developing a rule for generating DL architecture and data. The work[(7)] proposes a novel semantic boundary learning (SBL) strategy for training deep-guidance decoders (DGDs). Using different encoders and feature extractors, we have confirmed the effectiveness of our approach on Cityscapes and the ADE20K most-frequent 31 classes. According to our results, the proposed DGD with SBL significantly improves the mIoU from 10.4% to 38.5% relative gain. As a result of combining semantic web and metaheuristic strategies,[(8)] proposes how web-based Learning Objects (LO) can be recommended based on learners' preferences. To recommend LO in virtual learning environments, existing resources from the Web are used. As a data consolidation method, the e-Learning Integration Ontology (e-LION) semantic model can be used to enrich machine learning analysis of various e-learning knowledge bases[(9)]. A semantic mapping to the source schema can be developed using the OWL 2 ontology (e-LION) is online available. A semantics-aware content-based recommender system, ICRS, was proposed, driven by AI techniques, that uses textual and contextual knowledge more meaningfully for personalized e-learning[(10)]. By using ConceptNet term expansion and contextual graph structure to augment recommendations, the Intelligent Content based Recommendation System (ICRS) framework infers semantic relations (concepts, relations, materials) using weighted values. The proposed recommender uses four ML-based models and a robust DL-based model, which of course are trained and tested using a semantic dataset created and tested for a specific domain based on the learner's interests.

In the paper [11], the main purpose is to illustrate how Web 3.0 technology can be used in e-learning. This essay will also summarize some of the benefits of this technology. They also explain in the end of the essay what challenges Web 3.0 technology will face in the near future. As a result of a systematic review, it was found that semantic networks, virtual reality, augmented reality, intelligent tutoring systems, etc. In the field of education, they are often considered to embody web 3.0 technology. This paper proposes a novel approach for evaluating relevance between search queries and Web pages based on each individual user by integrating a user component into a neural network for personalization, and proposes three strategies based on where the user component is embedded. The result is highly personalized relevance computation as a result of incrementally adding a user component to a non-personalized neural network. It provides quality calibrated results to the chosen users while ensuring no side-effects to others.

1.1 Research Gap

Based on the background study for this system, some of the research gaps would be focused are as follows,

- Research can focus on methods that automate or assist in the annotation process, ensuring semantic metadata is consistently and correctly assigned to content.
- To develop semantic search and retrieval algorithms in e-learning systems, advanced algorithms must be developed.
- It is necessary to explore specific security and privacy concerns in semantic content retrieval to incorporate security measures.
- In e-learning, there is a gap in terms of standardized evaluation metrics and methodologies. User satisfaction, retrieval accuracy, response time, and scalability can all be considered in evaluation frameworks.

Through this architecture, the learner has access to concept-oriented, relevant results in the e-learning domain, which solves the problems associated with traditional keyword searching. As part of this architecture, security-related issues are also addressed. Security threats to online e-learning are relentlessly inventive. They continuously develop new techniques to annoy, steal, and harm the system, masters of disguise and manipulation. There are now a lot of security threats online related to e-learning. The E-learning system faces several threats that are directly or indirectly related to it. There are many types of malware threats, such as spyware, phishing, SQL injections, and session hijackings. Figure 1 shows the layers in proposed framework.

Data Layer	Gathering raw information and build the keywords
Semantic Layer	Ontology Modeling & Mapping, Building Semantic Word, Structure & Query Processor
Security Layer	Content Encryption, Theft Protection, Identify Learner Login and Mange Credential Rule
Suggestion Layer	Suggest relevant information based on Ontology relation and Learner Interest

Fig 1. Proposed Framework

1.2 Research contributions

Contribution of this research fall into the following categories:

- Doing the semantic search with sparkling thoughts and enhance the possibilities of semantic model in the E-learning system.
- Developing a workflow of the secure semantic e-learning model with help of Ontology.
- Building an enriched semantic e-learning course model.
- Implementation of a learner interest algorithm helps to retrieve the probability of semantic content in web environment.

2 Methodology

The proposed architecture for semantic e-learning web concept retrieval employs conceptual representations of content other than keywords as domain knowledge and delivers conceptual representations of needs of learners. This architecture accomplishes concept representations, query generation based on semantics, and retrieval of appropriate results in order of quality and relevance using the learner's involvement.

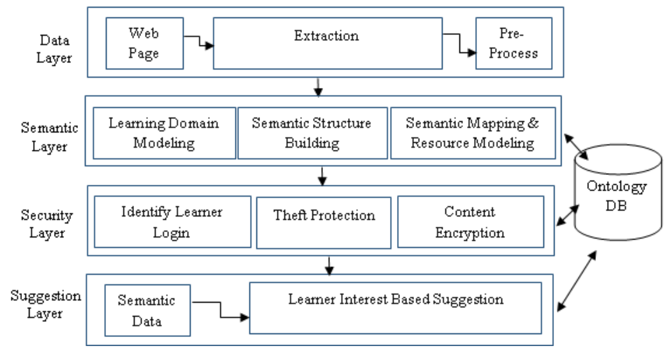

Fig 2. Flow of the Proposed Work

2.1 Data Layer

The Data layer done the data extraction from the web and cleaning process. Raw HTML file were extracted from the web. Learning model needs the valid data. So, the html file need to clean and clear the unwanted elements.

2.1.1 Extract Data

A web crawler extracts web content from web pages on various topics, domains, and courses. Collected web pages are temporarily stored in a local database for future search links and related web pages. Crawler results are sent to a preprocessor to get the raw content from these unstructured web concept documents. Use website links with automatic HTML content extraction algorithms.

2.1.2 Pre-Processing

During the e-learning process, document (Content) resources play an important role, since they address the concept that the learner tries to comprehend in detail. It must be possible to access them, make sure they are available, and make it easy for them to be found. Learners are presented with indexed resources on a concept as soon as they are in the vicinity of that concept. In order to find the best documentaries that fit his information needs, the learner has to browse the online resources. It is possible for the learner to deviate from his learning objective of a concept in this way, and an undesired amount of time and effort may be wasted. Prior to the matching of ontology concepts to unstructured e-learning materials, the content is preprocessed. HTML parsing is used to remove hollow HTML tags from the content extracted from the web. The unwanted words in the web document content, such as pronouns, articles, and symbols, are removed after the text has been extracted. As part of the cleaning process, stemming will be done to convert words into roots.

2.2 Semantic Layer

The semantic layer is in charge of building the semantic content structure with ontology mapping of the e-learning content for better associated knowledge discovery for the learners. With the Learning Domain Modeling & Semantic Structure Indexing, Semantic Mapping & Learning Resources Modeling, and Query Processor, this layer builds the ontology modelling for the content structure. The layer afterward uses a hierarchical semantic structure construction with the source DUT. A semantic structure is continued in e-learning content through ontology concept mapping. By integrating information from unrelated ontologies, it creates a concept tree that includes semantic correspondence between the elements. As a final step, the concept mapping tree is constructed using the best similarities. To retrieve semantic information for learners, the query processor is used.

2.2.1 Learning Domain Modeling & Semantic Structure Building

Learning Domain Modeling (LDM) is a data generation and usage schema process that is used to extend existing information access methods. The LDM used here is based on the concepts of the specific predefined DUT ontology as well as the semantic entities' meanings. These entities can be linked to formal descriptions, adding semantics and connectivity to the RDF. The RDF created by the Data Layer is converted into a knowledge base using the DUT ontologies. That is, the content of the web page corresponds to a concept in the predefined ontology. The LDM process associates web contents with their corresponding SEMWORD and semantic entities. In the same scenario as a keyword-based system, web contents are only associated with the keywords.

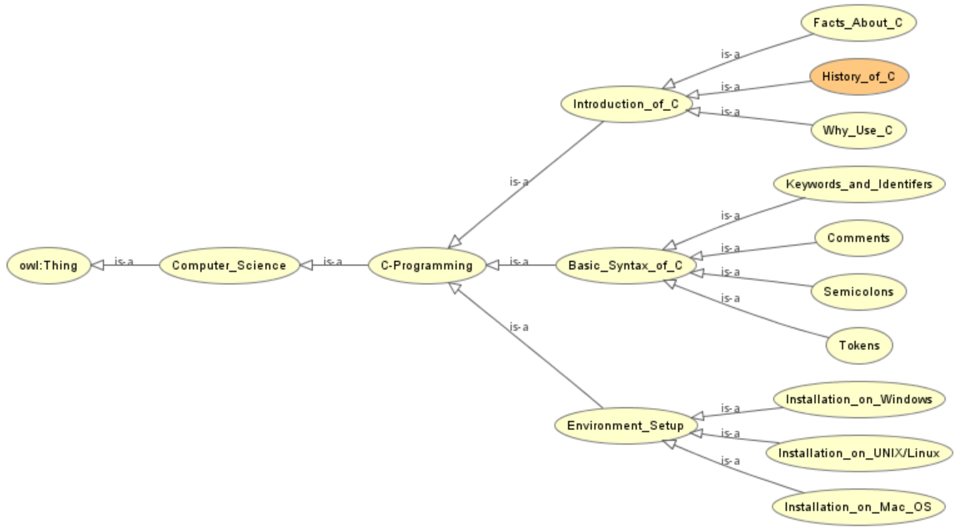

Fig 3. Domain Modeling

The knowledge base's annotated web content is the result of an ontology model with semantic entities.

2.2.2 Semantic Mapping & Learning Resource Modeling

Semantic mapping is the technique of calculating how well a segment of web content is mapped to an ontological concept. As a result, the indexer generates a weighted semantic indexing. Important keywords generated by HTML file tags such as H1, Title, Meta, and Anchor tags are taken into account. The presence of a concept in the URL of the content will be emphasized. The content is maintain as Semantic Model related resource.

2.2.3 Query Processor

The learner's plain keywords are constructed as a combination of SEMWORD and converted into semantic queries by matching the concepts in the DUT ontology. SEMWORD is the logical combination of the keywords. The learner receives the extended semantic query as an ontology suggestion. Using the suggestion, the learner chooses his search concept and submits it to the semantic content retriever.

```
# filename: sample.rq

SELECT ?CSubtopic
WHERE
{ ss:cprogrammingss:SubTopic ?CSubtopic . }
```

Fig 4. Sample Query

The final list of suggestions is the intersection of the set of online resources that include the SEMWORD and the semantic meaning. A table structure with two columns is utilized to extract the intersecting list. The first column contains the expanded query's query terms, while the second column has a list of concepts that match those query words. The weights obtained by the enhanced Learner Interest algorithm are used to determine relevance.

```
Algorithm SEMANTIC CONTENT RETRIVAL
{
Input: UQ-User Query, Raw Web Content- C
Output: Semantic Retrieval Content List
Procedure:
    1.  Extract Web Content Using URL
    2.  Remove HTML tags
    3.  Remove less meaningful terms or stop words.
    4.  Apply Stemming and find the root words.
    5.  Store into concept hierarchy of the Ontology Database
    6.  Read User Query Q = (Q1, Q2, ..., Qn)
    7.  Suggest SEMWORD Based on Query
    8.  Retrieve Related Content to the SEMWORD
    9.  Store it into the List of Tables.
    10. Re-Order the content based on User Interest
}
```

Fig 5. Semantic Content Retrival

2.3 Security Layer

The security layer includes a different security threat that occurs in the e-learning system in this layer. As a result, in the work, the document security threat includes content encryption and theft protection. The secure authentication process then includes authenticating the learner's login assistance in order to restrict access to the system to only the authenticated user and not unauthorized users. This layer prevents unauthorized users from misusing authenticated users' logins. This layer is also responsible for sub-modules like Content Encryption, Identify Learner Login, and Theft Protection.

2.3.1 Content Encryption

Any of the security approaches should be used to protect the content of this e-learning system from hackers. Hackers may observe the pattern of content management and the likelihood of discovering patterns for hacking. As a result, the work employs a novel technique known as Two Key Encryption Technique (TKET). The double-s in this TKET refers to the first letter of the guide's name and the scholar name of this thesis. The technique employs a novel approach to tightly encrypting the content and most likely employs dynamic patterns for encryption. The TKET is a method of containing the format of content encryption with the Row Key and Column Key. The row and column of the encryption key value must be the same while encrypting content using TKET encryption. The count of the row and column value holds "6". The row key (SUNDAR) and column key (EUNAIC) is a dynamically assigned value. The key is dynamically assigned for every encryption process. Thus, the hacker cannot probably observe the patterns.

```
Algorithm TKET
{
Input: I-Input Text, M- Matrix
Output: R- Row Key, C- Column Key, ECT- Encrypted Cipher Text
        1.  if( Column of Matrix = Row of Matrix)
        2.  {
        3.  for (int text=0; text<count(I);text++)
        4.  {
        5.  int temp=text[i];
        6.  Search Text 'Temp' in Matrix 'M';
        7.  R= Find Row key and Return Key value;
        8.  C= Find Column key and Return Key value;
        9.  temp =R+C;
        10. text[i]=temp;
        11. }
        12. ECT=text;
        13. Return ECT;
        14. }
        15. else {
        16. Error Message and Exit;
        17. }
}
```

Fig 6. Two-Key Encryption Technique

The algorithm for Two-Key Ecryption technique is depicted in Figure 6. The Algorithm represents encryption process of the e-learning content using two-key based encypted text. The input text is represented in the matrix that counts the every words of the content. The text words are fetched as row wise and encrypt the text using return key value and same as for column and return column key value. Finally, the encrypted text based on the two-keys are representation in the matrix.

The example encryption key and value of the matrix are shown in Table 1, the "Row Key=SUNDAR" and "Column Key=EUNAIC". The matrix value for the row and column key is represented with the alphabet content.

Table 1. Encryption Key and Value Matrix

Two Key(s)	**S**	**U**	**N**	**D**	**A**	**R**
E	A	B	C	D	E	F
U	G	H	I	J	K	L
N	M	N	O	P	Q	R
A	S	T	U	V	W	X
I	Y	Z	-	-	-	-
C	-	-	-	-	-	-

With this example encryption key table, the sample content is encrypted using the value of the key is shown in Table 1. The table depicts that the Original Text "PROGRAM" is encrypted using the TKET with the encryption key value from Table 2 . Then the Encrypted Cipher Text is given in the following table.

Table 2. Original and Encrypted Text

Original Text	**P**	**R**	**O**	**G**	**R**	**A**	**M**
Encrypted Cipher Text	ND	NR	NU	UU	EF	EE	NS

2.3.2 Theft Protection

Thieves can use course information in a variety of ways. This includes stealing the entire course or, more typically, taking individual texts from it. The learners are not permitted to replicate or steal content from this e-learning system. The system safeguards the material by limiting some alternatives for the learners. When the learners attempt to copy the material, they choose all alternatives and right-click to copy the content. As a result, the system disables options such as right-click pop-up menu, choose content, and shortcut key option for theft prevention. As a result, learners cannot reproduce or steal the material of this e-learning system without the knowledge of the experts

2.3.3 Identify Learner Login

E-learning system saves the IP-Address, Username, Login Time, Logout Time, and Login Mode information into the database with each login. The login mode of the learners is determined by the login details of each login. The primary goal of this login mode verification is to assist in verifying the learner's login from their PC, known PC, or unknown PC. The authentication fails for many times and the login is lockdown for the learners, if the learners uses their PC during login authentication. If the learner uses a known PC (guest PC) for login authentication, the authentication lockdown is set to 6 times to ensure that the learner logs in correctly. If the learner uses an unfamiliar PC (browsing center), the authentication lockout restricts the proper login to a maximum of '3' times.

2.4 Suggestion Layer

From many research noticed in a learning cycle, that each time whenever a learner is in front of a particular concept in the course, the related concepts play a significant role to initiate or strengthen his understanding of this concept. As a result, the proposed Semantic model is designed to connect the previous and next concepts with the current one. The linked ideas describe the logical path that the student must take in order to understand all of the topics provided in the course in an intuitive and effective manner. In our approach, learning different courses supplied by the domain is done in a different way than the linear learning technique, which consists of splitting a course into concepts, chapters, Units, and Topics. These concepts are apprehended concept by concept by following the relational logic modelled by DUT ontology. The retrieval list from the semantic layer is ordered by the suggestion layer based on the learner's interest. Learner interest is calculated in the following ways:

- The Learner activity is recorded on each navigation and search. The SEMWORD and semantic concept may be at the top of the list.

- The learner asks himself questions concerning the particular of the present notions. In this situation, he can compare the two concepts using a concept from another semantic axis. This helps him to uncover the differences between the two concepts and develop a clear mental image of their meaning.

The student must first comprehend other ideas that are required to understand the present concepts. In this situation, he can direct his search toward the missing ideas by selecting the First semantic connection that connects the concepts.

3 Results and Discussion

The proposed framework was created and tested as an online software application using Asp.Net and the. Net framework 4. Dynamic HTML (HTML, CSS, and JQuery) was used to create the user interface, while ASP.NET with IIS Server and RDF.NET was used to provide the business logic. Core i7 processor, 16 GB RAM, and 1 TB hard disc are included in the development hardware environment. The test data is added from various computer science subject areas such as Java, CPP, and C. The semantic extraction module is used in this experiment to extract essential ideas from the DUT and translate them into semantic patterns. Following that, a total of queries from the experiment data domains were input into the Proposed System to execute semantic query extension. The semantic query and semantic content are used in the search. Precision (also called positive predictive value) is the fraction of relevant concepts among the retrieved concepts, while recall (also known as sensitivity) is the fraction of relevant concepts that were retrieved. Both precision and recall are therefore based on relevance. Figures 7 and 8 shows the Precision and Recall of the User Search.

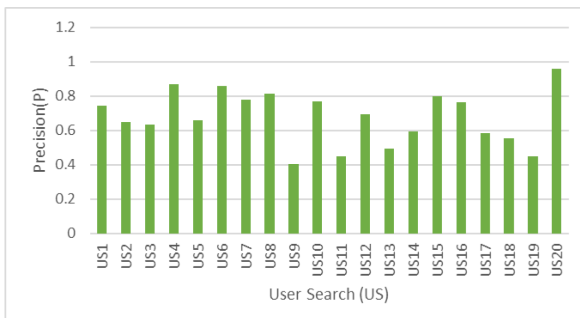

Fig 7. Precision

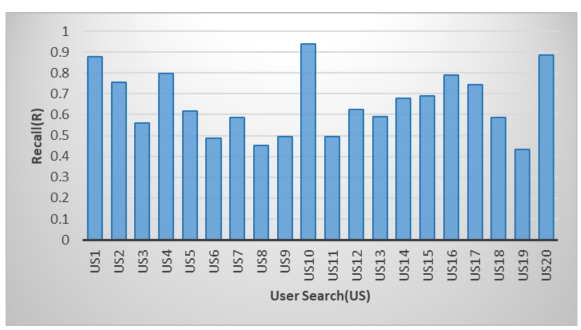

Fig 8. Recall

$$Precision\ (P) = \frac{No.of\ Related\ Concept\ Retrived}{Total\ No.of\ Concepts\ Retrived} \tag{1}$$

$$Recall\ (R) = \frac{No.of\ Retrived\ Relevant\ Concept}{Total\ No.of\ Relevant\ Concepts} \tag{2}$$

F-measures are calculated as harmonic means of precision and recall. When describing the model's performance and comparing models, it is helpful to take both precision and recall into account when evaluating a model. The F-Measure values for the User Search are shown in Figure 9.

$$F - Measure\,(F) = 2PR/(P+R) \tag{3}$$

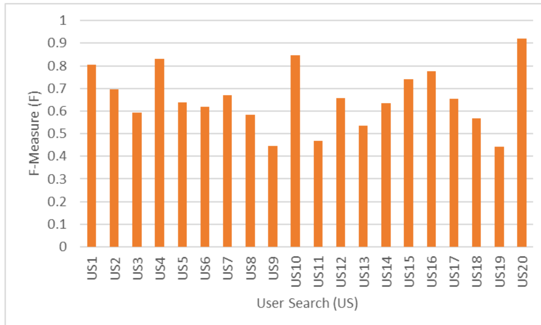

Fig 9. F-Measure

Response time includes the time it takes for the computer to process the query, send back the response, and then transmit it back to the learner. An interactive system's response time is often used as a measure of its performance. Figure 10 shows the Response Time for the User Search.

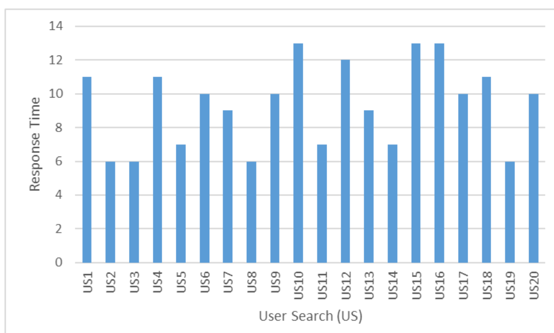

Fig 10. Response Time

3.1 Comparative Analysis

This section includes the comparative analysis for the existing e-learning systems with the proposed system SEMWORD. The existing system has the following objective work:

- As part of the e-Learning Integration ONtology (e-LION) [8] semantic model, different knowledge bases for e-learning are consolidated to allow for enhanced machine learning analysis. In order to develop semantic mappings to the source schema, it needs to be developed as an OWL 2 ontology. Based on four case studies involving predictions and time-series forecasts of students' interactions regarding grades, along with Semantic Web Rule Language (SWRL) reasoning rules for classifying student behavior, the proposed semantic approach is validated.
- The aim of the work SAIFCER [9] is to present an intelligent method for retrieving web content and recommending it according to a student's preferences, such as Learning Styles (LS) and knowledge level, as learning objects. This work aims to combine some tutor information with web content as part of the retrieval process of LOs.

Based on the analysis of the existing works, e-LION [8] and SCAIFCER [9] is compared with the proposed SEMWORD to analyze the benefits of it. The proposed method SEMWORD has its advanced representation and manipulation of learning materials: The proposed semantic e-learning model enables the advanced representation and manipulation of learning materials, which can improve the efficiency and effectiveness of online learning experiences. The model also enables the re-use of learning materials, which can save time and effort in creating new materials and can facilitate the sharing of resources among educators. The proposed system includes a novel encryption algorithm to ensure the security of the content, protecting both the learners and the educational institutions from potential security threats.The system is designed to provide personalized recommendations to learners based on their interests and preferences, which can improve engagement and motivation. The use of Semantic Web technology in e-learning in a multidimensional way is innovative and has the potential to improve the effectiveness of e-learning. This could lead to increased adoption and use of e-learning in educational institutions and organizations. Thus the proposed model SEMWORD gives better results than existing systems.

The existing systems e-LION[8] and SAIFCER[9] are compared with the proposed system SEMWORD by evaluating the performance metrics such as progression rate and response time with corresponds to the user search.

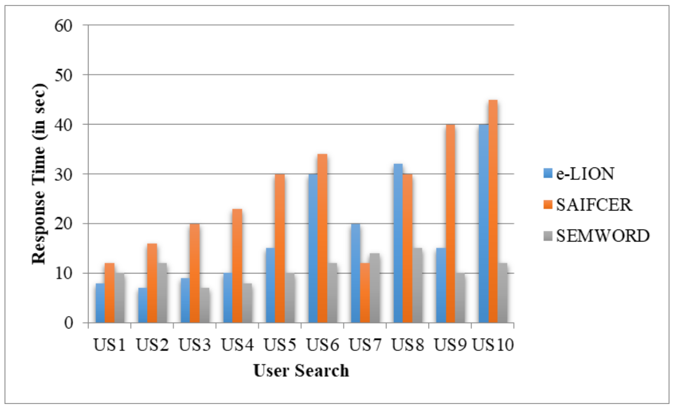

Fig 11. Response Time for Different E-Learning System

The response time for the user search based on the different e-learning system is shown in Figure 11 . The figure shows that the proposed model SEMWORD provides quick response time for the user's search results than other systems. Because the proposed work used SEMWORD instead of the keyword based search that gives quick response for the user search according to the personalization.

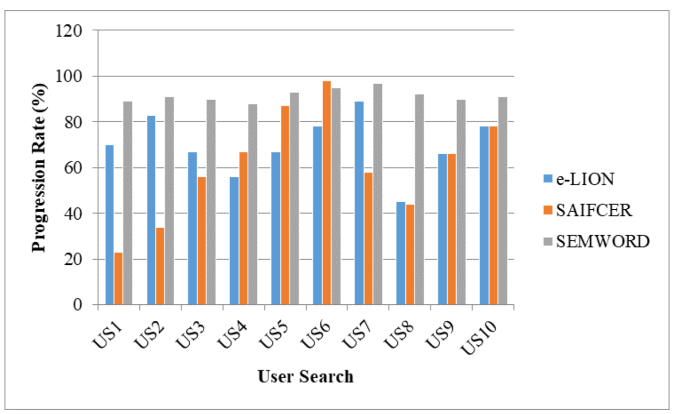

Fig 12. Progression Rate

The progression rate for the existing and proposed e-learning system for the user search is shown in Figure 12 . The figure depicts that the rate of progesssion is high for proposed model than other models with corresponds to the user search. If the system aquires quick response rate that provides good progression rate. Thus the progession rate for the SEMWORD is high for all the user seach than other models.

4 Conclusion

The research focuses on three key areas: describing the semantics of learning materials, defining learning contexts, and structuring learning materials. It provides better content representation, facilitates better organizing, and enhances learning experience by adopting these approaches. By introducing a new content encryption algorithm (TKET), the research addresses security-related issues. A secure algorithm protects learning materials from unauthorized access and tampering. A unique aspect of this research is how Semantic Web technology is integrated into e-learning, how it is used extensively across a wide variety of dimensions, and how it is enhanced by introducing a novel content encryption algorithm. Furthermore, the study demonstrates the benefits of improving the descriptions of the content and structure of the learning material and the benefits of making it accessible. By using the novel content encryption algorithm, the system also addresses security-related issues.

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