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Cognitive Knowledge-Based Algorithms for Dynamic Knowledge Representation of Adaptive Feedback

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Abstract: Historically, the creation of knowledge-based systems was perceived as a human transfer of expertise to the developed system. This perspective operated on the assumption that the necessary knowledge already existed and merely needed to be gathered and incorporated. Typically, this involved acquiring knowledge through expert interviews and translating it into production rules. However, this approach encountered challenges in adequately representing diverse knowledge types. The presence of various knowledge types and the lack of robust justifications for the rules rendered the system maintenance time-consuming and arduous. Consequently, this method was primarily viable for constructing prototypes, prompting a transition from the transfer method to the modeling approach. The modeling approach diverges from simulating the entire cognitive process of an expert and instead aims to create a model that produces similar outcomes in problem-solving. While several knowledge modeling techniques for delivering feedback in computer-based learning environments have been proposed, our research indicates that these techniques are often static, involve a manual knowledge elicitation process, and heavily rely on the volatile knowledge of experts. Consequently, there is a pressing need to streamline this process with a dynamic approach to knowledge representation in an adaptive feedback environment. This research seeks to introduce and assess the performance of knowledge elicitation, knowledge bonding, and adaptive feedback algorithms in representing knowledge for adaptive feedback. The proposed strategy utilizes the Cognitive Knowledge Base (CKB) to formalize knowledge based on an Object-Attribute-Relation (OAR) model. This technique empowers the CKB to autonomously decide on the type of feedback to provide. Conclusions drawn from the recommendations of the adaptive feedback algorithm align with prior research affirming the appropriateness of feedback in specific scenarios.

Keywords*: Adaptation, Learning Environment, Domain Modeling, Student Modeling, Algorithm*

1. Introduction

Cognitive Knowledge-Based Algorithms are designed to mimic and leverage human-like cognitive processes in order to perform tasks that typically require human intelligence. These algorithms are motivated by the idea of simulating human thought processes, reasoning, and problem-solving abilities, and interacting with users in a way that is more natural and adaptable. These algorithms have applications across various domains, from education and healthcare to finance and technology.

Cognitive knowledge-based algorithms play a crucial role in online learning environments by leveraging cognitive science principles to enhance the learning experience. These algorithms aim to understand and adapt to the cognitive processes of learners, providing personalized and effective learning knowledge-based algorithms are applied in online learning through strategies such as: Adaptive Learning Systems; Learning Analytics; Intelligent Tutoring Systems; Natural Language Processing (NLP); Emotion Recognition; Memory Enhancement; Collaborative Learning; and Gamification. Implementing cognitive knowledge-based algorithms in online learning requires a multidisciplinary approach, combining expertise in cognitive science, artificial intelligence, data analytics, and education. As technology advances, the potential for more sophisticated and effective algorithms in online learning continues to grow, providing learners with increasingly personalized and impactful educational experiences. Implementing cognitive knowledge-based algorithms for dynamic knowledge representation and adaptive feedback requires a robust understanding of both educational principles and technological capabilities. The integration of these algorithms can significantly enhance the personalized and effective nature of online learning experiences.

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A system designed to represent knowledge is generally characterized as a knowledge-based system (KBS). A knowledge-based system's knowledge base is its most important component. The definition of a knowledge base given by Dignum and van de Riet (1991) is a collection of statements that describe what is known about the real world, combined with some constraints that specify which claims are true in all possible worlds and which ones should be true. Initially, the prevailing perspective involved the direct transfer of human expertise into implemented knowledge bases. This transfer approach assumed that all necessary knowledge already existed, necessitating only its gathering and incorporation into the system. (Wielinga et al., 1992). Typically, the relevant knowledge is collected through expert interviews and incorporated in the form of production standards (Puerto et al., 2019). However, this technique had difficulty in accurately capturing multiple knowledge categories (Studer et al., 1998). The availability of multiple knowledge kinds and the lack of sufficient reasons for regulations made the maintenance process complex and time-consuming. Consequently, this approach was largely suitable for producing small-scale prototypes, forcing a move from the transfer strategy to the modeling approach (Ramirez and Valdes, 2012; Yurin et al., 2018). The modeling technique does not attempt to duplicate an expert's entire cognitive process, but rather to build a model that produces similar results in problem solving. KBS can be classified as linguistic knowledge bases (Fellbaum, 1998; Baker, 2014; Speer and Havasi, 2012), expert knowledge bases (Driankov et al., 2013; Kerr-Wilson and Pedrycz, 2016; Kung and Su, 2007), ontology (Fensel, 2003; Sánchez, 2010), and, more recently, cognitive knowledge bases (Fensel, 2003; Sánchez, 2010). (Wang, 2015b).

Linguistic knowledge bases aim to model human grammar, encompassing syntax, semantics, phonology, morphology, and the lexicon. Examples include ConceptNet, FrameNet, and WordNet (Bimba et al., 2016). ConceptNet, for instance, is a common-sense knowledge base that describes human knowledge and its expressions, focusing on eliciting common-sense knowledge about the real world (Agarwal et al., 2015a,b).

ConceptNet, a common-sense knowledge base, aims to capture real-world common-sense knowledge (Bimba et al., 2016). It utilizes a graph representation where nodes signify concepts composed of action verbs (Bicocchi et al., 2011). In contrast, FrameNet, developed using frame semantics theory, serves as a lexicon of the English language, understandable by both humans and machines. Unlike ConceptNet's graph representation, FrameNet represents knowledge as relationships between frames and an annotated corpus (Wandmacher et al., 2011; Baker, 2012). Frames, describing objects, situations, or events in a script-like manner, are central to FrameNet (Ruppenhofer et al., 2006). WordNet, a lexical database, connects words and their meanings through semantic and lexical similarities, representing knowledge as a semantic network of synsets (Bimba et al., 2016).

Fuzzy Cognitive Maps (FCM) offer a qualitative perspective for representing knowledge, especially in complex systems lacking precise mathematical models. FCM provides a balance between fuzzy knowledge and its representation, presenting causal relationships in a fuzzy-graph structure that allows for the propagation of causality in both backward and forward chaining (Salmeron et al., 2019). FCMs find applications in soft knowledge domains where concepts, relationships, and meta-system language are inherently fuzzy (Mazzuto et al., 2018; Zhang et al., 2019).

Expert knowledge bases, representing domain knowledge for problem-solving, utilize rules with antecedents (IF part) and consequents (THEN part). These rules can express relations, recommendations, directives, strategies, and heuristics (Michael, 2005). Expert knowledge bases are categorized as logic rule-based or fuzzy rule-based systems. In a logical rule-based system, knowledge is represented in binary logic, where the antecedent's truth leads to the consequent's truth. In contrast, a fuzzy rule-based system allows for partial truth in the consequent when the antecedent is true, enabling efficient representation of continuous variables (Banerjee et al., 2001). Fuzzy logic, employed in fuzzy rule-based systems, expresses human knowledge in imprecise terms such as rarely, sometimes, often, occasionally, etc. (Michael, 2005).

Ontology, a subfield of metaphysics, arranges knowledge as a taxonomy of concepts with values, qualities, and relations. It is described as a formal, clear specification of a shared conceptualization (Studer et al., 1998). Ontologies consist of classes (domain concepts), relations (concept relationships), and examples (real-world phenomena). Based on conceptualization and generality levels, ontologies are divided as application ontology, domain ontology, generic ontology, and representation ontology (Bimba et al., 2016). Application ontologies describe relationships between concepts for a specific task in a domain, domain ontologies are valid within a specific domain, generic ontologies apply across multiple domains, and representation ontologies capture knowledge independent of problem-solving methodologies.

(CKB) represents knowledge as a formal notion utilizing an Object-Attribute-Relation (OAR) model based on concept algebra (Valipour and Yingxu, 2015). The emergence of CKB addresses limits in operations on acquired knowledge and inadequate transformability between diverse knowledge sources (Wang, 2015a) In CKB, knowledge is modified as a dynamic concept network, replicating human knowledge processing (Bimba et al., 2016). Cognitive units inside CKB reflect notions recognizing and modeling both concrete and abstract entities (Wang, 2015b).

Research in the design and development of computer-based learning environments is a multi-disciplinary endeavor that integrates research methods from computer science, education, and psychology. Within this context, computer scientists are primarily focused on refining algorithms, models, and automation, whereas educators are dedicated to assessing instructional algorithms and their impact on student learning. The overarching goal is to introduce and assess the performance of algorithms for representing knowledge in adaptive feedback within a computer-based learning environment. Consequently, the primary objective of this study is to present and evaluate the effectiveness of the proposed algorithms in capturing the knowledge needed for adaptive feedback in a computer-based learning setting. Our methodology emphasizes the dynamic integration of knowledge into the Cognitive Knowledge Base (CKB). Unlike manual processes, this dynamic approach enables the system to adapt seamlessly to changing information landscapes. By employing advanced algorithms, knowledge is identified, captured, and integrated in real-time, ensuring that the CKB is always up-to-date and reflective of the current state of knowledge within the learning environment

The focus of this research is to introduce and assess the performance of knowledge elicitation, knowledge bonding, and adaptive feedback algorithms in representing knowledge for adaptive feedback. The proposed strategy leverages the Cognitive Knowledge Base (CKB) to formalize knowledge based on an Object-Attribute-Relation (OAR) model. This innovative approach empowers the CKB to autonomously decide on the type of feedback to provide, marking a departure from static methodologies that lack adaptability. Our methodology involves the dynamic incorporation of knowledge into the Cognitive Knowledge Base. The knowledge elicitation process is not a manual, labor-intensive task but rather a streamlined, adaptive algorithm that identifies, captures, and bonds knowledge seamlessly. The OAR model facilitates a structured representation, allowing the CKB to navigate through complex knowledge relationships and make informed decisions regarding the type of feedback to deliver. The adaptive feedback algorithm, built upon these dynamic knowledge representation techniques, aligns its recommendations with prior research, affirming the appropriateness of feedback in specific scenarios. This ensures that the feedback provided is not only contextually relevant but also tailored to the evolving needs of the learner or user.

The adaptive feedback algorithm proposed represents a significant advancement in personalized learning, aiming to tailor feedback based on individual learner qualities, with a specific emphasis on adaptability. By utilizing learner profiling and adaptability assessments, the algorithm dynamically selects and customizes feedback, creating a responsive and evolving learning environment. Its strength lies in navigating the complexities of individualized learning, employing a dynamic and iterative model that evolves over time based on learner responses. The algorithm's success is measured by improved engagement, comprehension, and skill development, with continuous assessment contributing to ongoing refinement. Positioned as a valuable tool in educational technology, ongoing research and development in this area hold promise for further advancements in personalized learning experiences.

Section two of this research outlines three algorithms designed to represent knowledge for adaptive feedback in a computer-based learning environment. Moving forward, Section 3 delineates the experimental procedures and details the processes for collecting data. The findings obtained from evaluating the performance of the three algorithms are then presented in Section 4. Subsequently, Section 5 engages in a comprehensive discussion of the assessed results. Finally, Section 6 delves into the implications of the findings and outlines potential avenues for future research

2. Algorithms for Dynamic Knowledge Representation of Adaptive Feedback

At present, prevalent techniques used for knowledge representation in adaptive learning environments, such as linguistic knowledge bases, expert knowledge bases, and ontologies, typically establish relationships between pairs of concepts (Bimba et al., 2017). However, the introduction of a Cognitive Knowledge Base (CKB) employing an Object, Attribute, Relations (OAR) model transcends this limitation by providing a framework to determine relationships of multiple concepts with a single concept. The proposed strategy relies on the Object-Attribute-Relation (OAR) model for formalizing knowledge within the Cognitive Knowledge Base. This model provides a structured representation that facilitates efficient navigation through intricate knowledge relationships. By employing the OAR model, the CKB gains the ability to discern relevant attributes, relations, and objects, enhancing its capacity to make informed decisions regarding the type of adaptive feedback to be delivered. From the perspective of adaptive feedback, this involves automatically updating the CKB based on optimal performances of diverse students solving various problems and receiving individualized feedback corresponding to their specific knowledge levels of a particular concept.

The proposed adaptive feedback model empowers the CKB to autonomously determine the type of feedback to provide. During the initial stages of CKB construction, the knowledge bonding process selects random combinations of required attributes to ensure optimal student performance. As more students engage with the system, the CKB learns and refines its optimal combination of concepts to deliver influential feedback to the student. The architecture of the suggested adaptive feedback model comprises three key modules: 1) knowledge elicitation, 2) knowledge bonding, and 3) adaptive feedback, as depicted in Figure 1.

The adaptive feedback module receives two inputs: the concept input (C), encompassing student, domain, and pedagogical concepts, and the problem-solving state input (PS), which includes attributes from student and domain models. In the initial modeling phase, the system represents learning materials, pedagogical principles, and student concepts through the knowledge elicitation module.

During knowledge elicitation, a concept is selected, and the knowledge acquisition algorithm acquires its attributes, defining the concept's attribute space. The internal relationship is then established with the acquired attributes, aiming to retain the newly acquired knowledge as a formal concept. Subsequently, the initiation of the knowledge bonding process involves establishing relational links between the recently acquired concept and older concepts in the knowledge base. The knowledge bonding algorithm analyses comparatively to establish a 1-to-n mapping of the recently defined concept with other older concepts in the knowledge base. Object, attribute, internal, and external relations between the concepts are determined, and the weights between influential concepts are adjusted. Finally, the knowledge base preserves the formal concept that has been established, representing it in the form of an Object-Attribute-Relation (OAR) model.

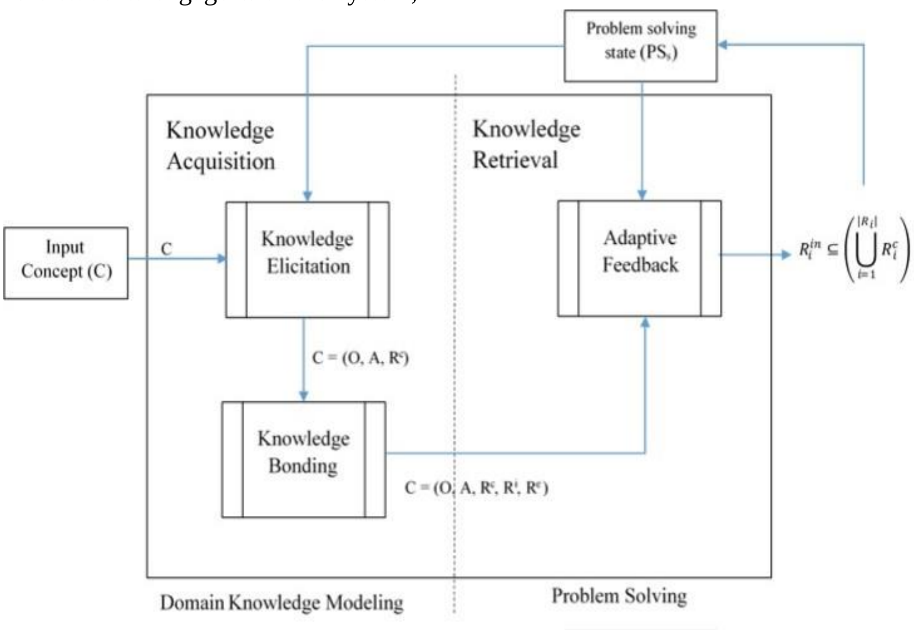

Figure 1: Adaptive Feedback Architecture for Physics Problem Solving

These concepts may have interrelationships in complicated contexts, establishing a conceptual network that represents the student's whole body of knowledge regarding the pedagogy and subject. Common relationships exploited by various systems include:

1. Prerequisite: Indicates that a student needs to be familiar with the first concept before studying the next related concept.

2. Is-a: Denotes that a concept is an instance of another concept.

3. Part-of: Describes a scenario where a concept is part of another concept.

4. Is similar: Signifies similarity between concepts.

5. Independent: Suggests that concepts are not dependent on each other.

6. Dependent: Implies dependency between concepts.

The adaptive feedback method enables users (students) to access acquired knowledge stored in the Cognitive Knowledge Base. The adaptive feedback algorithm permits the retrieval of acceptable feedback for students based on established weights between related ideas in the CKB. This algorithm models the present condition of the learner and compares it to existing models in the CKB to select relevant feedback depending on the student's attributes. The implementation specifics of the knowledge elicitation, bonding, and adaptive feedback algorithms are further explained.

2.1. Knowledge Elicitation Algorithm

Knowledge elicitation algorithms refer to a set of techniques or methods used to gather, extract, or obtain knowledge from human experts or other sources. These algorithms aim to capture information and expertise that may not be explicitly available or easily articulated. The process of knowledge elicitation is particularly relevant in fields where human expertise is crucial but not always readily accessible or well-documented. Some key aspects related to knowledge elicitation algorithms: Expert Systems; Interviews and Surveys; Cognitive Task Analysis; Protocols and Observation; Machine Learning Approaches; Natural Language Processing (NLP); Knowledge Elicitation Frameworks; and Modeling Expert Mental Models. Expert systems, focus on the integration of human-like decision-making processes into computational models. Interviews and surveys involve direct communication with experts to extract both explicit and implicit knowledge. While cognitive task analysis, is a method that dissects expert problem-solving strategies and decision-making processes. Protocols and observation in capture real-time behavior and decision-making patterns of experts. Integration of machine learning techniques for automated knowledge extraction, focuses on pattern recognition and data-driven approaches. NLP techniques are employed to decipher and extract knowledge from unstructured textual data, including documents and interviews. While Expert Mental Models delves into the intricate process of capturing not just explicit knowledge but also the mental models of experts, understanding their unique perspectives and problem-solving approaches. Knowledge elicitation algorithms may aim to capture not just the explicit knowledge but also the mental models of experts. This involves understanding how experts conceptualize and approach problems in their domain. The choice of a knowledge elicitation algorithm depends on the nature of the expertise being sought, the domain of application, and the available resources. The goal is to make implicit or tacit knowledge explicit and usable within computational systems or decision support tools. Successful knowledge elicitation can lead to the development of expert systems, decision support systems, or other applications where human expertise is crucial.

Knowledge elicitation algorithms play a pivotal role in extracting and harnessing the expertise inherent in human minds, particularly in domains where such knowledge is vital but not always readily accessible or well-documented. This document explores various aspects related to knowledge elicitation algorithms, encompassing expert systems, interviews, surveys, cognitive task analysis, observation protocols, machine learning approaches, natural language processing (NLP), knowledge elicitation frameworks, and the modeling of expert mental models. The focus extends beyond capturing explicit knowledge to include the nuances of experts' mental models, delving into how they conceptualize and approach problems within their domains. The choice of a knowledge elicitation algorithm is contingent upon the nature of the expertise sought, the domain of application, and the available resources. Ultimately, the goal is to transform implicit or tacit knowledge into explicit and usable forms within computational systems or decision support tools, leading to the development of expert systems and decision support applications.

Based on the architecture of the adaptive feedback model, we suggest an enhanced representation of concepts within pedagogical, domain, and student models. In this framework, all information within these models is regarded as concepts. Illustrated in Figure 1, the knowledge elicitation phase operates under the assumption of a flawless Concept Attribute (CA) space, portraying the knowledge base as a semantic network. The CA space encompasses concepts and their associated attributes. The input to the knowledge elicitation algorithm is a concept, represented as C Ó .O;A;Ri/, with the key steps outlined in Algorithm 1.

During the data acquisition stage, the input data comprises attributes related to pedagogy, domain, student, or the problem-solving state. If the input data represents a concept from pedagogy, domain, or student, the object of the concept and its attributes are elicited. Subsequently, the algorithm compares the concept to existing concepts within the knowledge base. If a match is found, the algorithm exits; otherwise, an index and timestamp are assigned to the new concept. Following this, the internal relationship Ri is determined, and a partial representation of the concept is generated as output.

In the case where the input data is a problem-solving state (PS), the algorithm reads the PS and generates a timestamp. The output in this scenario includes the PS and the timestamp. At this stage, the external relationship between the newly acquired concept C and Re, the error margin (in the case of PS), are yet to be determined. These relations will be generated by the existing concepts in the knowledge base, and their strengths will be updated during the knowledge bonding stage based on the generated error margin.

Algorithm 1: Knowledge Elicitation Algorithm

```
Data: C_n; O; A
Result: .O; A Ó .A_1; A_2; A_3:::A_n/; R^i; null; null/, C_n category, C_n index or PS_sID, time stamp
initialization;
while C_n is available do
    read C_n;
    Determine C_n category (pedagogy, domain, student or problem solving state (PS_s);
    if C_n category = pedagogy || domain || student then
        read (O and A );
    else if C_n = PS_s;                                  /* PS_s is the problem solving state */
     then
        read PS_s Ó .S_p; PS_sID/ ;         /* PS_sID is problem solving state ID and S_p is
         performance */
        generate acquisition time stamp;
        output: (PS_s, time stamp)
    else
        return (Concept not understood!)
    if !(Knowledge base full) then
        compare C_n attributes with existing concepts;
        if (Full concept match) then
            return (concept exists!)
        else
            assign an index to C_n;
            generate acquisition time stamp;
            calculate R^i Ó O • A;
            determine partial concept C = O; A Ó .A_1; A_2; A_3:::A_n/; R^i; null; null;
            output: O; A Ó .A_1; A_2; A_3:::A_n/; R^i; null; null; C_n category; C_n; index or PS_sID, time stamp;
    end
    else
        return (Knowledge base full!)
    end
end
```

2.2. Knowledge Bonding Algorithm

As of my last knowledge update in January 2022, the term "Knowledge Bonding Algorithm" does not appear to be widely recognized or used in the field of artificial intelligence, machine learning, or related domains. It's possible that this term has been introduced or gained significance in a more recent context or specific niche within these fields.

The program establishes subordinate ties between the new thought and all of the previous ideas in the Cognitive Knowledge Base in the second step of knowledge bonding (CKB). The knowledge bonding procedure discusses comparative analysis, which is used in this matching analysis, as well as the addition of the new concept C to the CKB model. The input to the knowledge bonding process includes. O;A Ó .A1;A2;A3:::An/, Ri, null, null), C category, C index, and timestamp. The output of the knowledge bonding algorithm (Algorithm 2) is the newly acquired concept and an updated weight between related concepts, which is then incorporated into the CKB model.

Algorithm 2: Knowledge Bonding Algorithm

```
Data: .O; A Ó .A1; A2; A3:::An/; Ri; null; null/, Cn category, Cn index, PSs, time stamp
Result: .O; A Ó .A1; A2; A3:::An/; Ri; Re/, Cn category, Cn index, time stamp,Rin
read data;
while Ci is available in CKB ;                    /* where Ci is all existing concepts */
 do
    read Cn;
    if (Cn = PSs ) ;                              /* PSs is the problem solving state */
     then
        Retrieve existing problem solving state PSsi using PSsID ;
        compute error margin epss = 1 * 0:7.Ps/ + 0:3.Pt/ where 0 f epss f 1;
        compute weight adjustment value wi+1 = wi * epss where 0 f wi+1 f 1; /* wi is the previous
         weight and wi+1 is the current weight */
        adjust weight between concepts wspi = (‡ Rin_spi, i=1, wi) / (Rin_spi) where 0 f wspi f 1;
        return (Weight adjusted!!!);
    end
    else
        compute Re_i = Ci • Cn ;
        compute similarity Cn í Ci = (AªAi / AãAi) = { 1      Cn = Ci
                                                   { .0; 1/  Cn › Ci â Cn < Ci â Cn > Ci ;
                                                   { 0      Cn ' Ci
        determine super-concept Ai Ó A;
        determine sub-concept A Ó Ai;
        determine equivalent-concept Ai = A Æ Oi = O Æ Ri = Ri_i;
        determine relationship type Stk;
        assign similarity index Si Ó .Ci; Stk/; .Ci+1; Stk+1/; .Ci+2; Stk+2/:::;
        S = S + Si;
        Re = Re + Re_i;
        enter concept Cn : O; A Ó .A1; A2; A3; :::An/; Ri; Re, Cn category, Cn index, time stamp, similarity
         index S
    end
end
```

The index number for the new concept C is determined by incrementing the index number of the last concept C entered into the knowledge base by the knowledge elicitation algorithm. When the input concept C represents a problem-solving state (PS), the error margin (e) is computed based on the student's score and time of completion. Subsequently, the problem-solving state is identified, and the strength between the involved concepts is updated.

The knowledge bonding method performs three conditional checks for every concept C in the knowledge base during the formation of external linkages. To begin with, sub-concepts from the ith concept in the knowledge base (Ai Ó A) are found via the similarity check in relation to the new idea C. This is the point where the present concept C's intents are a subset of the new concept C's intentions. As a subset of an existing concept, the new idea's intentions are compared against super-concepts in the knowledge base in the second check. The third step is to compare C and C's intentions to find equivalent concepts. The similarity index is recorded as the database index of the ith idea and the type of similarity (St) after a related match is identified. Lastly, the cognitive knowledge base stores the aggregated relationships (R), similarity index, and all input parameters to the knowledge bonding process as a fused idea.

Knowledge extraction represents final process in the proposed cognitive knowledge-based model. It enables students to the access adaptive feedback through the adaptive feedback algorithm. The retrieval operations allow the output of adaptive feedback based on the adaptation characteristics of means, target, goal and strategy.

2.3. Adaptive Feedback Algorithm

The adaptive feedback algorithm's goal is to determine the best input for each learner depending on their adaptable qualities. The adaptive feedback algorithm described here suggests a personalized approach to providing feedback to learners, tailoring the feedback based on individual characteristics and adaptability. The algorithm aims to determine the most effective input or guidance for each learner by considering their unique qualities. This approach acknowledges and responds to the fact that learners vary in their learning styles, preferences, and abilities to adapt to different instructional methods. The adaptive feedback method receives the partial problem-solving state PS as input. PS is made up of attributes from both the domain and student models. The problem-solving state, as indicated in Eq. 1, includes the student's cognitive style, knowledge level, goal (anticipated performance and completion time), problem difficulty, and domain topic.

$$PSs =. Scs;Skl;Ps;Pt;Cp;Dc/ \quad (1)$$

The algorithm iteratively determines the similarity between the current problem-solving state PS and the knowledge base's existing problem-solving states PSi. A list is created for all states that exceed a specified threshold. The problem-solving state with the largest cumulative weight is then chosen, and its impact on student performance, as specified by the knowledge bonding algorithm (Algorithm 3), is produced.

Algorithm 3: Adaptive Feedback Algorithm

```
Data: PS_s, time stamp
Result: R^in
read data;
create and initialize problem solving state list PS_sL
while PS_si is available do
    compute similarity PS_s í PS_si = (|A ª A_i| / |A ã A_i|) = { 1      PS_s = PS_si
                                                               { .0; 1/ PS_s › PS_si â PS_s < PS_si â PS_s > PS_si ;
                                                               { 0      PS_s ‘ PS_si
    if PS_s í PS_si > TH ;                          /* TH is the similarity threshold */
    then
        retrieve PS_si;
        add to problem solving state list PS_sL = PS_sL + PS_si;
        current section becomes this one;
    else
        Create random PS_s i
    end
end
determine highest PS_si;
output the influence of related concepts of the highest PS_si, R_i^in Ó • Σ_{i=1}^{|R_i|} R_i^c;
```

Therefore, in a learning session where the problem-solving state is identified, relevant feedback is provided based on the existing knowledge of the most similar state in the knowledge base. This approach leverages the content-addressed mechanism of a Cognitive Knowledge Base (CKB) for knowledge retrieval and manipulation, facilitated by the structural models. The overall objective is to enhance the learning experience by providing tailored and adaptive feedback that aligns with each learner's unique characteristics and promotes effective learning. The success of the adaptive feedback algorithm would be reflected in improved learner engagement, comprehension, and overall learning outcomes.

3. Experimental data

The adaptive feedback algorithm, a cornerstone of our strategy, is developed on the principles of dynamic knowledge representation. By aligning recommendations with prior research findings, the algorithm ensures that the feedback generated is not only contextually relevant but also in line with established best practices. This iterative and adaptive approach guarantees that the feedback evolves alongside the learner or user, maintaining its effectiveness across various scenarios and learning contexts.

Several knowledge modeling techniques have been proposed for delivering feedback in computer-based learning environments. However, our research suggests that the employed techniques are often static, involve a manual knowledge elicitation process, and heavily rely on volatile expert knowledge. Consequently, there is a need to streamline this process with a dynamic approach to knowledge representation in an adaptive feedback environment. The objective of this experiment is to introduce and assess the effectiveness of the knowledge elicitation (Algorithm 1), knowledge bonding (Algorithm 2), and adaptive feedback algorithms (Algorithm 3) in representing knowledge for adaptive feedback.

There are three algorithms proposed for the autonomous process of eliciting knowledge, bonding knowledge, and the provision of adaptive feedback. To evaluate the performance of these algorithms, data from pedagogy, Physics domain, and students were collected. The cognitive apprenticeship was considered as the pedagogical principle. The four main concepts used from this principle are the domain, sociology, sequencing, and instructional method as shown in Table 1. In Physics domain, four topics and 33 subtopics were considered. The process of acquiring problems from the 33 subtopics was conducted by 10 Physics experts from Center for Foundation Studies in Science (CFS), University of Malaya. The experts provided 160 problems and their solutions, from the four topics, with different levels of difficulty as shown in Table 2.

In eliciting knowledge for the student model, 50 students were used. The Group Embedded Figure Test (GEFT) was used to determine the student's cognitive style (Witkin et al., 1971; Khatib and Hosseinpur, 2011; Demick, 2014; Guo and Yang, 2018). The students were expected to locate simple visual images embedded in more complex visual images. The first section of the test which was used for practice, consists of seven easy problems with a time limit of two minutes. The second and third sections consists of nine more complex problems, with a time limit of five minutes each. At the end of the sessions, students who scored 12 and above out of 18 are grouped as field independent, while students with scores of 11 and below are considered as field dependent.

The data collected consists of 28 concepts and 3394 objects. These vast amount of data from the three main models of pedagogy, domain, and student were acquired using the adaptive feedback tool, which was developed based on the three algorithms proposed.

S/N	Concepts	Description
1	pedagogy	the method and practice of teaching, especially as an academic subject or theoretical concept
2	domain	a specified sphere of activity or knowledge.
3	sociology	the process where students learn skills in the context of their skill application within a culture defined by expert practice
4	sequencing	the changing learning needs of students at different knowledge levels acquisition in order to sequence the learning contents.
5	instructional method	the processes which help students acquire and use cognitive strategies for discovering, utilising, and managing knowledge
6	topic	a matter dealt with in a subject
7	sub-topic	a matter dealt with in a topic
8	problem	an inquiry starting from given conditions to investigate or demonstrate a fact or result
9	solution	a means of solving a problem or dealing with a difficult situation
10	solution details	a breakdown of the solution
11	difficulty	how hard or easy a problem is
12	feedback	information about reactions to a a student's performance of a task, etc. which is used as a basis for improvement.
13	student	a person who is studying at a university or other place of higher education
14	performance	a task or operation seen in terms of how successfully it is
15	time	the duration of solving a problem
16	score	the result of solving a problem
17	knowledge level	a proficiency of a student in a certain topic
18	cognitive style	cognitive style is usually described as a personality dimension which influences attitudes, values, and social interaction.
19	working solution	a detail of the working steps to solving a problem
20	free body diagram	a diagram used to show the relative magnitude and direction of all forces acting upon an object in a given situation
21	known	a variable whose value has been provided within a problem
22	unknown	a variable whose value has not been provided within a problem
23	equation	a statement that the values of two mathematical expressions are equal
24	principle	a general scientific theorem or law that has numerous special applications across a wide field.
25	answer	the final result of the solution to a problem
26	variable	a concept that does not have a constant value
27	gender	the state of being male or female
28	age	the length of time that a person has lived or a thing has existed

Table 1 List of Concepts

Table 2

Distribution of Problems in Introductory Physics

S/N	Topic	Difficult	Intermediate	Easy	Total
1	Static	5	2	1	8
2	Linear Motion	26	32	26	84
3	Rotational Motion	10	12	16	38
4	Gravitation	10	10	10	30
5	Total	51	56	53	160

4. Analysis of Results

This analysis involves a comprehensive assessment of the proposed knowledge elicitation, knowledge bonding, and adaptive feedback algorithms. Performance metrics, including accuracy, responsiveness, and adaptability, will be analyzed to measure the effectiveness of the proposed approach in capturing and representing knowledge dynamically. By utilizing a diverse set of metrics, we aim to provide a nuanced understanding of the capabilities and limitations of our approach. The process of eliciting knowledge in the proposed cognitive knowledge base model involves the establishment of the relationship between concepts, objects, and attributes with internal relations C Ó .O;A;Ri/. While knowledge bonding defines the magnitude of the internal relationship and determines the external relationship be-tween objects. Figure 2 shows a sample of the results involving these processes. The knowledge elicitation algorithm connects the objects in the pedagogy, domain, and student models, to their various attributes. The output to this process as shown in Figure 2, is .O;A Ó A ;A ;A :::A /. Then, the knowledge bonding algorithm calculates the value of the internal and external relationships. O;A Ó .A ;A ;A :::A /;Ri;Re/. In the knowledge elicitation presented in Figure 2, the attributes of the topic mechanics, Question15179151326, and Student0059 are clearly represented, while in the knowledge bonding, the magnitude of the relationship between the Kinematics-Linear Motion sub-topic and Question15179151326 (internal relationship), Question15179151326 and Question15232892029 (external relationship), and Student0059 and Student0028 (external relationship) are shown as 0.077, 0.036, and 0.5 respectively. Details of the sample questions and their attributes are presented in Table 3, while, features of the students and their attributes are shown in Table 4.

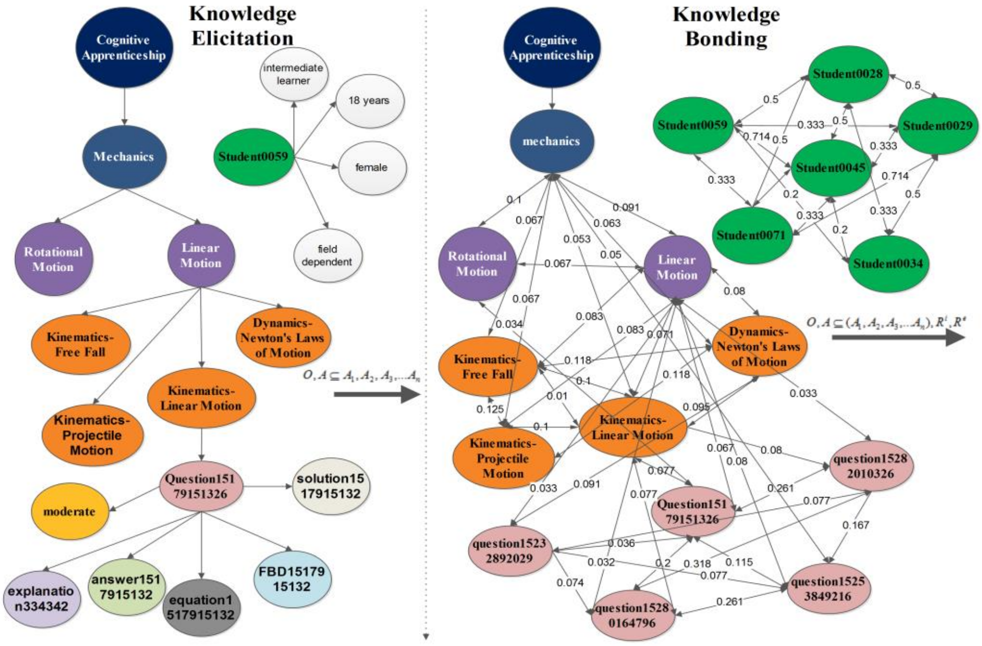

Figure 2: Cross-Section of The Cognitive Knowledge BaseDynamic Knowledge Representation of Adaptive Feedback

The adaptive feedback algorithm generates the value for the appropriate feedback to be provided to the student based on the problem-solving state. Figure 3, shows a sample of the generated weight value for providing an FT3 feedback type to PSS49(0.21) and PSS61(0.46) problem solving states.

Table 3: Sample Question with Attributes

S/N	ID	Question	Sub-topic	Principle	Solution	Difficulty
1	question15179151326	By applying the brakes, a driver reduces his car's velocity from $20ms^{*1}$ to $10ms^{*1}$ after travelling a distance of 30m. Find the deceleration of the car.	Kinetic Linear Motion	equation of motion	v = final velocity, u = initial velocity, s = distance, a = acceleration $v^2 = u^2 + 2as$ $a = \frac{v^2 * u^2}{s}$ $a = \frac{20^2 * 10^2}{30}$ $= \frac{300}{30} = 10ms^{*2}$	moderate
2	question15232892029	A 6 N force on a spring produces an extension of 2 cm. What is the extension when the force is increased to 18 N? State any assumption you made in calculating your answer.	Dynamics -Newton's Laws of Motion	Law of Conservation of Energy	$F1 = 6N; X1 = 2cm;$ $F2 = 18N; X2 = ?$ $F = kX$ $k = \frac{F1}{X1}$ $= \frac{6}{2} = 3$ $X2 = \frac{18}{3} = 6cm$	easy
3	question15280164796	A rock is thrown straight down with an initial velocity of 14.5 m/s from a cliff. What is the rock's displacement after 2.0 s? (Acceleration due to gravity is $9{:}81ms^{*2}$.)	Kinetic Linear Motion	equation of motion of motion	$s = v_i t + \frac{1}{2}at^2$ $= .14{:}5/.2{:}0/ + \frac{1}{2}.9{:}81/.2{:}0/^2$ $= 48{:}62m$	moderate
4	question15253849216	A feather is dropped on the moon from a height of 1.40 meters. The acceleration of gravity on the moon is $1{:}67ms^{*2}$. Determine the time for the feather to fall to the surface of the moon.	Kinetic Linear Motion	equation of motion	$s = v_{it} + \frac{1}{2}at^2$ when initial velocity is zero $s = \frac{1}{t}at^2$ implies $t = \frac{2s}{a}$ $t = \frac{2*1{:}4}{1{:}67}$ t=1.30s	easy
5	question15282010326	A bird, accelerating from rest at a constant rate, experiences a displacement of 28 m in 11 s. What is the final velocity after 11 s?	Kinetic Linear Motion	equation of motion	$v_{avg} = \frac{v_f + v_i}{2}$ $v_f = 2v_{avg} * v_i$ $= 2.\frac{28}{11}/ * 0$ $= 5{:}1ms^{*1}$	moderate

Table 4: Sample Students and their Characteristics

S/N	ID	Knowledge Level	Cognitive Style	Age	Gender
1	Student0028	novice learner	field dependent	18 Years	male
2	Student0029	novice learner	field independent	18 Years	male
3	Student0034	expert learner	field independent	18 Years	male
4	Student0045	intermediate learner	field dependent	18 Years	female
5	Student0059	intermediate learner	field dependent	18 Years	female
6	Student0071	novice learner	field independent	18 Years	male

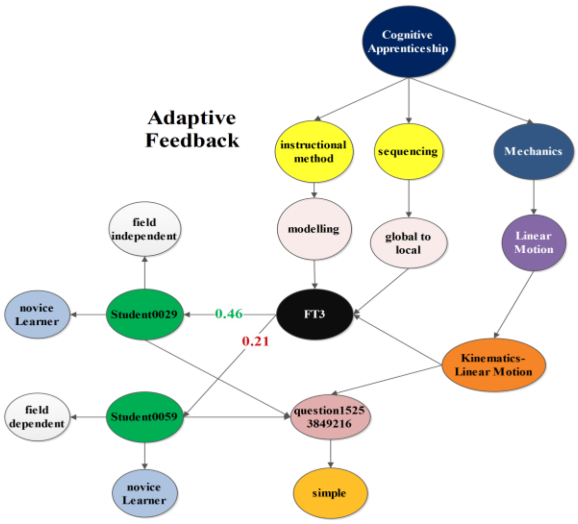

Figure 3: Provision of Adaptive Feedback

Dynamic Knowledge Representation of Adaptive Feedback

During the course of the student's interactions with the adaptive feedback tool, five different feedback types were suggested for 21 possible problem-solving states. Figure 4, shows that the FT3 was suggested for eight different problem solving states. Subsequently, FT4 was used in five different problem solving states as shown in Figure 5. FT14 was recommended for two different problem solving states as displayed in Figure 6. While, FT15 was proposed to six different problem solving states as represented in Figure 7.

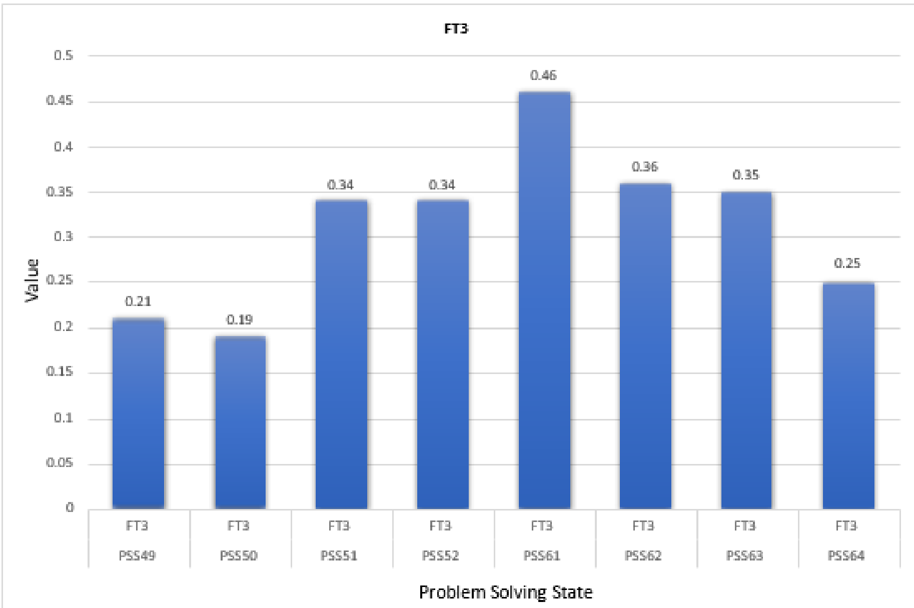

Figure 4: Adaptive Feedback Type 3

Dynamic Knowledge Representation of Adaptive Feedback

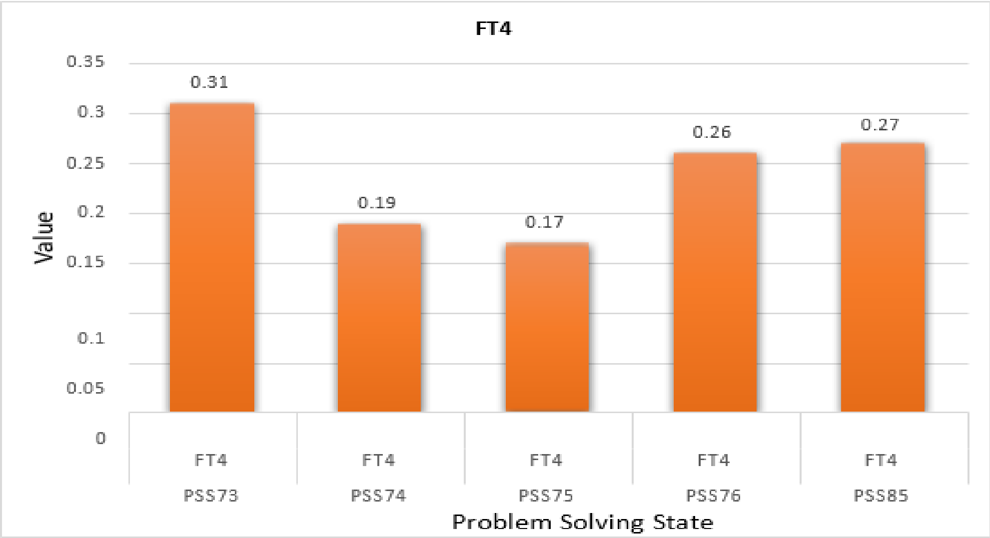

Figure 5: Adaptive Feedback Type 4

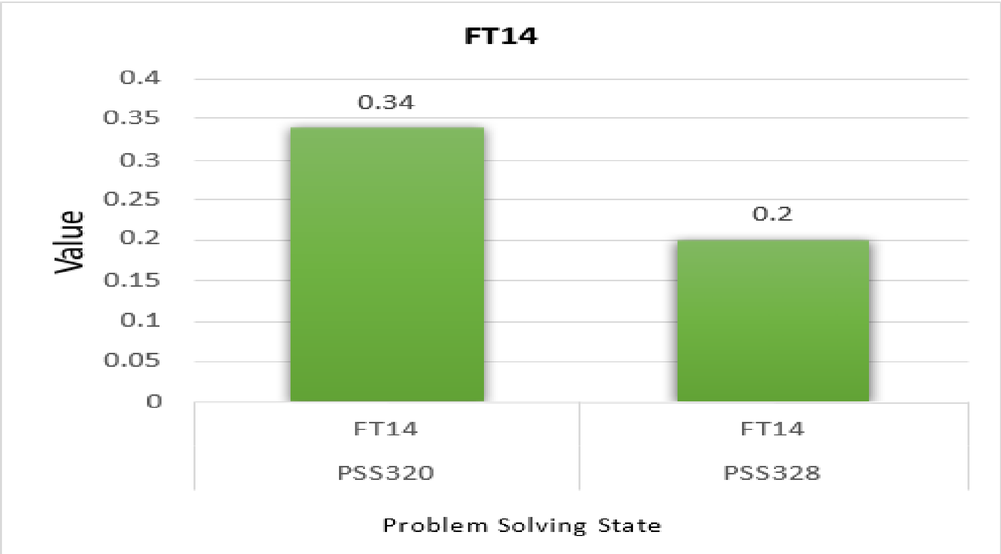

Figure 6: Adaptive Feedback Type 14

Dynamic Knowledge Representation of Adaptive Feedback

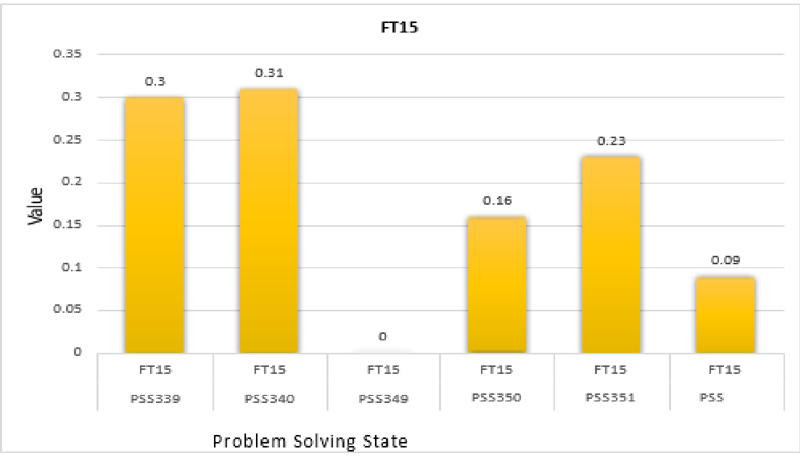

Figure 7: Adaptive Feedback Type 15

5. Discussion

This section will provide a concise summary of the study's key findings, highlighting the performance of the proposed knowledge elicitation, bonding, and adaptive feedback algorithms. It will also touch upon the success of the dynamic knowledge representation approach in addressing the limitations of traditional static methodologies. The dynamic knowledge representation of adaptive feedback using the CKB, involves three main algorithms. The main aim of this experiment is to determine the ability of these algorithms in representing knowledge of adaptive feedback. The knowledge elicitation algorithm is able to represent the characteristics of the pedagogy, domain, and student models and their attributes as shown in Figure 2. These results show an obvious relationship between all the objects in the pedagogy, domain, and student models.

The knowledge bonding algorithm is able to establish a connecting value, for the relationships between objects in a certain model, and between objects and attributes within that model as shown in Figure 2.A clear indication of the validity of these relationships is shown in a sample of the data shown in Table 5. For example, question15179151326, question15280164796, and question15282010326 all have the same sub-topic, principle, and difficulty level. However, our knowledge bonding algorithm sets the relationship between question15179151326 and question15280164796 as 0.2, while the relationship between question15179151326 and question15282010326 as 0.261. From this experiment, we found that the problem and solution of question15179151326 is more closely related to question15282010326, than question15280164796. The proposed knowledge bonding algorithm is able to determine these similarities autonomously, without any expert rules. Subsequently, the least similar questions are question15232892029 and question15179151326 with a value of 0.036. This is because they have different

sub-topic, principle, level of difficulty, and solution. The establishments of these relationships allow the adaptive feedback algorithm to determine the appropriate similar work example to be provided to a student solving a particular problem. The advantage of this knowledge bonding process is that, it does not require any expert rules and it is dynamic. Thus, if a new problem is elicited, the relationships are recalculated and the similarities are determined.

Another example, is the relationship between students as shown in Table 6. Student0029 and Student0071 have a high similarity value of 0.714, because they have the same knowledge level, cognitive style, age, and gender. The list similarity value of 0.2 was established between Student0045 and Student0034, because they only have age as a common attribute. Establishing the relationship between students allows the adaptive feedback process to provide a similar student's solution or similar student's worked example as feedback, when the sociology attribute of the cognitive apprenticeship principle is considered. Based on the results in Table 6, the knowledge bonding algorithm provides a convincing estimate of the relationship between students.

The results from the adaptive feedback algorithm as shown in Figures 4 to Figure 7, provides knowledge on the appropriate type of feedback to be provided at various circumstances. From Figure 4, we deduce that providing feedback based on a modeling instructional method and a global to local sequencing (pedagogical model), to field independent, novice learners (student model), who is solving simple Physics problem (domain model) is most effect. This result conforms to findings in other researches, which suggests that low-achieving learners benefit more from immediate and direct feedback (Mason and Bruning, 2001; Moreno, 2004). Novices or struggling students need support and explicit guidance during the learning process thus, directive or hints may not be as helpful as more explicit, directive feedback (Moreno, 2004).

Table 5 Relationship Between Questions

Questions	question15179151326	question15232892029	question15253849216	question15280164796	question15282010326
question15179151326	1.0	0.036	0.115	0.2	0.261
question15232892029	0.036	1.0	0.077	0.074	0.077
question15253849216	0.115	0.077	1.0	0.261	0.167
question15280164796	0.2	0.074	0.261	1.0	0.318
question15282010326	0.261	0.077	0.167	0.318	1.0

Table 6 Relationship Between Students

Student	Student0028	Student0029	Student0034	Student0045	Student0059	Student0071
Student0028	1.0	0.5	0.333	0.5	0.5	0.5
Student0029	0.5	1.0	0.5	0.333	0.333	0.714
Student0034	0.333	0.5	1.0	0.2	0.2	0.5
Student0045	0.5	0.333	0.2	1.0	0.741	0.333
Student0059	0.5	0.333	0.2	0.714	1.0	0.333
Student0071	0.5	0.714	0.5	0.333	0.333	1.0

In respect to findings in Figure 5, providing feedback based on the modeling instructional method, increase complexity sequencing is more beneficial to field dependent, novice learners, who are solving simple Physics problems. In comparison of these results with Figure 4, the field dependent learners benefit more when feedback is provided with increasing complexity sequencing technique, while field independent learners benefit more with global to local sequencing technique.

As shown in Figure 6, a field dependent, intermediate learners benefit more from an articulation instructional method, with increase complexity sequencing when solving very difficult problems, than field independent, novice learners. This conforms with previous experiments that indicate high-achieving learners, benefit more with delayed feedback (Clariana, 1990). Experienced students may view a moderate or difficult question as relatively easy, thus, benefit from delayed feedback (Gaynor, 1981).

Based on findings as indicated in Figure 7, a field independent, novice learner solving a simple Physics problem, those not benefit from feedback based on reflection instructional method and global to local state of sequencing. This conforms with the research that suggest low-achieving learners need scaffolding (Graesser et al., 2005).

6. Conclusion

Linguistic knowledge bases, exemplified by ConceptNet, FrameNet, and WordNet, aim to model human grammar comprehensively. ConceptNet utilizes a graph representation for real-world common-sense knowledge, while FrameNet employs frame semantics theory with relationships between frames. WordNet, a lexical database, connects words and meanings through a semantic network. Fuzzy Cognitive Maps offer a qualitative approach for complex systems, balancing fuzzy knowledge representation using causal relationships. Expert knowledge bases use rules, categorized as logical or fuzzy systems, with fuzzy logic accommodating partial truth. Ontology organizes knowledge as a taxonomy of concepts, values, and relations, with application, domain, generic, and representation ontologies serving distinct roles in capturing and organizing knowledge across various domains and problem-solving methodologies

The development and implementation of the adaptive feedback algorithm represent a significant stride toward personalized and effective learning experiences. The algorithm's primary objective is to tailor feedback based on individual learner qualities, emphasizing adaptability as a key determinant for determining the most suitable input. This approach recognizes the diversity among learners and acknowledges the importance of catering to their unique learning styles, preferences, and prior knowledge. The adaptive feedback algorithm operates on a learner-centric paradigm, utilizing learner profiling and adaptability assessments to dynamically select and customize feedback. By continuously monitoring learner progress and iteratively adjusting the feedback strategy, the algorithm creates a responsive and evolving learning environment. The integration of the algorithm with learning content ensures a seamless and cohesive experience, aligning feedback with instructional materials to reinforce comprehension and skill acquisition.

One of the algorithm's strengths lies in its ability to navigate the intricacies of individualized learning, acknowledging that learners are not uniform in their responses to instructional methods. By employing a dynamic and iterative learning model, the algorithm evolves over time, learning from the effectiveness of previous feedback interactions and adapting to the learner's evolving needs.

The objective of this research is to introduce and evaluate the performance of the proposed algorithms on representing knowledge on adaptive feedback. The three algorithms proposed which are the knowledge elicitation, knowledge bonding, and adaptive feedback algorithm, were evaluated based on the autonomous representation of knowledge of adaptive feedback. The knowledge elicitation algorithm produced a representation of the characteristics of the pedagogy, domain, and student models with their attributes. The knowledge bonding algorithm successfully generated values for object-object, object-attribute relationships. Results indicated a clear validity of these relationships between similar physics problems and students. Subsequently, the adaptive feedback algorithm was able to determine the type of feedback to be provided to a student based on the current problem-solving state. Deductions from the suggestions of the adaptive feedback algorithm, conforms to previous research studies on the appropriateness of feedback in certain scenarios. The outcomes of this research have broader implications for the field of computer-based learning environments. Our research contributes to the broader fields of computer science, education, and psychology by presenting an innovative and dynamic approach to knowledge-based systems. The successful implementation of the proposed strategy will establish its significance in enhancing the adaptability and effectiveness of computer-based learning environments. The dynamic knowledge representation approach, coupled with an adaptive feedback algorithm, holds the potential to significantly enhance the learning experience. By tailoring feedback to individual learning needs and dynamically updating knowledge representations, the proposed strategy aligns with the evolving landscape of education technology. The study's findings will pave the way for future research avenues, exploring enhancements to dynamic knowledge representation, knowledge bonding, and adaptive feedback algorithms. The goal is to continually refine and optimize these approaches for broader applicability in various educational settings, ensuring sustained adaptability and effectiveness.

We conclude based on the aim of this case study, that the provision of adaptive feedback using the proposed model is an effective strategy for autonomous knowledge acquisition in an adaptive learning environment. Limitations of this study are moderate. More interactions by the students with the adaptive learning tool is desirable, but was not possible due to the nature of interaction with human subjects. In future, a predictive model can be developed from the data accumulated for the provision of adaptive feedback. If successful, the model will have the ability to predict the appropriate feedback required for a certain problem-solving state, without the dependence on student's continuous interactions. In conclusion, this research marks a significant stride towards a dynamic and adaptive approach to knowledge-based systems. The utilization of the Cognitive Knowledge Base and the Object-Attribute-Relation model offers a structured and autonomous means of knowledge representation. The adaptive feedback algorithm enhances the practicality and relevance of feedback, transcending static and expert-dependent approaches. This research contributes to the ongoing evolution of knowledge-based systems, paving the way for more efficient and adaptable solutions in various domains. As we move forward, the adaptive feedback algorithm holds promise for revolutionizing how we approach personalized learning experiences. Its learner-centric design, adaptability emphasis, and integration with instructional content position it as a valuable tool in the realm of educational technology. Further research and development in this area will likely lead to even more sophisticated and nuanced adaptive feedback systems, fostering a future where learning is truly tailored to the unique qualities of each individual learner.

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