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A COGNITIVE KNOWLEDGE-BASED MODEL FOR AN ACADEMIC ADAPTIVE E-ADVISING SYSTEM

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ABSTRACT

Aim/Purpose	This study describes a conceptual model, based on the principles of concept algebra that can provide intelligent academic advice using adaptive, knowledge-based feedback. The proposed model advises students based on their traits and academic history. The system aims to deliver adaptive advice to students using historical data from previous and current students. This data-driven approach utilizes a cognitive knowledge-based (CKB) model to update the weights (values that indicate the strength of relationships between concepts) that exist between student's performances and recommended courses.
Background	A research study conducted at the Public Authority for Applied Education and Training (PAAET), a higher education institution in Kuwait, indicates that students' have positive perceptions of the e-Advising system. Most students believe that PAAET's e-Advising system is effective because it allows them to check their academic status, provides a clear vision of their academic timeline, and is a convenient, user-friendly, and attractive online service. Student advising can be a tedious element of academic life but is necessary to fill

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the gap between student performance and degree requirements. Higher education institutions have prioritized assisting undecided students with career decisions for decades. An important feature of e-Advising systems is personalized feedback, where tailored advice is provided based on students' characteristics and other external parameters. Previous e-Advising systems provide students with advice without taking into consideration their different attributes and goals.

Methodology This research describes a model for an e-Advising system that enables students to select courses recommended based on their personalities and academic performance. Three algorithms are used to provide students with adaptive course selection advice: the knowledge elicitation algorithm that represents students' personalities and academic information, the knowledge bonding algorithm that combines related concepts or ideas within the knowledge base, and the adaptive e-Advising model that recommends relevant courses. The knowledge elicitation algorithm acquires student and academic characteristics from data provided, while the knowledge bonding algorithm fuses the newly acquired features with existing information in the database. The adaptive e-Advising algorithm provides recommended courses to students based on existing cognitive knowledge to overcome the issues associated with traditional knowledge representation methods.

Contribution The design and implementation of an adaptive e-Advising system are challenging because it relies on both academic and student traits. A model that incorporates the conceptual interaction between the various academic and student-specific components is needed to manage these challenges. While other e-Advising systems provide students with general advice, these earlier models are too rudimentary to take student characteristics (e.g., knowledge level, learning style, performance, demographics) into consideration. For the online systems that have replaced face-to-face academic advising to be effective, they need to take into consideration the dynamic nature of contemporary students and academic settings.

Findings The proposed algorithms can accommodate a highly diverse student body by providing information tailored to each student. The academic and student elements are represented as an Object-Attribute-Relationship (OAR) model.

Recommendations for Practitioners The model proposed here provides insight into the potential relationships between students' characteristics and their academic standing. Furthermore, this novel e-Advising system provides large quantities of data and a platform through which to query students, which should enable developing more effective, knowledge-based approaches to academic advising.

Recommendation for Researchers The proposed model provides researches with a framework to incorporate various academic and student characteristics to determine the optimal advisory factors that affect a student's performance.

Impact on Society The proposed model will benefit e-Advising system developers in implementing updateable algorithms that can be tested and improved to provide adaptive advice to students. The proposed approach can provide new insight to advisors on possible relationships between student's characteristics and current academic settings. Thus, providing a means to develop new curriculums and approaches to learning.

Future Research In future studies, the proposed algorithms will be implemented, and the adaptive e-Advising model will be tested on real-world data and then further improved to cater to specific academic settings. The proposed model will benefit e-Advising system developers in implementing updateable algorithms that can be tested and improved to provide adaptive advisory to students. The approach proposed can provide new insight to advisors on possible relationships between student's characteristics and current academic settings. Thus, providing a means to develop new curriculums and approaches to course recommendation.

Keywords e-advising, academic advising, academic model, student model, cognitive knowledge-based model, course selection, adaptive algorithm

INTRODUCTION

With the increasing number of students entering higher education, and with the complexity of credit-based learning in the current academic environment, higher education institutions are faced with new information-related administrative challenges. Academic advising is an essential and time-consuming effort in academic life. Modern technology has penetrated students' life and moved advising away from face-to-face interactions to an online environment where they have access to advisors and academic tools anytime, anywhere, which should help them to make better academic choices. However, the absence of effective academic advising leads students to make certain adverse decisions. One of the potential factors underlying high dropout rates is poor academic advising (Peterson's, 2015; Stevens et al., 2018).

Academic advising is one of the fundamental duties of university faculty. Students meet with their advisors to plan their upcoming course schedules and the trajectory of their academic careers (Al-hunaiyyan et al., 2019). The changing attributes of contemporary students, the complexities of learning establishments, the view of advising, and the current advising framework underlie the need to bring innovation into academic advising (Al-hunaiyyan et al., 2019). With all of the issues related to academic advising, faculty advisors are requesting assistance with the advising process. Expert-based advising systems have been proposed to assist in advising students. These systems model the techniques used by human experts when advising students (Alfarsi et al., 2017). Expert-based systems have contributed to many fields by applying artificial intelligence to different areas of human problem-solving. However, expert-based academic advising systems are still static and do not take the dynamic nature of student's characteristics into consideration (Nambiar & Dutta, 2010).

Challenges emerge when giving precise and helpful information to students about how to lead fulfilling academic careers, chose rewarding lifelong careers, and identify suitable alternatives (Awad, 2018). There is a present, pressing need to guarantee that students utilize the available information to make educated choices concerning their academic plan. Adaptive advising systems enhance the recommendation process through personalization, based on students' characteristics such as student's knowledge level, learning style, demographics, and domain-related factors such as course difficulty and tutor personality (Brusilovsky, 1998; Stoyanov & Kirchner, 2004). Adaptive systems behave according to the input received from their environment. Effective input classification (e.g., students' traits) allows adaptive systems to provide an output that is specifically tailored to the input. The main feature of an adaptive advising system is to provide students with personalized feedback (Newman et al., 2013). This adaptive feedback is useful because students have distinct qualities, including but not limited to their knowledge level, performance, learning style, and socioeconomics. According to Narciss et al. (2014), channeling advice according to students' attributes and other external parameters is a promising method to actualize the adaptation of electronic academic advising (e-Advising) systems. Adaptive advice, unlike generic advice, is dynamic; so, when different students engage with the system, they get different results (Le, 2016). Many different ways to achieve this goal have been proposed (Al-hunaiyyan et al., 2019; Farid et al., 2015). These research efforts identify existing gaps and create novel structures and instructive frameworks to analyze student learning and deliver an adaptive e-Advising system that advises students intelligently using knowledge-based adaptive feedback. This data-driven approach utilizes cognitive knowledge-based (CKB) modeling to update the weights between student performance and recommended courses. In CKB models, knowledge is represented using object-attribute relationships (OAR) based on concept algebra (Valipour & Yingxu, 2015). In such systems, a dynamic concept network is utilized to process knowledge similarly to human processing (Bimba, et al., 2016). Concrete and abstract concepts are represented and modeled using cognitive units (Wang, 2015). The proposed model will allow e-Advising system developers to implement updateable algorithms that enable effective, adaptive academic advising. The proposed approach would also provide insight to advisors into potential relationships between student characteristics, academic settings, and student outcomes; thereby, providing a means to develop new curriculums and approaches to learning that are knowledge-based.

The following paper is organized into sections. Section two contains a literature review on student advising systems and the challenges faced by current methods. The third section presents the proposed adaptive e-Advising model, including the algorithms and the representation of the input factors affecting the feedback provided to students regarding course selection. The design and implementation of the proposed system are discussed in the fourth section, which is followed by the conclusion.

LITERATURE REVIEW

ACADEMIC ADVICE

Academic advising is the process of assisting students in overcoming difficulties that might obstruct their academic progress and helping them to discover their capabilities (Ahmad, 2015). Although student advising is described by Moeder-Chandler (2018) as a tedious aspect of academic life, it is necessary to fill the gap between students' performance and academic degree requirements (Stevens et al., 2018). Therefore, higher education institutions have assisted undecided students on career decisions for decades (Stevens et al., 2018). There is a positive association between academic advising and student retention, satisfaction, and academic performance (Awad, 2018; Mahfouz, 2015; Smith & Allen, 2014; Swecker et al., 2013; Young-Jones et al., 2013).

With the increasing importance of credit-based learning and the contemporary academic environment, an effective, reliable academic advising system is essential to academic success (Nguyen et al., 2008). The credit-hour system in Arab universities was launched in the early 1980s, and its success depends heavily on academic advising (Ahmed, 2002; Hern et al., 2019). According to Nguyen et al. (2008), academic advising models vary considerably, and little thought is given to the efficiency and adequacy of these models. They introduced a robust academic advising framework that focused on combining technology-enhanced learning theories into a pedagogy-driven and service-oriented architecture (Banat, 2015).

An interesting study by Banat (2015) highlights advising-related issues at Al-Quds University, as seen by students, and its consequences on students' academic success. Three hundred and sixty-nine full-time college students at Al-Quds University were surveyed. Academic advising issues were estimated utilizing a 45-item questionnaire and grade point average (GPA) to gauge student's performance. This assessment revealed that 74.8% percent of respondents had experienced academic advising issues.

Several studies have investigated the impact of academic e-Advising on students. Zuhrieh and Shubair (2014) revealed that students appear to favor a blended advising approach. In such an approach, the advising process utilizes an e-Advising system and traditional face-to-face advising. According to the authors, this mixed approach best facilitates student success. Jaggars and Karp (2016) examine the use of technology and encourage advising reform because technology alone is insufficient. They suggest that academic advisors should teach students how to self-advise to get the most out of e-Advising systems. A recent study conducted in Applied Education and Training (PAAET), a higher education institution in Kuwait, examined usability aspects, students' perceptions, and attitudes toward an e-Advising system (Al-hunaiyyan et al., 2019). Results indicate that students have positive perceptions and that most students believe that the e-Advisor is effective because it allows them to check their academic status, provides a clear vision of their academic timeline, and is a convenient, user-friendly, and attractive online service. However, the outcome of the study revealed that PAAET's e-Advising system is not adaptive, i.e., students receive the same advice irrespective of their different academic characteristics, history, and goals.

E-Advising Systems

Many studies have been dedicated to developing and evaluating e-Advising systems, models, and frameworks. A model for a web-based academic advising system was proposed by Afify and Nasr (2017), while Demirkol and Seneler (2019) assessed a student information system in terms of user emotions, performance, and perceived usability. Furthermore, Daramola et al. (2014) described the structure and implementation of a course advisory expert system that utilizes rule-based reasoning to intelligently suggest courses depending on the student's academic history. Similarly, Shatnawi et al. (2014) proposed an intelligent framework that utilizes association rule mining to support both students and advisors in the course selection process. Their framework enables students to improve their academic performance by proposing courses that fulfill the requirements of their chosen major.

Moreover, Hingorani and Askari-Danesh (2014) describe an advising system designed to help improve students' retention and graduation rates at a southeastern university. The advising system involves collaboration between students and instructors through a web-based system, which worked remarkably well in which both students and instructors were satisfied. Also, Engin et al. (2014) discuss the development of a course advising system that successfully recommends courses to undergraduate students. In terms of intelligent advising, Al-Ghamdi et al. (2012) developed an expert-based advising system for computer science postgraduate students at King Abdulaziz University to replace traditional face-to-face advising. The proposed system allows the students to select courses each semester according to their study plan and graduation requirements without needing to consult advisors.

Chen and Upah (2018) introduced a system based on predictive analytics to provide advice to undecided students concerning selecting or changing their major. They compared students who received predictive analytics-based advice with students who did not use the propensity score matching technique. Results indicated that students who received predictive analytics-based advice were more likely to change their program of study. Hagemann et al. (2019) proposed a course recommendation system that presents thematic relationships between course modules. This advising system helps students understand how course modules relate to the learning outcomes required for a particular career. Similarly, Eckroth and Anderson (2019) developed a backtracking search paradigm to provide students with advice on double majors, course overrides, early graduation, and transfer credits. Table 1 contains a summary of these implemented e-Advising systems. To the best of our knowledge, it seems that no system to date has adaptive capabilities.

Table 1: Comparison of e-Advising Systems

S/N	System	Purpose	Method	Adaptive
1	Expert advising system (Al-Ghamdi et al., 2012)	Select courses for each semester according to the study plan and graduation requirements	N/A	None
2	Course advisory expert system (Daramola et al., 2014)	Course selection in a particular semester	rule-based reasoning	None
3	Intelligent system (Shatnawi et al., 2014)	Provides advice in selecting and prioritizing courses	association rule mining	None
4	Web-based academic advising system (Afify & Nasr, 2017)	Academic advising	N/A	None
5	Predictive analytics academic advising system (Chen & Upah, 2018)	Provide advice to undecided students to select an appropriate program of study	Data analytic	None
6	Academic recommender system (Hagemann et al., 2019)	Provides recommendation to students on academic modules based on their academic goals	Vector Space Model (VSM)	None
7	Tarot (Eckroth & Anderson, 2019)	Provides students with advice on double majors, course overrides, early graduation, and transfer credits.	Backtracking search paradigm	None

Student Modelling for E-Advisory System

To incorporate adaptation into an e-Advising system, it is necessary to model the different characteristics of the students (Chrysafiadi & Virvou, 2013). The first step in constructing a student model is to consider which student characteristics are most relevant to include in an e-Advising system (Gonzalez et al., 2005). The stable characteristics of a student include learning style, demographics, learning objectives, and goals. The dynamic parameters are concerned with the adaptive student's characteristics. Examples of these include learning actions, collaborations, and behaviors. Additionally, domain-dependent attributes of the student involve the student's knowledge level and performance in specific courses.

Based on previous studies in cognitive science and neurophysiology (Hampton, 1997), the foundations of human knowledge in the long-term memory can be represented in an OAR model. This is based on the synaptic structure of human memory, which represents the hierarchical and dynamic neural clusters of knowledge retained in memory as well as the logical model of knowledge bases (Wang, 2014). The CKB model is a structure that manipulates knowledge as a dynamic concept network like human knowledge processing (Wang et al., 2011; Wang, 2008). In CKB methods, a concept is a cognitive unit that identifies and models real-world concrete entities and a perceived-world (abstract entity) (Wang, 2015). The basic unit of knowledge for a CKB approach is a formal concept represented using an OAR model according to concept algebra (Valipour & Yingxu, 2015).

The main objective of this research is to provide adaptive advising to students during an e-Advising session. Therefore, we incorporated the student's learning style, performance, knowledge level, and demographics into their interactions with the e-Advising system. The student's current learning style can impact the way students handle certain courses (Martin et al., 2020). Understanding the different learning styles and how these affect student performance can help to determine what courses to take and when (Normadhi et al., 2019). Based on Fleming's VARK model, students can be visual, auditory, reading/writing, or kinesthetic learners (Leite et al., 2010). The performance of the student can be assessed based on students' grades (Al-hunaiyyan et al., 2019). These characteristics are dynamic and need to be accessed regularly to develop a proper model of the student. In the case of suggesting appropriate courses based on student performance, the accumulated data on the interactions of the student will be used to advise them on courses based on their grades from a favorite social setting. The knowledge level of the student includes their current cumulative grade point average (CGPA), which is based on the average performance of the student in all of the courses undertaken. Through interaction with the e-Advising system, the student's CGPA is updated as they progress through academic semesters (Al-hunaiyyan et al., 2019). Student demographics include age, sex, and year of study.

Cognitive Knowledge-Based Model for Adaptive e-Advising System

The selection of student characteristics (e.g., learning style, prior knowledge, and goals) is crucial in the early stages of developing a student model (Andrew Thomas, 2019). In adaptive systems, these characteristics can be identified in several ways, including artificial intelligence (AI) techniques (Brusilovsky, 1998). It is essential to consider which aspects of the student's characteristics are to be modeled given the type of system being developed (Gonzalez et al., 2006). Faithfully modeling the most relevant stable, dynamic, and domain-dependent characteristics is crucial to effectively implement adaptation into an interactive feedback system (Chrysafiadi & Virvou, 2013).

The proposed adaptive e-Advising model aims to categorize students based on their traits and direct them to appropriate courses. The attribute relationship was developed based on input from academic and student models, as shown in Figure 1.

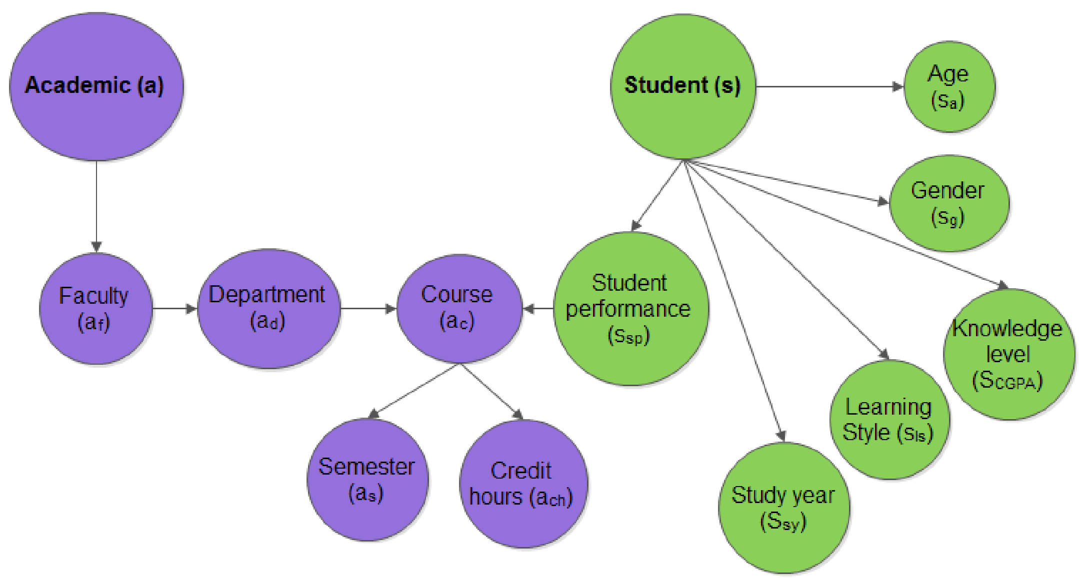

Figure 1: Adaptive e-Advising attribute relationship

The academic model consists of various elements used to define specific courses and their attributes, for example, credit hours and the semester in which the courses were undertaken. Other attributes of the course (e.g., tutor) can be included, but the present prototype only focuses on two attributes of courses. The student model consists of the personal attributes of the student that could influence their performance in a specific course. Students have different knowledge levels, learning styles, and personal attributes, which affect when they should undertake a particular course (Normadhi et al., 2019). The link between the student model and the academic model is the performance of a student in a particular course (Andrew Thomas, 2019). All of the attributes of the student and the academic model determine the performance of the student in a specific course, as shown in the relationship in Figure 1. The goal is to ensure that the adaptive e-Advising model proposes a course at the appropriate time that maximizes student performance.

In general, each concept in the adaptive e-Advising model is represented according to the OAR model. The academic and student model can be represented as an OAR model (Equation 2).

$$C_{ac_i} \subseteq (AC_i, A_i, R_i^c, R_i^o),\ C_{s_j} \subseteq \left(S_j, A_j, R_j^c, R_j^o\right) \quad (2)$$

Where

- C_{ac_i} is the academic structure, AC_i is a set of an instance of the academic environment ($AC_i \neq \emptyset$). For example, Academic Institution (AC)

  $$AC_i = AC_1, AC_2, AC_3, \ldots\ AC_n,$$

  A_i *is the attributes of* AC
  R_i^c *is the internal relationship within the attributes of AC*

  R_i^o is the output relationship of the attributes of AC

- C_{s_j} is the student model, S_j is a non-empty set of the attributes of a student (such as Student S)

  $S_j = S_1, S_2, S_3 \ldots S_m$

  A_j *is the attributes of* S_j
  R_j^c *is the internal relationship within the attributes of* S_j

  R_j^o is the output relationship of the attributes of S_j

The objective here is to identify the connection between performance and the recommended courses during a specific academic session. To define this relationship and achieve dynamic knowledge representation based on a large number of existing data and continuous input from new students, Equation 3 describes the relationship between outcome (performance) and multiple other concepts within the model.

$$R_i^{in} \subseteq \bigcup_{i=1}^{|R_i|} R_i^c \qquad (3)$$

Where R_i^{in} is the current concept that needs to be optimized based on internal relationships R_i^c that exist between multiple concepts within the knowledge base. Equation 4 depicts the impact of the attributes of concepts within the student model on performance.

$$R_p^{in} \subseteq (R_a^c\ \cup\ R_s^c) \qquad (4)$$

Where

- $R_a^c\ \subseteq (A_{ad} \cup\ A_{ac} \cup\ A_{ad} \cup A_{ad}\ )$
- $R_s^c\ \subseteq (S_{sy} \cup\ S_{sa} \cup\ S_{sg} \cup S_{scgpa} \cup S_{sy})$

The two main modules involved in the adaptive e-Advising system are knowledge manipulation and retrieval modules (Figure 2).

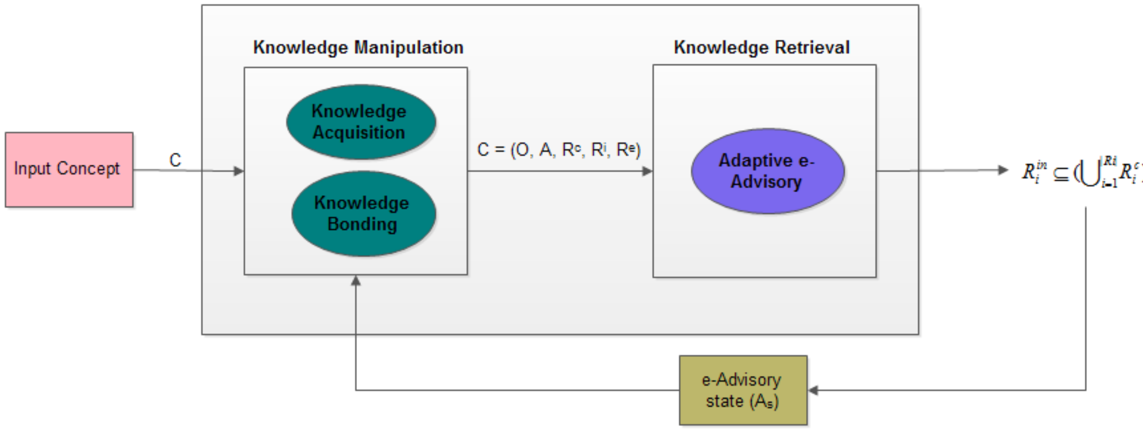

Figure 2: Adaptive e-Advising Model

In the knowledge manipulation module, concepts are acquired and integrated into the knowledge base using the knowledge elicitation and knowledge bonding algorithms, respectively. The knowledge elicitation expects to hold recently acquired knowledge as a formal concept. After that, the internal relationship of an idea is discovered, and, upon its completion, the knowledge bonding algorithm begins, which aims to inter-relate the concept and ideas in the knowledge base. The algorithm creates a 1-to-n map of the concepts and equivalent concepts in the CKB model. Through this mapping, the object, attribute, and any internal and external relationships are utilized. In complicated settings, these ideas can be interrelated to produce a conceptual network where all of the student and academic data can be presented. The knowledge retrieval process allows students to utilize CKB methods to retrieve stored knowledge. The architecture supports the provision of recommended courses to students based on the adaptive e-Advising algorithm.

There are two inputs to the e-Advising system: the input concept (C), which consists of academic and student concepts; and the e-Advising state (A_s), which includes attributes of the student and domain models. In the first modeling phase, the academic data and concept of a student are represented in the system through the knowledge elicitation module. The concept (C) is presented at the knowledge elicitation stage, and its corresponding objects and attributes are represented to produce $C = (O, A, R^c)$ where O is the instance of the concept, A is the attributes of the concept, and R^c is a set of internal relationships associated with the concept. The knowledge elicitation algorithm is responsible for determining the objects, attributes, and internal relationships of the concept at any given time. At the knowledge bonding stage, the external relationships of the concept and its influence on other concepts are defined. This is a dynamic process that alters the existing structure of the knowledge base. The new concept adjusts the already existing bonds between other concepts. This results in an updated representation of the concept $C = (O, A, R^c, R^i, R^e)$. At this stage, learning occurs. The fixed weights between the concepts are adjusted or randomly initialized based on the modeling phase. In the initial modeling phase, when there is no input from the student or faculty, the weights are initialized. In the subsequent modeling phase, when there is input available from the student's interaction with the system, the weights are adjusted based on the student's results. This allows the appropriate prediction of the right combination of concepts for a particular type of student. Finally, the adaptive e-Advising module models the current state of a student and compares it with the existing models in the knowledge base. It then provides tailored course suggestions based on the best combination of the concepts stored in the knowledge base. The result of the student's interaction during the recommendation process is then fed into the system as a new concept through the knowledge elicitation module.

Algorithms for Knowledge Modeling and Manipulation in an E-Advising System

Knowledge manipulation and adaptive e-Advising are the two fundamental procedures in the proposed model. The knowledge manipulation phase involves two specific algorithms, namely, the knowledge elicitation algorithm and the knowledge bonding algorithm. The adaptive e-Advising algorithms are utilized in the recommendation phase.

Knowledge elicitation algorithm

This paper proposes an enhanced representation of the concepts in the academic and student model. As indicated by the structure of the CKB model, all of the information in these models is represented as ideas. As shown in Figure 1, the knowledge elicitation stage presumes an ideal concept attribute (CA) space, which presents the knowledge base as a network of semantic objects. The CA space encompasses different ideas and their relating properties. The concept is represented as a five-tuple C Δ (O, A, R^o, R^i, R^e) and is the primary input for the knowledge elicitation algorithm, described in Algorithm 1:

Data: C_n
Result: {O, A ⊆ (A_1, A_2, A_3...A_n), R^o}, Cn category, A_s or Cn index, timestamp
initialization;
while C_n is available
Determine C_n category (academic or student);
if C_n category = student then
read multiple C_n;
C_n = multiple C_n;
else
read C_n;
else if C_n = A_s /* A_s is the current student advising state */
then
read A_s ⊆ (S_p, A_sID) /* S_p is the student's performance and AsID is the student's advising state ID */
else
    return (Concept not understood!)
if !(Disk full) then
look into LCB for relating properties;
contrast C_n traits with existing ideas;
if (Complete idea match) then
return (idea exists!);
else
assign an index to C_n;
create timestamp;
calculate R^c ⊆ O × A;
determine partial concept
C = {O, A ⊆ (A_1, A_2, A_3...A_n), R^o };
output {O, A ⊆ (A_1, A_2, A_3...An), R^o}, C_n category, Cn index, timestamp;
end
else
return (Disk full!);
end
end

Algorithm 1: Knowledge Elicitation Algorithm

The external connections between the recently gained C_n, R^i, and R^o have yet to be resolved and will be updated with existing information during the knowledge bonding phase. During the knowledge elicitation phase, the student's advising state A_s has yet to be determined. After the first advising session, As is determined and refined based on the students' interactions in the knowledge bonding stage.

Knowledge bonding algorithm

The knowledge bonding algorithm represents the second stage of knowledge manipulation. During this stage, the algorithm creates subordinate relationships between the obtained concept and every single concept in the CKB model. The output of the knowledge bonding algorithm is the recently gained concept consolidated in the CKB model. The knowledge bonding algorithm is listed in Algorithm 2.

Data (Input): $\{O, A \subseteq (A_1, A_2, A_3...A_n), R_c\}$, C_n category, C_n index, timestamp
Result: $\{O, A \subseteq (A_1, A_2, A_3...A_n), R^o, R^i, R^e\}$, C_n category, C_n index, time stamp, C_n layer, Similarity index $S \subseteq \{(C_i, St_k),(C_{i+1}, St_{k+1}),(C_{i+2}, St_{k+2})...\}$
read C_n;
while (Ci is available in CKB) do
compute $R_i^o = C_n \times C_i$;
compute $R_i^i = C_i \times C_n$;
compute similarity $Cn \sim Ci = \left|\frac{A \cap A_i}{A \cup A_i}\right|$;
$= \begin{cases} 1 & C_n = C_i \\ (0,1) & C_n \leftrightarrow C_i \vee C_n < C_i \vee C_n > C_i; \\ 0 & C_n \neq C_i \end{cases}$
Determine sub-concept $A_i \subseteq A$;
Determine super-concept $A \subseteq A_i$;
Determine related-concept $A_i \cap A$;
Determine independent-concept $A \cap A_i$;
Determine equivalent-concept $A_i = A \wedge Oi = O \wedge Rc = R_c^i$;
Determine similarity type St ;
Similarity index $S_i \subseteq \{(C_i, St_k),(C_{i+1}, St_{k+1}),(C_{i+2}, St_{k+2})...\}$;
$S = S + S_i$;
$R^o = R^o + R_i^o$;
$R^i = R^i + R_i^i$;
end
determine C_n layer;
enter concept C_n : $\{O, A \subseteq (A_1, A_2, A_3...A_n), R^o, R^i, R^e\}$, C_n category, C_n index, timestamp, C_n layer, Similarity index $S \subseteq \{(C_i, St_k),(C_{i+1}, St_{k+1}),(C_{i+2}, St_{k+2})...\}$;
end

Algorithm 2: Knowledge Bonding Algorithm

The index number of the latest concept C_n is derived by increasing the identity number of the previous concept C_{n-1} recorded in the knowledge base using the elicitation algorithm. While building outer connections, the knowledge bonding algorithm completes five contingent checks (similarity type, St) against every available concept C_i in the knowledge base. In the beginning, the comparability check recognizes sub-concepts amongst the recently acquired idea C_n and the *i*th idea within the knowledge base $A_i \subseteq A$. In the next phase, the aim of the newly acquired concept C_i is a subset of the recent concept C_n. The subsequent check blends the recent concept with other concepts within the knowledge base, and the recently acquired concept acts as a subset of the current concept. Related concepts are distinguished in the third step where the intersection of C_i and C_n is not null, $A_i \cap A \neq$

null. Next, the autonomous concepts are presented as null intersections between the intents of C_i and C_n. The concluding check determines the similarity between ideas by harmonizing the intents of C_i and C_n. The index of the *i*th idea existing in the knowledge base and the St are logged as the similarity index when an equivalent counterpart is identified. In the end, the recently acquired idea is resolved and combined with the relationships R^o, R^i, the similarity index, along with input variables using the knowledge bonding algorithm to form a bonded concept within the CKB model.

Adaptive e-advising algorithm

Providing appropriate recommendations based on students' characteristics by the e-Advising system is challenging. The adaptive e-Advising algorithm aims to determine the proper courses for different students based on their advising state. The input for the adaptive e-Advising algorithm is the partial advising state As, which consists of attributes from the academic and student models. As shown in Equation 5, the advising state considers the students' age, sex, knowledge level, learning style, study year, and performance along with their academic department, course history, semester, and credit hours.

$$A_s \subseteq (s_a, s_g, s_{CGPA}, s_{ls}, s_{sp}, a_d, a_c, a_s, a_{ch}) \qquad (5)$$

The similarity between the current advising state A_s and existing advising states A_{si} in the knowledge base is determined iteratively. All of the states that are above a certain threshold are stored as a list. As shown in Algorithm 3, the output of the algorithm is the advising state with the highest cumulative weight and its influence on the student's performance, defined by the knowledge bonding algorithm. Thus, during an advising session when the advising state is determined, the most appropriate course is suggested based on existing information from the most similar state in the knowledge base. In this approach, the content-based mechanism of a CKB model for knowledge retrieval and manipulation is utilized to support the multiple models.

Data: A_s, timestamp
Result: R_{in}
read data;
Create and initialize the advising state list A_sL
while A_{si} is available do
    compute similarity As ~ Asi = $\left|\frac{A \cap A_i}{A \cup A_i}\right|$;

$$=\begin{cases} 1 & A_s = A_{si} \\ (0,1) & A_s \leftrightarrow A_{si} \ \vee \ A_s < A_{si} \vee A_s > A_{si}; \\ 0 & A_s \neq A_{si} \end{cases}$$

    if (A_s ~ A_{si} > TH)   /* TH is the similarity threshold */
    then
        Retrieve A_{si};
        Add to advising state list $A_sL_i = A_sL + A_{si}$;
    else
        Create random A_{si}
determine the highest A_{si};
output the recommended courses based on the student's advising state A_{si}, $R_i^{in} \subseteq \bigcup_{i=1}^{|R_i|} R_i^c$;
end

Algorithm 3: Adaptive e-Advising Algorithm

DISCUSSION

The implementation and design of an adaptive e-Advising system are challenging because of its dependence on both academic and student traits. A model that describes the conceptual interaction between the different academic components and students is required to overcome this challenge. In the past, e-Advising systems have provided general advice to students but did not consider the complex and dynamic nature of contemporary students. Therefore, an adaptive e-Advising system is needed to resolve these issues.

This research describes a model, based on the principles of concept algebra that gives intelligent advice using adaptive, knowledge-based feedback. The proposed model provides students with adaptive advising services tailored to their traits and academic performance based on historical data from previous and current students. This data-driven approach utilizes the CKB model to update the weights between student performance and course selection.

Unlike previously proposed methods, this CKB model is dynamic and doesn't depend on expert knowledge, which allows the system to generate feedback based on data collected from students' interactions with the system. This technique, unlike expert-based and intelligent advising systems, is data-driven and continually updated (Daramola et al., 2014; Shatnawi et al., 2014; Eckroth & Anderson, 2019). The proposed adaptive e-Advising system recommends the most appropriate courses for students at every academic level based on their characteristics. In contrast, previously proposed systems advise students based on rules developed by experts or probabilistic techniques that do not consider students unique characteristics and goals (Daramola et al., 2014; Afify & Nasr, 2017; Chen & Upah, 2018; Hagemann et al., 2019)

The viability of any knowledge management framework depends on the knowledge presentation method. The proposed knowledge manipulation technique of the CKB model proposed here is unique because it is based on human knowledge processing. A new model is necessary due to the deficiencies of conventional knowledge representation methods, which are not dynamic and depend highly on expert knowledge.

CONCLUSION

This paper proposed a new CKB method with the ability to acquire and represent accumulative, dynamic student characteristics at both the academic and personal levels in an e-Advising system. The proposed adaptive e-Advising model utilizes concept algebra to achieve the goal of developing a new academic and student model. The new model reveals the internal relationship of the student's characteristics and the external relationship with the academic environment and setup. The objective is to resolve challenges in e-Advising by providing students with appropriate course suggestions using a model of the target academic setup.

A new CKB model of e-Advising is proposed based on concept algebra. The new model is comprised of two main modules: knowledge manipulation and knowledge retrieval. During the knowledge manipulation phase, knowledge elicitation and bonding algorithms are used. The knowledge retrieval phase deals with the adaptive e-Advising algorithm. The knowledge elicitation algorithm uses existing student and academic data, along with currently acquired data, to construct object-concept-attribute relationships. During knowledge bonding, new concepts are aligned with existing knowledge within the CKB model. When proposing appropriate courses for students, the adaptive e-Advising algorithm calculates the most suitable course for that particular student based on their characteristics and objectives. This proposed e-Advising system is aimed at autonomously recommending appropriate courses to students based on knowledge acquired over time. This eliminates the need for static expert knowledge when making decisions on dynamic occurrences due to the vast, diverse, and evolving nature of knowledge.

The main contribution of this research is the provision of an adaptive e-Advising algorithm. The purpose of the algorithm is to provide practical advice to students based on academic and student traits. Currently, only the design of the model and algorithm have been provided. In future studies, the proposed algorithms will be implemented, and the adaptive e-Advising model will be tested on real-world data and then further improved to cater to specific academic settings. The proposed model will benefit e-Advising system developers in implementing updateable algorithms that can be tested and improved to provide adaptive advisory to students. The approach proposed can provide new insight to advisors on possible relationships between student's characteristics and current academic settings. Thus, providing a means to develop new curriculums and approaches to course recommendation.

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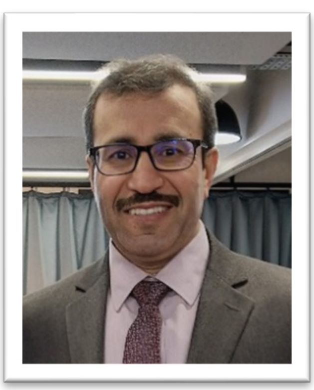

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