MAPPING KNOWLEDGE: EVALUATING CONCEPT MAPS USING SOCIAL NETWORK ANALYSIS AND NETWORK SIMILARITY MEASURES

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ABSTRACT

Traditional multiple-choice questions (MCQs) primarily assess factual recall and application but often fail to capture the depth and structure of student understanding. Addressing this limitation, the present study introduces a novel framework that leverages Social Network Analysis (SNA) and network similarity measures to evaluate concept maps generated from students' MCQ responses. The framework enhances assessment by identifying key concepts and assigning weighted importance based on degree centrality and influential nodes. By comparing student-constructed concept maps with an instructor's reference map, it assesses the coherence and completeness of student knowledge. The study also evaluates learning depth through both self-constructed and quiz-derived concept maps, offering insights into students' conceptual development. Furthermore, it clusters students based on performance, uncovers learning patterns, and identifies weaker concepts, unknown concepts, and misconceptions. This integrated approach facilitates efficient and consistent assessment, enables personalized instruction, and supports targeted pedagogical interventions, ultimately contributing to improved learning outcomes and deeper knowledge acquisition.

Keywords: *Concept Map, Learning Analytics, Social Network Analysis, Influential nodes, Degree Centrality, Similarity Measures, Jaccard Similarity, Cosine Similarity.*

1. INTRODUCTION

Concept map (CM) is an effective method for visually organizing and representing knowledge. Developed by Joseph Novak and inspired by David Ausubel's learning theory[1], they consist of nodes representing concepts, connected by labelled lines that define their relationships. This structured approach helps learners grasp complex ideas, identify connections, and enhance their understanding. Widely used in education, concept maps assist students in consolidating knowledge, developing critical thinking skills, and improving comprehension[2]. They provide a structured way for learners to articulate their understanding of a subject and pinpoint areas requiring further exploration. Educators utilize concept maps as instructional aids and assessment tools to evaluate student progress and conceptual depth.

A concept map visually represents relationships between ideas using linking phrases such as "has," "which are in," or "can be", as shown in figure 1. Each concept is expressed as a word or phrase, with connections forming meaningful statements known as propositions. For instance, a concept map might include: "Water → has → molecules → which are in →motion."

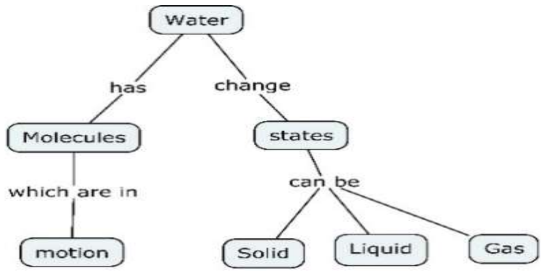

Figure 1. Sample Concept map

This method, known as Concept Mapping, facilitates a deeper comprehension of interrelated concepts. Novak and Gowin introduced concept maps based on Ausubel's Meaningful Learning Theory, which emphasizes that learning occurs when new knowledge is linked to pre-existing concepts. These maps effectively identify student misconceptions and areas needing conceptual refinement by visually organizing information. Assessing concept maps can be a time-intensive process for educators. Automating this evaluation can enhance efficiency and enable timely feedback.

Concept maps share structural similarities with network analysis, as both rely on nodes (concepts) and edges (relationships)[3]. Network analysis employs metrics like degree, centrality, clustering coefficients, and path lengths to examine connectivity patterns. This research explores the application of Social Network Analysis (SNA) techniques to assess student-generated concept maps. By analysing these maps, the study aims to evaluate the coherence, complexity, and depth of student understanding. The relationships between concepts provide insights into how well students have structured their knowledge. This approach helps identify misconceptions, gaps, and areas requiring further instruction.

The core concern of this study is the gap between surface-level assessment of factual knowledge through MCQs and the need for deeper insight into student understanding. While concept maps can capture knowledge structures, their manual evaluation is subjective and inefficient. This research justifies integrating Social Network Analysis (SNA) to analyse concept maps—both self-constructed and MCQ-derived—to provide scalable, consistent, and meaningful assessment of learning. By identifying conceptual gaps, misconceptions, and learning patterns, this approach enhances personalized instruction and supports deeper conceptual development.

Additionally, this research introduces quantitative measures to assess the quality and organization of concept maps, enabling more objective and efficient evaluations. By leveraging network analysis, educators can enhance learning assessments and refine teaching strategies to improve student comprehension. Combining concept maps with SNA creates a comprehensive framework for evaluating students' comprehension of a topic. SNA can help identify central nodes in the concept map, indicating key concepts around which others revolve[4]. This insight helps educators prioritize and emphasize essential content. Educators can use this information to adapt teaching strategies and provide targeted support where needed. Thus, the combination of concept maps, SNA, and learning analytics creates a powerful framework for promoting effective learning and teaching processes[5]. It enables educators to gain valuable insights into student comprehension, measure learning outcomes, and refine instructional methods based on data-driven evidence.

To evaluate students' understanding of a topic, both Multiple Choice Questions (MCQ) and concept maps are used: MCQ assess factual recall and application of knowledge and concept maps are used to evaluate the ability to recognize relationships and visually structure knowledge. By adapting the insights from quiz results into concept maps, educators can gain a comprehensive understanding of learners' strengths, weaknesses, and areas needing additional instruction. The novelty of the proposed work lies in integrating Social Network Analysis (SNA) and network similarity measures to systematically assess student concept maps against expert models.

The objective of this study is to evaluate the effectiveness of Social Network Analysis (SNA) in assessing concept maps (CMs) derived from students' MCQ responses. It introduces an innovative framework that integrates SNA and network similarity measures to enhance assessment efficiency, consistency, and structural validation of concepts. By identifying key concepts and assigning weighted importance based on degree centrality and influential nodes, the framework provides a comprehensive evaluation relative to an instructor-constructed reference map. It assesses students' conceptual clarity, clusters them based on performance, and uncovers learning patterns. Additionally, it identifies weaker concepts, unknown concepts, and misconceptions, offering valuable insights for targeted learning. This approach supports deeper knowledge acquisition

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and fosters more accurate conceptual development, ultimately enhancing the learning process.

The structure of this research paper is as follows: It begins with a review of existing literature, examining various concept map evaluation techniques, particularly network analysis and similarity measures, while highlighting their limitations. Next, the methodology and system framework are presented. This framework is then implemented to evaluate students' concept maps in an educational context. The results are analysed, and finally, the proposed framework is compared with other network-based concept map analyses, demonstrating its effectiveness and advantages.

2. LITERATURE REVIEW

The study[6] researches “common” evaluation dimensions in concept map assessment frameworks. Educators must choose the best model for their goals and course scope. Group concept maps are described, understood, and employed using points, clusters, and distances to comprehend construct relationships. This research[7] quantifies cluster link strength and directionality using network analysis and group concept mapping.

The research[8] suggests semi-automated concept map creation and resource recommendation using a recommender system. This work builds fuzzy systems to improve student learning assistance comprehension. The study introduces a recommender system that suggests resources to users, who take a related test. The initial concept map is based on the users' mastery of each topic after the test. The system's input to the learner at each phase completes the map and learning process. This method will continue until the concept map and learning process are complete.

[9]proposed a paper on concept maps, outlining a method consisting of three steps: concept map development, knowledge level identification, and generation of personalized learning paths. The authors thoroughly explain each phase, highlighting the algorithm's characteristics and the benefits of concept maps. They provide a comprehensive description of the case study and evaluation findings, demonstrating the algorithm's effectiveness. Nevertheless, the research contributes significantly by offering an algorithm for automatic learning path development using concept maps. The authors emphasize the importance of personalized learning paths in adaptive learning systems and the potential of idea maps in their creation.

The study [10] presents the findings of the SNA analysis, revealing valuable insights into communication and collaboration patterns among students. The authors discuss the implications of these findings for designing and facilitating online PBL courses, emphasizing the importance of building a sense of community and promoting active engagement. The paper's strengths lie in the extensive description of the case study, SNA methodologies, and the practical recommendations for enhancing online PBL experiences. However, it lacks a discussion on the limitations and potential biases of the SNA approach, such as self-selection and homophily. Despite this drawback, the research serves as a valuable case study for employing SNA as a learning analytics tool in online PBL. The authors provide a comprehensive overview of the SNA methodologies used, while acknowledging the limitations and biases that may arise.

The framework in the study [11]using Social Network Analysis (SNA) and Bayesian Network for a sustainable computer-based formative assessment system. The system analyses interaction patterns and learning behaviours to provide personalized feedback to learners. The study describes the architecture, components, and methods of SNA and Bayesian network analysis. Experimental data demonstrate that the system enhances learner performance by identifying performance determinants and analyzing learner interaction patterns. The research contributes significantly to learning analytics by showcasing how SNA and Bayesian network analysis can improve formative assessment methods and deliver individualized feedback, ultimately enhancing learning outcomes.

This study[12] created and analysed knowledge networks using 74,761 Zhihu and 62,368 Stack Overflow topics. The regression investigation showed that knowledge concept adoption is influenced by their structure and links. This study improved the understanding of knowledge adoption on an online knowledge-sharing platform and provides a structural analysis tool for large-scale online content data.

The linguistic properties of natural science phrases are examined using natural language processing and network analysis[13]. Contrast examples were used between languages. Wikipedia term networks are extracted using NLP. Network analysis helped explain science term terminology and relationships. German and English Wikipedia’s rank theory, time, energy, and system as the most important physics topics.

Science networks behave like scale-free, complicated systems. These findings can help assess scientific learners' language use. In education, natural language processing and network analysis can extract information from language corpora.

This study[14] uses social network and concept network characteristics to classify connectivist learners. 10598 data points from a 12-week Chinese cMOOC called “Internet Driven Education Reform: Dialogue between Theory and Practice” were collected. Social network analysis, Latent Dirichlet Allocation, K-means cluster analysis, and lag sequential analysis discover “connected creative learners”, “social learners”, “reflective learners”, “wandering learners”, and “marginal learners”. This study offers cMOOC design advice based on its findings. This study identifies five sorts of cMOOC learners to help designers and facilitators create better cMOOCs.

The students' comprehension of triangle concepts [15] are investigated through concept maps. The examination of the maps utilizing degree centralities from social network analysis has provided new perspectives using this novel method. A concept map was examined for leadership needs using social network analysis[16]. Strategies and effects for improving concept map analysis and stakeholder feedback are discussed.

This paper [17] outlines the desirable properties of graph similarity functions and the limitations of present methods in detecting substantial connectivity changes in graphs. DELTACON, a systematic, simple, and efficient method for comparing two networks with the identical nodes, is introduced. Experiments on synthetic and real graphs show that proposed similarity measuring method is better.

The article [18]suggests seven methods for measuring the similarity of concept maps in course modules. Identifying the structural and didactic features of maps to reveal instructional links across course modules. Relevant case studies analyse the recommended similarity metrics. The study[19] demonstrates the significance of content and application validity in domain ontologies when using concept maps. A concept map on elementary geometry was compared to empirical criterion maps using similarity techniques to determine content validity. Knowledge Space Theory predicted problem-solving behaviour to prove its validity. Results show concept map content and application validity, validating the validation framework's practicality.

A novel method [20]for assessing node structure similarity using relative entropy and local structure is presented in this paper. The new technique measures each node's structural attribute as unique data. Quantifying node similarity is like quantifying structural information similarity. Relative entropy measures structural information differences between nodes. Complex network nodes' structural similarity is measured by their relative entropy. The method proved to be more accurate than the existing methods.

In the paper, [21], a collaborative approach that involves analysing student learning behaviour and using this information to design personalized learning paths. The algorithm suggested in the study consisted of a collaborative analysis of learning behaviour, identification of knowledge gaps, and the creation of tailored learning paths. The paper's extensive description of the algorithm and learning path planning processes is a key highlight. Nonetheless, the research contributes significantly to personalized learning by introducing a novel method for learning path planning based on collaborative analysis.

Concept networks[22] were constructed using student concept maps. Student concept networks varied in structure, with some networks being more interconnected. Even after controlling for network size, concept networks with longer average shortest path lengths predicted higher quiz scores. This study shows how network science can measure a learner's conceptual organization.

SimGNN[23], a neural network method designed to learn graph similarity. The paper provides a detailed explanation of SimGNN's components and training process. Experimental results demonstrate that SimGNN outperforms other graph similarity algorithms in terms of accuracy and efficiency on benchmark datasets. The authors effectively describe the architecture and components of SimGNN, making it accessible even for readers with limited knowledge of neural networks. However, the paper lacks exploration of SimGNN's model interpretability, which could be considered a limitation. It would have been valuable to discuss how the learned similarity function can be evaluated and applied to downstream tasks, as neural networks are often regarded as "black box" models. Nevertheless, SimGNN shows promise as a graph similarity calculation approach, offering state-of-the-art accuracy and efficiency.

Educational mobile augmented reality games[24] combine contextual and interactive learning with fun. This study uses content analysis, concept mapping, and social network analysis to investigate young, middle-aged, and senior feedback on location-based mobile augmented reality (MAR) games. MAR games foster constructivist learning, which is active, socially supported knowledge production. This study used network text analysis to examine structural elements affecting knowledge acceptance. This study [25]introduces an unsupervised learning approach using graph neural networks, specifically Node2Vec and GraphSAGE, to analyze concept maps. By identifying clusters and relationships, the method reduces manual analysis effort and enhances understanding of student knowledge representations, providing scalable insights to improve educational assessment and validate teaching effectiveness.

The research articles that were looked at provided insight into the usefulness of using graphs, social network analysis, and similarity metrics in the field of education. Graphs were skilfully employed to illustrate the connections between distinct concepts, allowing for the creation of several pathways, from which the relevant ones were identified according to particular standards. Analyzing social networks was essential in identifying nodes that were both active and inactive. Similarity metrics also functioned as a way to group data. These approaches present interesting directions for further research aimed at improving the framework for evaluating student performance. Table 1 provides the limitations of the existing systems.

Table 1 Limitations of the existing system

Sl.No	Method	Description	Drawbacks
1	Concept Map-Based Learning Path Generation Algorithm[21]	Proposes an automatic algorithm to generate adaptive learning paths using concept maps.	Lacks detailed validation of generated learning paths with expert benchmarks.
2	Network Science for Concept Map Analysis[22]	Uses network science to analyze the structure of concept maps created by psychology undergraduates.	Focuses only on structural properties, without linking to learning outcomes or misconceptions.
3	SimgNN (Graph Neural Network) for Graph Similarity Computation[23]	Introduces a deep learning-based approach for computing graph similarity efficiently.	Prioritizes computational efficiency over educational applicability and validation.
4	Network Analysis in Mobile Augmented Reality (AR) Gaming[24]	Applies network analysis to concept maps generated in a mobile AR learning environment.	Limited scalability beyond AR-based educational contexts.

Existing studies analyze concept map structures and apply Social Network Analysis (SNA) metrics but often lack systematic comparison with expert models and a unified evaluation framework. Most focus on specific metrics like centrality or similarity without integrating them into a comprehensive assessment. Algorithmic efficiency is prioritized over educational relevance, leaving the link between map organization and quiz performance underexplored. Misconception detection and adaptive learning integration remain underdeveloped. Current models also fall short in dynamically personalizing learning paths. This study addresses these gaps by proposing a novel framework that compares student concept maps with expert benchmarks using network similarity measures. It enables personalized feedback, supports curriculum refinement, and advances adaptive learning through meaningful, network-based evaluation of learning outcomes.

Current research lacks a comprehensive framework to effectively evaluate Concept maps from MCQ responses against expert models, limiting effective assessment and personalized learning.

This study is based on the hypothesis that applying Social Network Analysis (SNA) to concept maps derived from students' MCQ responses offers a more structured and effective approach to evaluating conceptual understanding, uncovering learning gaps, and enabling personalized instruction than traditional assessment methods..

3. SYSTEM FRAMEWORK AND METHODOLOGY

The framework used for this research is shown in Figure 2. The concepts and their relationships for the topic under study are identified by the instructor. Based on these identified concepts and relationships, the instructor creates an MCQ. The MCQ is designed so that each question corresponds to a single concept, while also potentially relating to multiple other questions or concepts. A tool is developed using the NetworkX package in Python to generate concept maps from the quiz. This tool creates a reference concept map for the topic based on actual quiz responses. In a concept map network, influential nodes can be considered as key concepts that play a significant role in the overall structure and understanding of the topic. These nodes have a high impact on learning and knowledge representation because they are central to connecting various subtopics and ideas. Identifying influential nodes helps in improving educational strategies, assessing student understanding, and refining learning resources. The most influential nodes are identified from concept map network, typically measured using centrality metrics like degree, betweenness and closeness[26].

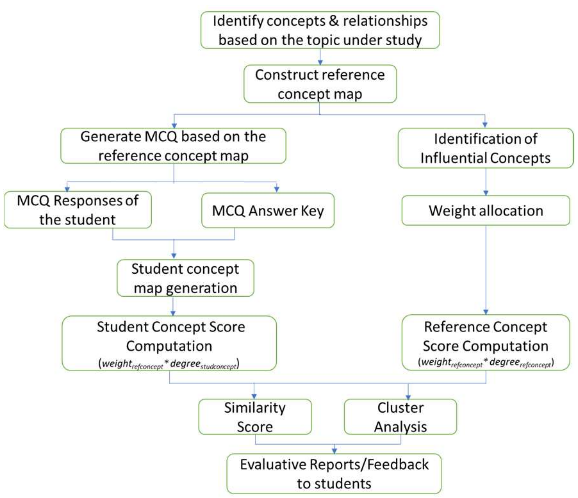

Figure 2. System Framework

Assigning weights to concepts is a process used in assessments to determine the relative importance or value of different responses or solutions[27]. This technique allows assessors to assign points to responses based on their importance and excellence. The process of assigning weights to responses might vary based on factors such as the intricacy of the question, the level of knowledge required, and the desired learning objectives. Through the allocation of weights, assessors are able to differentiate pupils' levels of understanding, analytical abilities, and creativity, so guaranteeing fair and unbiased evaluations. This technique is widely used in academic and professional settings to assess people' proficiency and pinpoint areas for improvement.

In this study, weights are assigned to each concept based on its influence and degree within the concept map network. The score for each concept is then calculated by multiplying its assigned weight by its degree, ensuring that both its significance and connectivity are reflected in the final evaluation.

Students concept maps are generated based on their responses to the quiz. Correct answers represent understanding of specific concepts, resulting in the creation of nodes in the map. When a student correctly answers another question related to a concept, an edge is formed between these concepts, indicating comprehension of their relationship. However, certain nodes and edges may be omitted in the concept map, indicating a lack of clear understanding. These student-created concept maps serve to visualize the topic's concepts and organize their interconnections according to the knowledge they have gained. The concept scores in the student's concept map are calculated by considering the weights assigned to concepts in the reference concept map and the current degree of each concept in the student's concept map.

The concept maps derived from quiz responses are then compared against the instructor's reference concept map using network similarity measures such as Jaccard and cosine similarity[28]. The Jaccard Similarity between two nodes, A and B, is defined as: $Jaccard\ Similarity(A, B) = \frac{|N(A) \cap N(B)|}{|N(A) \cup N(B)|}$, where N(A) and N(B) represent the sets of neighbours of nodes A and B, respectively[28]. This index can be extended to incorporate edge weights by replacing the neighbor sets with weighted adjacency vectors. In this case, the similarity is given by:

$$Jaccard\ Similarity(A, B) = \frac{\sum_{i \in A \cup B} \max\left(W_{A,i}, W_{B,i}\right)}{\sum_{i \in A \cap B} \min\left(W_{A,i}, W_{B,i}\right)}$$

$w_{A,i}$ and $w_{B,i}$ denote the weights of the edges from node A and node B to their common neighbour i. The numerator sums the minimum weights for shared neighbours, while the denominator sums the maximum weights for all unique neighbours.

On the other hand, Cosine Similarity measures the cosine of the angle between two vectors, making it a useful metric for comparing adjacency vectors or connection patterns. It emphasizes the relative alignment of shared connections rather than their absolute magnitude.

$$Cosine\ Similarity(|X,Y|) = \frac{x.y}{||x||\ \ ||y||}$$

Cosine similarity and Jaccard similarity measure node or network similarity in different ways. Cosine similarity compares adjacency vectors to assess how well connection patterns align and is less affected by variations in node degrees. In contrast, Jaccard similarity calculates the ratio of shared neighbours to the total number of unique neighbours, emphasizing exact overlap. While cosine similarity is useful for identifying patterns in connection strength, Jaccard similarity is better suited for detecting clusters based on common neighbours.

The resulting similarity scores allow students to evaluate their understanding of individual concepts as well as their overall grasp of the topic. This evaluation provides insights into how effectively a student or group of students has understood the topic.

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Concept Map Generation

The initial step in this study involves identifying the concepts and their relationship for the topic under study, followed by the manual creation of a prototype concept map using Lucid chart. The relationships between concepts 'A' and 'B' in the concept map serve as the basis for formulating questions that connect both concepts.

MCQs are then designed to assess students' understanding of fundamental concepts within the specific subject area. The MCQ consisted of 50 questions, each representing a distinct concept from the chosen topic. To ensure a comprehensive evaluation, here, the study focuses on software engineering, a field in computer science that specializes in developing and maintaining software systems.

The instructor reference concept map is created to visually represent utilizing the NetworkX library in Python as illustrated in Figure 3. The MCQ pertained to distinct concepts including software development tools and techniques, version control systems, testing frameworks, and continuous integration and delivery. The objective is to evaluate the participants' comprehension of these concepts. The quiz responses are utilized in the construction of a concept map, a graphical representation of interconnections among concepts in the form of nodes and edges/links. A group of 30 postgraduate students in Computer Science was selected to participate in the MCQ assessment on the chosen topic. In the first stage, students complete the quiz to evaluate their understanding of individual concepts. Their responses are then used to generate concept maps, providing a visual representation of their grasp of the relationships between concepts. Table 2 presents the response patterns of each student for each concept pair, where Concept A and Concept B are related. Each concept is assessed with one question. Solid comprehension (score 2) is achieved when both questions—one for each concept—are answered correctly. Partial knowledge (score 1) is demonstrated when only one of the two questions is answered correctly. A score of 0 indicates a lack of understanding, where both questions are answered incorrectly.

Table 2 Student Response Patterns for Concept Pairs

Response Pattern	Score	Understanding Level
Both questions correct	2	Solid Comprehension
One correct, one incorrect	1	Partial Comprehension
Both incorrect	0	Lack of Understanding

Subsequently, a concept map is created to visually represent the level of comprehension of each student. Figure 4 shows the concept map generated for a student based on the responses to the MCQ.

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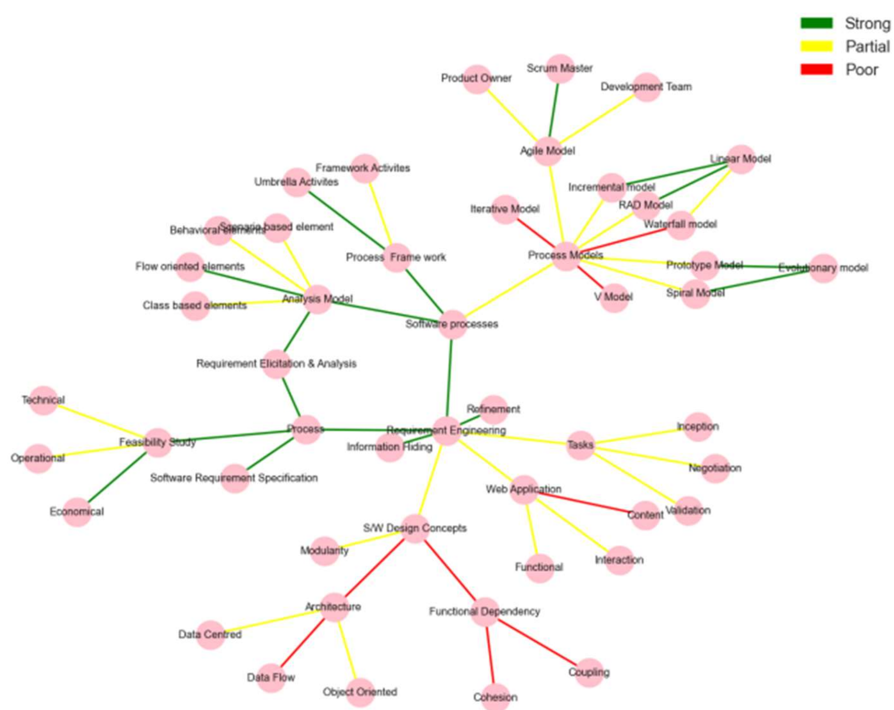

Figure 4 Concept map generated for a student

The student-generated concept map illustrates their understanding of concept relationships, with green edges signifying complete or solid comprehension, yellow edges indicating partial understanding, and red edges representing insufficient understanding. After constructing the concept map, it is compared to the reference concept map (reference concept map), and the performance of the students are analysed.

4.2 Identification of Influential Nodes

To facilitate the analysis of the answer-key concept map, a connection table is constructed. The connection table presents a tabular representation of all nodes in the map, along with their respective degrees. The table includes the node name and its degree as features. By applying the concept of Influence in Social Network Analysis, the most important concepts are identified. Influence refers to the effectiveness of a node on other nodes. Nodes with the highest degree are expected to be connected to a common node, which is recognized as the influential or most important node.

Understanding the influential concept leads to the exploration of related concepts. Figure shows the influential nodes(concepts) colour coded in the reference concept map. Blue nodes denote the most influential node, while orange nodes represent those with the highest degree. Yellow nodes represent nodes with a degree value lower than the highest degree but higher than the average degree. Remaining nodes are represented as pink nodes.

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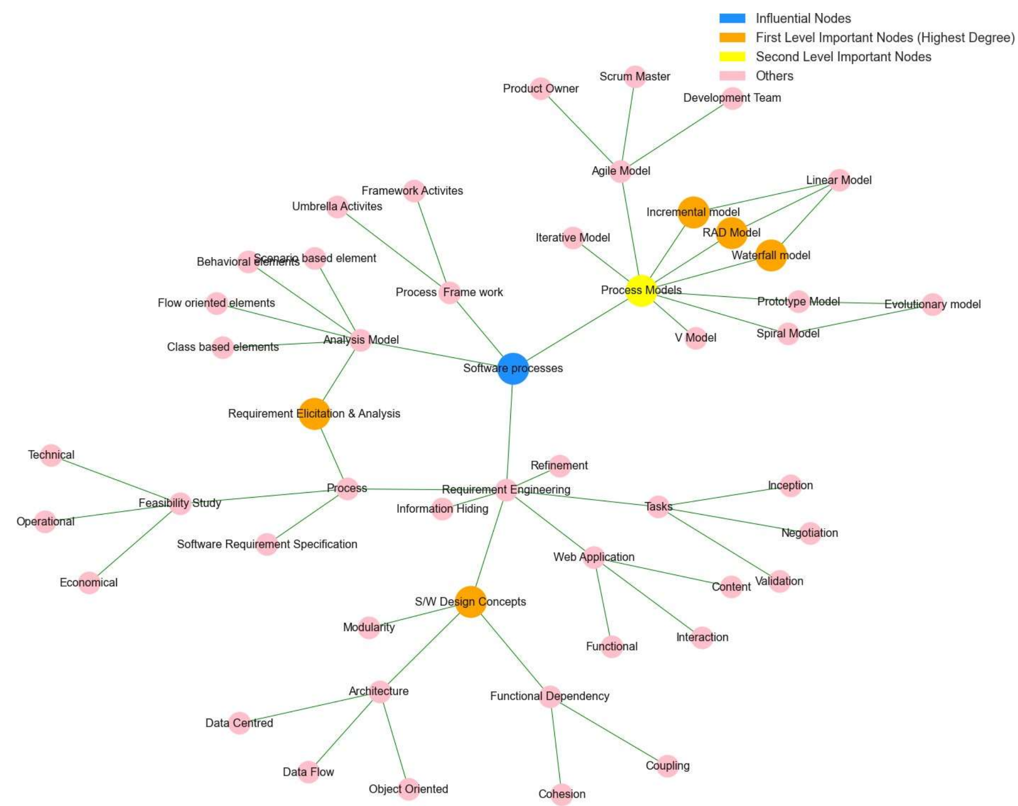

Figure 5 Influential nodes in concept map

The levels of influential nodes facilitate the identification of the most relevant concepts, enabling `students to focus on specific topics during their learning process. A solid comprehension of these concepts and their relationships assists students in achieving high scores in examinations.

4.3 Concept Weight Assignments

In order to further analyse the important nodes, a weight is assigned to each node, which is then added as an additional feature in the Connection table. The weight allocations for the nodes are presented in Table 2. For each node, the product of its weight and degree is calculated, resulting in a new feature known as the PWD

Condition	Weight
Influential Node	5
Max (Degree)	4
Greater than Mean (Degree) and Less than Max (Degree)	3
Mean (Degree)	2
Less than Mean (Degree) (Remaining nodes)	1

Table 3 Weight Allocation (Product Of Weight And Degree).

The PWD feature, obtained by multiplying the weight and degree, is utilized for subsequent analysis. Figure 6 shows the connection table of few concepts with PWD attributes.

	Concept	Degree	Weight	PWD
0	Agile Model	4	2	8
1	Analysis Model	6	2	12
2	Architecture	4	2	8
3	Behavioral elements	1	1	1
4	Class based elements	1	1	1
5	Cohesion	1	1	1

Figure 6 Connection Table with 'PWD' attributes

4.4 Student Performance & Distribution

Students were instructed to study a specific topic, followed by an MCQ assessment on the same subject. A concept map is generated for each student based on the MCQ responses. Correct answers indicate an understanding of specific concepts, leading to the creation of nodes(concepts) in the map. If a student correctly answers another question related to a concept, an edge is established between them, representing comprehension of their relationship. However, missing nodes or edges indicate gaps in understanding. A connection table is then created for each student. The degree of the student's map is multiplied by the Weight feature from the reference concept map connection table, producing the PS (PWD of Student Table) feature. This PS value is then compared to PWD, and the resulting similarity score reflects the student's level of understanding.

	Question	Degree	Weight	PS	PWD
0	Agile Model	4.0	2	8.0	8
1	Analysis Model	6.0	2	12.0	12
2	Architecture	2.0	2	4.0	8
3	Behavioral elements	1.0	1	1.0	1
4	Class based elements	1.0	1	1.0	1
5	Cohesion	0.0	1	0.0	1

Figure 7 Connection Table of a student

Jaccard similarity and cosine similarity are both widely used similarity measures in natural language processing and information retrieval. Jaccard similarity evaluates the intersection and union of two sets, producing values between 0 and 1, whereas cosine similarity calculates the cosine of the angle between two non-zero vectors, ranging from -1 to 1. In this study, both methods were implemented and compared. The results showed that Jaccard similarity yielded values more closely aligned with students' grades, which were determined based on the actual score in percentage. The findings indicate that Jaccard similarity provided significantly more accurate representations of student performance than cosine similarity. Additionally, Jaccard similarity considers variations in conceptual understanding by accounting for graph nodes and measuring both overlap and uniqueness, whereas cosine similarity focuses solely on the angle between vectors, disregarding node presence. As a result, Jaccard similarity is more suitable for graph-based similarity assessments.

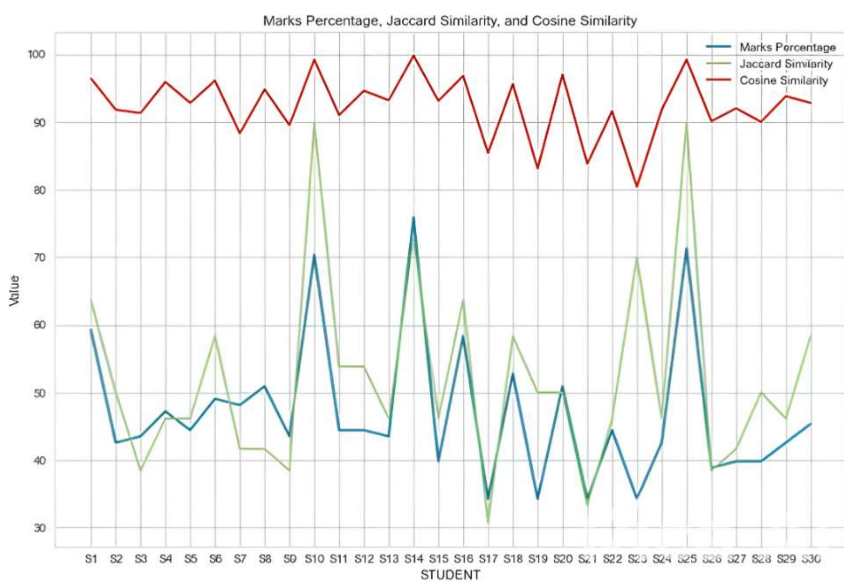

Figure 8 Comparison of Score Percentage, Jaccard Similarity, and Cosine Similarity

The distribution of values describes how a dataset's values are spread or dispersed among different ranges. Understanding the distribution is crucial for data analysis and statistics as it reveals underlying patterns and properties. A normal distribution, characterized by a bell-shaped curve with most values near the mean, is common. Analysing the distribution helps identify outliers, assess the need for normalization or standardization, and guide the selection of appropriate statistical tests and models.

Examining the distribution plot in Figure 9 which plots Jaccard Similarity Scores, it is evident that the majority of values are below the mean. The test revealed that a significant number of students performed below their potential. This could be attributed to their unfamiliarity with the concept map ideology and influential nodes, leading to difficulties in identifying concepts and connections.

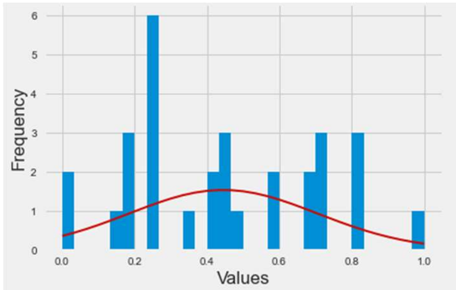

Figure 9 Distribution of Student scores

4.5 Clustering

Silhouette clustering compares similarity within clusters and dissimilarity across clusters to evaluate clustering quality. It provides a quantitative assessment of clustering algorithms. The silhouette score measures a data point's match within its own cluster and mismatch with neighbouring clusters. A higher score indicates a better match within the cluster. The overall silhouette score is the average of individual scores, representing the clustering solution's quality.

In Figure 10, Batch 1 of 30 students are grouped into four distinct clusters based on performance and similarity scores. The clustering analysis using K-Means with 4 clusters shows generally well-separated groups, as seen in the silhouette plot and scatter plot. Clusters 1, 2, and 3 have positive silhouette scores, indicating good cohesion. The scatter plot confirms this by showing well-formed clusters with centroids, but some points in Cluster 0 are close to other clusters. Both batches indicate that a significant portion of the student population consisted of students with low academic performance. These findings emphasize the need for revision as students struggle to connect concepts. Introducing the philosophy of connecting topics before learning establishes a stronger foundation and enhances practical application.

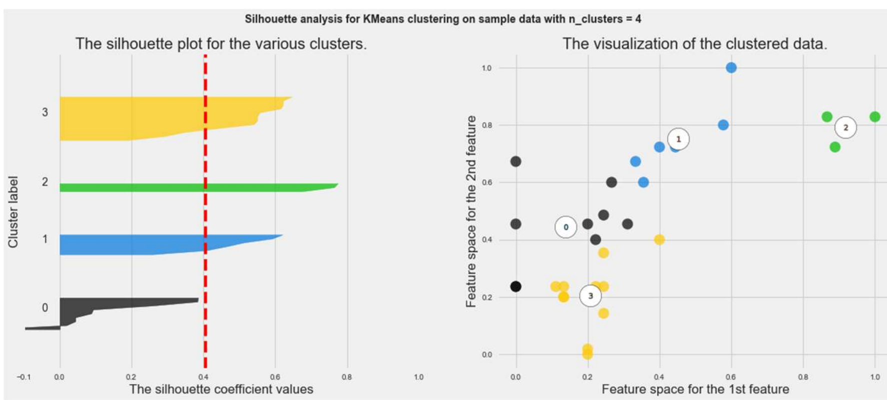

Figure 10 Student Clusters

4.6 Overall Student Performance and Conceptual Understanding

Figure 11 depicts the difference between the predicted product (PWD) and the actual product (PS) obtained by first four students. It visualizes the extent to which each student deviates from PWD, indicating their level of understanding across all fifty concepts. Deviance values are normalized using Min-Max normalization, ranging from 1 (no understanding) to 0 (clear understanding) for each concept. By calculating the average values, concepts were categorized as strong (average value < 0.3), partial (0.3-0.9) or poor (average value > 0.9) for the entire class.

Each concept's average value was calculated and categorised as either strong or weak for the entire class. The figure 12 represents the overall performance of the class based on the normalized deviance values. 'Umbrella Activities', 'Requirement Engineering', 'iterative model' is some of the poorly understood concepts, whereas concepts such as 'Information Hiding' 'linear model', 'incremental model' etc. comes under strongly grasped concepts.

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	Agile Model	Analysis Model	Architecture	Behavioral elements	Class based elements	Cohesion	Content	Coupling	Data Centred	Data Flow	...	Software Requirement Specification
0	1.00	1.0	1.00	1.0	1.0	1.0	1.0	1.0	1.0	1.0	...	1.0
1	1.00	1.0	0.50	1.0	1.0	0.0	0.0	0.0	1.0	0.0	...	1.0
2	0.00	1.0	0.25	1.0	1.0	0.0	0.0	0.0	1.0	0.0	...	0.0
3	0.25	1.0	0.75	1.0	1.0	0.0	1.0	0.0	1.0	1.0	...	0.0
4	1.00	1.0	0.50	1.0	1.0	1.0	0.0	0.0	1.0	1.0	...	0.0

Fig 11 Dataset of Computed Deviations for each Student

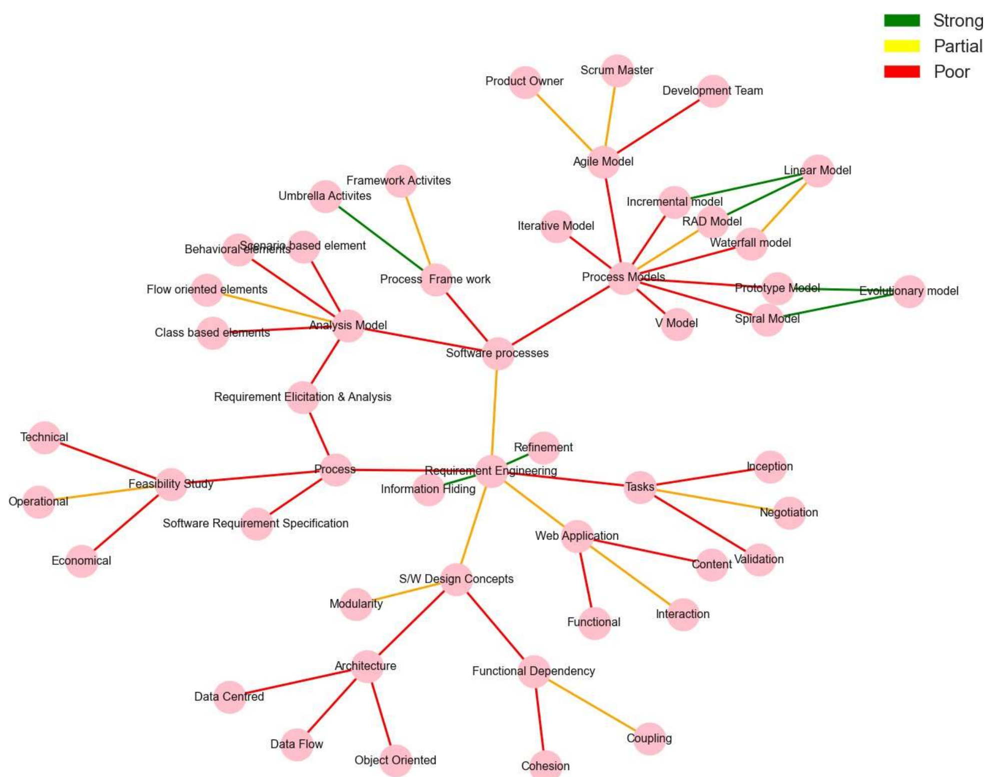

Figure 12 Overview of Class Performance

The given set of bar charts in the figure 13 represent concept clarity based on normalized deviance values of concept scores for students for each concept. The x-axis denotes the normalized deviance values, which range from 0.0 to 1.0, while the y-axis indicates the number of students in each category. A higher deviance value (closer to 1.0) suggests greater deviation from the expected concept clarity, indicating students with unclear understanding of concepts. A lower deviance value (closer to 0.0) indicates students whose concept scores align well with expectations, meaning they have better clarity. The set of graphs represents concept clarity across various process models based on normalized deviance values of student concept scores. Each individual bar chart likely corresponds to a different concept, such as Waterfall, Agile, Spiral, V-Model, RAD, Incremental models etc

.

Figure 13 Concept Clarity Based on Normalized Deviation

For the concept 'Agile Model', the distribution in the chart suggests that most students exhibit a high degree of conceptual deviation, implying that their understanding of the Agile Model is weak. For the concept 'iterative model', the chart shows two prominent bars with high number of students at 0.0, meaning a significant portion of students have a strong understanding of the Iterative Model. Another large group at 1.0, indicating a considerable number of students have poor clarity or misconceptions regarding this model. Almost no students fall in the intermediate range (0.2 to 0.8), suggesting a polarized understanding—either students grasp the concept well or struggle significantly. The bimodal distribution suggests a learning gap—some students clearly understand the Iterative Model, while others struggle.

Analysing the graphs across various concepts, a significant proportion of students have high deviance values, implying difficulties in understanding certain models. Some models may have lower deviance peaks, indicating better clarity among students. Variations in distribution suggest that some models are inherently more complex or require different teaching approaches. This highlights a need for reinforcement strategies, such as additional tutorials, interactive sessions, or assessments, to improve concept clarity for students who fall in the higher deviance categories.

4.7 Comparative Study of Concept Maps: Quiz-Derived vs. Directly Constructed

To compare learners' knowledge based on their MCQ responses, with their ability to visually organize and relate concepts in a concept map, the proposed MCQ-based concept map generation framework is used along with independent concept map construction to provide valuable insights into both basic and deeper conceptual understanding. Here, a structured quiz consisting of 20 questions representing 20 different concepts is designed, on the topic Artificial Intelligence. Figure 14 refers to the reference concept generated based on the actual MCQ responses.

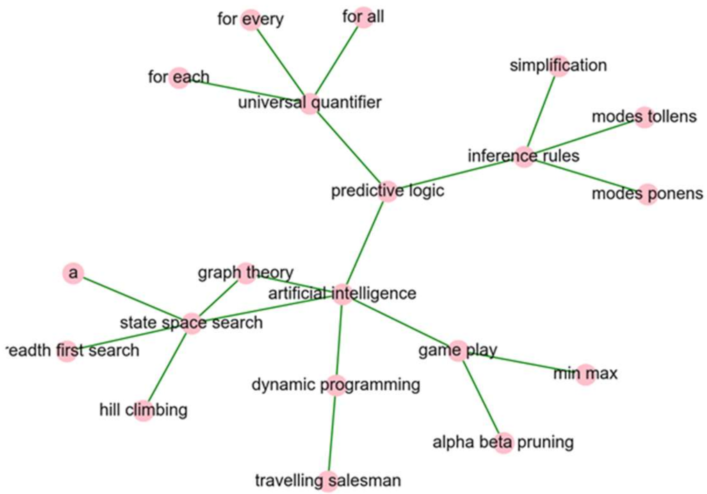

Figure 14 Reference Concept Map for Artificial Intelligence

The evaluation process consists of two stages: the MCQ and concept map construction. A group of 30 students participated in both stages, completing the MCQ and creating concept maps. In the first stage, the MCQ assesses students' understanding of individual concepts. Based on their responses, concept maps are generated to visually represent their comprehension and the relationships between concepts. The figure 15 illustrates a concept map generated based on a student response to the MCQs. In the second stage, students independently construct concept maps using a predefined list of keywords provided by the instructor[29]. This approach ensures consistency in the concepts being analysed while allowing students to demonstrate their ability to organize and connect concepts based on their understanding. Figure 6 illustrates the concept map constructed by a student based on the specific topic.

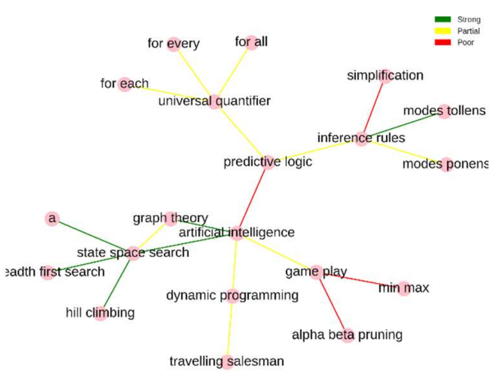

Figure 15 Student concept map generated from MCQ student

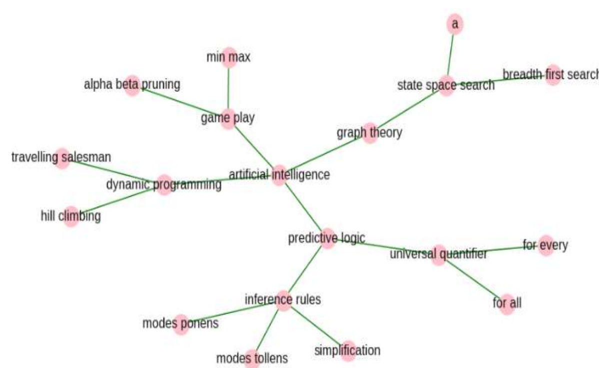

Figure 16 Concept map constructed by

The concept maps generated from MCQ responses and those independently constructed by students are evaluated against the reference concept map using the proposed framework. These insights help assess students' conceptual understanding and their ability to structure knowledge effectively. Since Jaccard Similarity is more suitable in this context, this measure is used to compare and evaluate both concept maps with reference concept maps. Figure 17 compares Jaccard similarity scores between concept maps generated from quiz responses and those independently constructed by students. The results suggest that direct concept map construction allows students to establish concept linkages more accurately. While direct construction primarily requires a general understanding of concepts for effective linking, quiz-based concept map generation demands a deeper level of comprehension. Consequently, direct concept map construction is well-suited for building foundational knowledge, whereas quiz-based concept mapping serves as a valuable tool for assessing and analyzing deeper conceptual understanding.

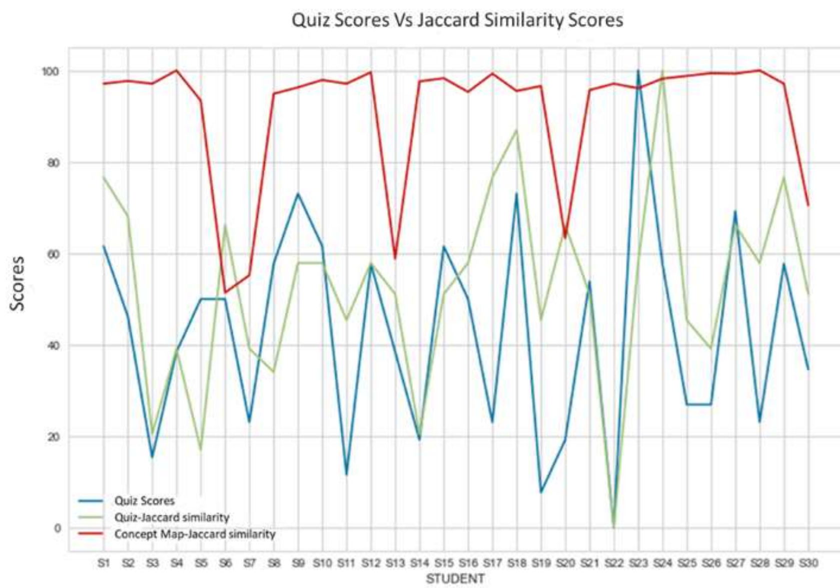

Figure 17 Comparison of Actual Score, Quiz-Based Similarity Score, and Concept Map Similarity Score

5. DISCUSSION

This study advances prior research by integrating quiz-based and independent concept map construction with network similarity metrics, specifically Jaccard and Cosine similarity, for systematic evaluation. Traditional concept map evaluation methods primarily focus on structural analysis, often lacking an objective means to assess conceptual alignment. In contrast, this study examines both structural and semantic understanding by comparing concept maps generated from quiz responses with those independently created by students. By applying automated network similarity measures, the framework provides a quantitative assessment of students' conceptual grasp, offering insights into their learning patterns. A key distinction highlighted in this study is that direct concept map construction primarily aids in developing a general understanding of concepts, whereas quiz-based concept maps require deeper comprehension, making them a more effective tool for evaluating higher-order thinking. This distinction has not been explicitly addressed in prior research.

The proposed framework effectively addresses the limitations of existing studies by providing a standardized and comprehensive approach to evaluating student-generated concept maps using Social Network Analysis (SNA). By integrating network similarity measures, it enhances assessment efficiency, consistency, and structural validation of concepts. Concept maps derived from MCQ responses provide a structured representation of students' knowledge, linking key concepts based on quiz performance. The use of centrality measures to identify influential nodes ensures that critical concepts are weighted appropriately, improving the accuracy of concept evaluation. By assigning weights to concepts and considering their connectivity within the network, the framework enables a more refined assessment of conceptual clarity.

A major contribution of this research is the correlation established between concept map organization and quiz performance. By comparing student-generated concept maps against an instructor-defined reference model, the framework highlights variations in understanding, identifies weaker concepts, and uncovers misconceptions. The application of Jaccard and Cosine similarity measures further validates the structural alignment of student knowledge with expert expectations. Table 4 gives a comparison of the proposed framework with other related frameworks.

Table 4 Comparison of the proposed framework with other related frameworks

Framework	**Traditional Concept Map Evaluation**[30]	**Network Science-Based Concept Map Analysis** [22]	**Concept Map-Based Learning Path Generation**[21]	**Graph Neural Network-Based Concept Map Analysis** [23]	**Proposed Model**
Method	Manual assessment based on structure and concept relationships	Uses network metrics (centrality, connectivity) to analyze concept maps	Algorithm for adaptive learning path generation	Applies unsupervised learning with GNNs for concept analysis	Integrates SNA with Jaccard & Cosine similarity for automated evaluation
Features	Focuses on hierarchical relationships, expert comparison	Identifies key concepts and structures in student maps	Uses concept maps to guide personalized learning	Identifies concept clusters, trends in student learning	Compares quiz-derived & independently constructed maps, weights concepts based on centrality
Advantages	Provides qualitative insights into concept understanding	Reveals knowledge structure differences among learners	Automates learning path recommendations	Automates large-scale analysis	Provides quantitative assessment, identifies misconceptions, supports adaptive learning
Limitations	Subjective, lacks scalability, time-consuming	Does not assess semantic accuracy or learning outcomes	Lacks direct validation against expert-defined models	Does not compare with expert-created maps for validation	Computationally intensive, may require refinement for large datasets

Moreover, this framework facilitates personalized learning by clustering students based on performance and providing targeted feedback. The identification of missing or misrepresented concepts allows educators to tailor instructional strategies, reinforcing areas that require improvement. Additionally, the ability to track learning patterns over time supports adaptive learning approaches, enabling dynamic curriculum adjustments to enhance knowledge acquisition.

This study differs from previous works by integrating both quiz-derived and self-constructed concept maps with Social Network Analysis (SNA) and network similarity measures, a combination not commonly explored in earlier literature. While prior studies have assessed either MCQ performance or concept maps in isolation, our framework bridges these methods, providing a more structured and quantifiable approach to evaluating conceptual understanding. The use of Jaccard and Cosine similarity, alongside centrality metrics, enabled the objective identification of key concepts, misconceptions, and learning gaps. In contrast to earlier works that offered limited insight into individual learning patterns, our student clustering approach facilitated personalized analysis. These findings demonstrate the successful achievement of our objectives and highlight the framework's potential for improving educational assessment beyond the capabilities of traditional techniques.

5.1 Limitations

Though similarity measures efficiently assess structural relationships, they do not fully capture semantic meaning or contextual depth. The reliance on an instructor-generated reference concept map introduces subjectivity, and the use of predefined keywords may restrict students' ability to express concepts in their own terms. Scalability challenges arise as the number of students and concepts increases, affecting computational efficiency. Additionally, the system lacks real-time

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feedback, limiting immediate student improvement. Although influential nodes and degree centrality help identify key concepts, they do not account for semantic weight. Future improvements could incorporate semantic similarity models, automated reference map generation, and adaptive feedback mechanisms.

6 CONCLUSION & FUTURE WORK

This study proposes a comprehensive framework that integrates quiz-based and independent concept map construction with network similarity measures to evaluate student understanding. Using Jaccard and Cosine similarity, along with degree centrality and influential node analysis, the framework provides a quantitative assessment of conceptual alignment. The findings support the initial hypothesis that applying Social Network Analysis (SNA) to concept maps offers a more structured evaluation than traditional methods. It effectively identifies key concepts, misconceptions, and knowledge gaps, while clustering students reveals personalized learning patterns. This validates the approach as a valuable tool for enhancing assessment and supporting targeted instructional strategies.

The data demonstrate that quiz-based and self-constructed concept maps reveal different but complementary aspects of student understanding—surface knowledge versus deeper conceptual connections. This highlights limitation of traditional assessments and emphasizes the need for multi-layered, personalized evaluation frameworks that objectively assess learning, identify misconceptions, and enable targeted feedback to improve educational outcomes.

Future research can integrate advanced network analysis techniques, machine learning for automated misconception detection, and adaptive learning strategies. Developing an interactive tool for real-time assessment will further enhance its application, fostering a personalized, data-driven educational experience.

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REFERENCES

[1] J. D. Novak and A. J. Cañas, "The Theory Underlying Concept Maps and How to Construct Them," *Tech. Rep. IHMC C. 2006-01*, no. May, pp. 1–31, 2006, [Online]. Available: http://www.ode.state.or.us/teachlearn/subjects/science/resources/msef2010-theory%7B_%7Dunderlying%7B_%7Dconcept%7B_%7Dmaps.pdf%5Cnpapers://dee23da0-e34b-4588-b624-f878b46d7b3d/Paper/p348

[2] F. Veiga, A. Gil-Del-Val, E. Iriondo, and U. Eslava, "Validation of the use of concept maps as an evaluation tool for the teaching and learning of mechanical and industrial engineering," *Int. J. Technol. Des. Educ.*, vol. 35, no. 1, pp. 383–401, Mar. 2024, doi: 10.1007/S10798-024-09903-8/TABLES/6.

[3] D. McLinden, "Concept maps as network data: Analysis of a concept map using the methods of social network analysis," *Eval. Program Plann.*, vol. 36, no. 1, pp. 40–48, Feb. 2013, doi: 10.1016/J.EVALPROGPLAN.2012.05.001.

[4] S. S. Singh, S. Muhuri, S. Mishra, D. Srivastava, H. K. Shakya, and N. Kumar, "Social Network Analysis: A Survey on Process, Tools, and Application," *ACM Comput. Surv.*, vol. 56, no. 8, Apr. 2024, doi: 10.1145/3648470.

[5] S. Daguati, B. Rütsche, and C. M. Thurn, "Describing Conceptual Knowledge in Concept Maps by Network Analysis," *Concept. Chang. Era Digit. Transform. 13th Int. Conf. Concept. Chang. - Program. Abstr.*, pp. 67–67, 2024.

[6] E. Da Silva, "Concept Maps: Evaluation Models for Educators," *J. Bus. Manag. Sci.*, vol. 2, no. 5, pp. 111–117, 2014.

[7] A. W. Goldman and M. Kane, "Concept mapping and network analysis: An analytic approach to measure ties among constructs," *Eval. Program Plann.*, vol. 47, pp. 9–17, 2014, doi: 10.1016/j.evalprogplan.2014.06.005.

[8] G. Mirbagheri, M. Hakimian, and A. A. Kardan, "Using a Recommender System to Suggest Educational Resources and Drawing a Semi-Automated Concept Map to Enhance the Learning Progress," *Proc. Int. Conf. E-Learning Work. 2019*, vol. 6, no. June, 2019.

[9] Z. Shou, X. Lu, Z. Wu, H. Yuan, H. Zhang, and J. Lai, "On Learning Path Planning Algorithm Based on Collaborative Analysis of Learning Behavior," *IEEE Access*, vol. 8, pp. 119863–119879, 2020, doi: 10.1109/ACCESS.2020.3005793.

[10] M. Saqr and A. Alamro, "The role of social network analysis as a learning analytics tool in online problem based learning," *BMC Med. Educ.*, vol. 19, no. 1, pp. 1–11, 2019, doi: 10.1186/s12909-019-1599-6.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[11] Y. Choi and Y. Il Cho, "Learning analytics using social network analysis and Bayesian network analysis in sustainable computer-based formative assessment system," *Sustain.*, vol. 12, no. 19, 2020, doi: 10.3390/SU12197950.

[12] Y. Li, Y. Wu, L. Zhang, and J. Chen, "The Impact of Network Structure on Knowledge Adoption: A Network Text Analysis on Knowledge-Sharing Platforms," *IEEE Trans. Comput. Soc. Syst.*, Feb. 2023, doi: 10.1109/TCSS.2023.3255588.

[13] P. Wulff, "Network analysis of terms in the natural sciences insights from Wikipedia through natural language processing and network analysis," *Educ. Inf. Technol.*, vol. 28, no. 11, pp. 14325–14346, 2023, doi: 10.1007/s10639-022-11531-5.

[14] Y. Xu and J. Du, "What participation types of learners are there in connectivist learning: an analysis of a cMOOC from the dual perspectives of social network and concept network characteristics," *Interact. Learn. Environ.*, vol. 31, no. 9, pp. 5424–5441, 2023, doi: 10.1080/10494820.2021.2007137.

[15] J. Haiyue and W. K. Yoong, "A Network Analysis of Concept Maps of Triangle Concepts," *Shap. Futur. Math. Educ. Proc. 33rd Annu. Conf. Math. Educ. Res. Gr. Australas.*, pp. 232–239, 2010.

[16] D. McLinden, "Concept maps as network data: Analysis of a concept map using the methods of social network analysis," *Eval. Program Plann.*, vol. 36, no. 1, pp. 40–48, 2013, doi: 10.1016/j.evalprogplan.2012.05.001.

[17] D. Koutra, "D ELTA C ON : A Principled Massive-Graph Similarity Function," *ACM Trans. ...*, vol. 10, no. 3, pp. 162–170, 2015, [Online]. Available: http://dl.acm.org/citation.cfm?id=2824443

[18] C. Limongelli, M. Lombardi, A. Marani, F. Sciarrone, and M. Temperini, "Concept maps similarity measures for educational applications," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 9684, pp. 361–367, 2016, doi: 10.1007/978-3-319-39583-8_42.

[19] C. M. Steiner and D. Albert, "Validating domain ontologies: A methodology exemplified for concept maps," *Cogent Educ.*, vol. 4, no. 1, 2017, doi: 10.1080/2331186X.2016.1263006.

[20] Q. Zhang, M. Li, and Y. Deng, "Measure the structure similarity of nodes in complex networks based on relative entropy," *Phys. A Stat. Mech. its Appl.*, vol. 491, no. October, pp. 749–763, 2018, doi: 10.1016/j.physa.2017.09.042.

[21] Y. Li, Z. Shao, X. Wang, X. Zhao, and Y. Guo, "A Concept Map-Based Learning Paths Automatic Generation Algorithm for Adaptive Learning Systems," *IEEE Access*, vol. 7, pp. 245–255, 2019, doi: 10.1109/ACCESS.2018.2885339.

[22] C. S. Q. Siew, "Using network science to analyze concept maps of psychology undergraduates," *Appl. Cogn. Psychol.*, vol. 33, no. 4, pp. 662–668, 2019, doi: 10.1002/acp.3484.

[23] Y. Bai, H. Ding, S. Bian, T. Chen, Y. Sun, and W. Wang, "SimgNN: A neural network approach to fast graph similarity computation," *WSDM 2019 - Proc. 12th ACM Int. Conf. Web Search Data Min.*, pp. 384–392, 2019, doi: 10.1145/3289600.3290967.

[24] K. Sdravopoulou, J. M. M. González, and M. D. Hidalgo-Ariza, "Network analysis for learners' concept maps while using mobile augmented reality gaming," *Appl. Sci.*, vol. 11, no. 21, 2021, doi: 10.3390/app11219929.

[25] V. Göhler and G. A. Yadav, "Analyzing Concept Maps in Computer Science Education: An Unsupervised Learning Approach with Graph Neural Networks," *Proc. 25th Annu. Conf. Inf. Technol. Educ. SIGITE 2024*, pp. 56–61, Dec. 2024, doi: 10.1145/3686852.3687071.

[26] K. Hajarathaiah, M. K. Enduri, S. Anamalamudi, A. Abdul, and J. Chen, "Node Significance Analysis in Complex Networks Using Machine Learning and Centrality Measures," *IEEE Access*, vol. 12, pp. 10186–10201, 2024, doi: 10.1109/ACCESS.2024.3355096.

[27] J. J. Salinas and J. Erochko, "Using Weighted Scoring Rubrics in Engineering Assessment," *Proc. Can. Eng. Educ. Assoc.*, pp. 1–5, 2015, doi: 10.24908/pceea.v0i0.5743.

[28] T. P. Rinjeni, A. Indriawan, and N. A. Rakhmawati, "Matching Scientific Article Titles using Cosine Similarity and Jaccard Similarity Algorithm," *Procedia Comput. Sci.*, vol. 234, pp. 553–560, 2024, doi: 10.1016/J.PROCS.2024.03.039.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[29] A. Kapuza, “How Concept Maps with and without a List of Concepts Differ: The Case of Statistics,” *Educ. Sci. 2020, Vol. 10, Page 91*, vol. 10, no. 4, p. 91, Mar. 2020, doi: 10.3390/EDUCSCI10040091.

[30] B. Cetin, N. Guler, and R. Sarica, “Using Generalizability Theory to Examine Different Concept Map Scoring Methods,” *Egit. Arastirmalari - Eurasian J. Educ. Res.*, vol. 2016, no. 66, pp. 211–228, 2016, doi: 10.14689/ejer.2016.66.12.