AN INTELLIGENT E-LEARNING COURSE RECOMMENDATION FRAMEWORK BASED ON STUDENT LEARNING STYLE

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ABSTRACT

As the drive to move from traditional face-to-face classroom learning to e-learning is ever in demand, the knowledge corpus exposed to students can be overwhelming because there is a need to automate certain functions of the e-learning framework. One of these functions is the course recommendation feature. Course recommendations help students save time and effort to explore the courses from a large pool of resources while considering multiple attributes such as social influence, prior knowledge, and learning style. These numerous criteria make the course recommendation a complex process that requires the researcher to promote online education and intelligently assist learners in identifying the relevant online courses. Although various researchers have put forward strategies to address course recommendation problems, learning style, a critical element in ensuring effective learning, has not been considered part of the course recommendation framework. This paper puts forward a learning style-based course recommendation framework that is expected to provide highly automated decision support for learners in identifying the most suitable course to improve their efficiency in e-learning. Additionally, based on this framework, instructors can analyze and re-evaluate the courses according to students' learning styles. The proposed framework reduces the time and effort involved in seeking relevant courses, thereby improving the learning experience.

Keywords: *Course Recommendation System (CRS); Learning Style; Course Categorization; Online Learning; e-learning*

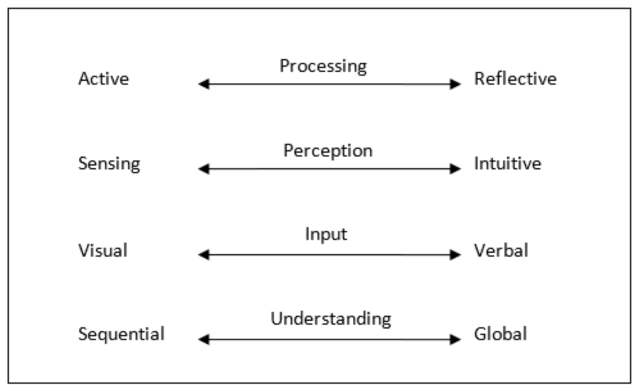
INTRODUCTION

The world came to a standstill in March 2020 due to the COVID-19 pandemic. According to UNESCO, approximately 1.38 billion learners around the globe at pre-primary, primary, lower-secondary, upper-secondary, and tertiary education levels could not attend school or university as of March 23, 2020 (McCarthy, 2020). The closure of educational institutions worldwide forced teachers' and learners' attention to online learning, which used to be a non-essential supplement to conventional face-to-face classes, as a mainstream method to ensure that education can continue to be delivered. With the help of a learning management system (LMS), e-learning systems provide a learner-centered environment. Learners can select a course of their choice without time and space constraints to participate in a flexible education environment. Such flexibility will help improve the learner's performance (Gulzar et al., 2015). However, due to the availability of many courses, learners might feel uncomfortable deciding what courses would be appropriate for them from their area of interest. In such brainstorming and time-consuming situations, only a recommender system can help make decisions related to course selection. This article will use frequent terms such as association rules, learning style, and cold start, which must be defined first. Association rules are used to infer rules from previous students' experiences to add to the recommendation process. Learning styles can be defined as how people prefer to learn (Brusilovsky & Millán, 2007). A classical cold-start problem arises when the recommender system does not find previous ratings of newly added courses. In this scenario, it gets challenging to recommend courses to students based on former student history or feedback.

Online learning traditionally suffers from high attrition rates due to a lack of commitment and student exuberance (Gasevic et al., 2014; Kennedy, 2014). Personalization is an essential feature of e-learning systems due to differences in learners' goals, backgrounds, personalities, and capabilities of a massive number of learners (Klašnja-Milićević et al., 2015). Personalization has the advantage as the learners are guided in the course selection process according to their interests and requirement (Nganji et al., 2011). Student learning styles are reflected in online courses to make learning easier and increase student learning efficiency (Lee & Choi, 2010). Proper understanding of learning styles can be utilized for identifying and implementing better teaching and learning strategies that can allow students to acquire efficient knowledge efficiently and effectively (Velázquez et al., 2012). Hence, new e-learning systems should incorporate personalization in learning styles to recommend personalized online courses to students.

Due to the anecdotal evidence of learners' preference for taking in information (Gokalp, 2013; Newton, 2015), comprehensive research is being carried out on learning-style-based automated frameworks in e-learning. There are several models of learning styles, such as Kolb learning styles (Cassidy, 2014), Honey & Mumford models (Cassidy, 2014), V-A-R-K models (Pritchard, 2009), and Felder-Silverman models (FSLSM) (Felder, 1988). These models require students to complete a questionnaire to determine their learning styles. Kolb's Learning Style Inventory (LSI) is represented by two learning modes. The LSI requires one to complete 12 sentences describing learning; each sentence has four endings measuring an individual's preferences. Honey and Mumford emphasize that no single style has an overwhelming advantage over any other; each has strengths and weaknesses, which may be important in one situation, but not in another. The proposed framework is based on FSLSM due to its strong influence on e-learning and the design of instruction. There are four dimensions in the FSLSM model, each having two opposites poles, as shown in Figure 1.

Figure 1. Felder-Silverman Learning Style Model



The differences in teaching methodology and student learning skills have reduced the effectiveness of learning and teaching processes (Felder, 1988). Curriculum design is a complicated process; hence, the engagement of all stakeholders, primarily those directly involved in student learning, is essential to successful curriculum development (Johnson, 2001). The learning style preferred by students is equally important; therefore, personalizing the teaching process based on learning styles can help improve the current teaching practices. Several strategies have been presented to incorporate learner preferences into the course design process (Graf & Kinshuk, 2009); however, little emphasis is given to course content categorization based on FSLSM. El-Bishouty et al. (2018) have developed a tool to assess the course design based on estimating learning objects' learning styles. Gope and Kumar Jain (2017) have also followed the same strategy, calculated the frequency of learning objects concerning their potential styles, and deduced the category of courses. However, these strategies lack integration of the course categories into the recommendation process. The course recommendation process can be augmented by first identifying the course categories based on the FSLSM model to help teachers analyze their courses according to various learning styles and recommend suitable courses to students matching their personalized learning styles.

This paper proposes a course recommendation framework by introducing instructor knowledge empowerment and studying other support factors essential in the course design process. It would facilitate instructors to evaluate the courses based on different learning styles. Students would also benefit by getting the right course matching their learning style. The proposed framework also addresses the traditional cold start problem of the recommendation methods; since it requires the courses and students' characteristics in the form of learning style only and does not depend on the rating or feedback of previous students for the recommendation. We have organized this paper as follows: (a) section 2 illustrates a brief literature review, and (b) section 3 discusses the proposed framework, followed by a conclusion focusing on limitations and the overall impact of proposed work in e-learning.

LITERATURE REVIEW

In a recent survey, Ashraf et al. (2021) organized the existing course recommendation research into numerous categories, including rule-based (Aher & Lobo, 2013), data mining (Ng & Linn, 2017), hybrid collaborative filtering (Ng & Linn, 2017), and semantic-based methods (Ibrahim et al., 2018). Various challenges and issues are also enumerated, such as the lack of a standard dataset, course sequence, and time-based assessments. Some researchers have adopted multiple factors to improve the overall performance of course recommendations, such as grades (Al-Badarenah & Alsakran, 2016) and student preferences (Ng & Linn, 2017). The detail of related work is presented here.Ng et al. (2017) have gathered student priorities and preferences through survey form and applied hybrid techniques combining topic analysis, tag analysis, and sentiment analysis to recommend courses to college students. Jhaveri et al. (2013) have developed a prototype based on students' requirements and interests while considering university constraints to recommend a degree course. However, other details are neglected in this study, including course prerequisites, completion requirements, etc. This research has also shed light on integrating an NLP-based query dialogue system for students' interaction with the system for suggested courses (Jhaveri et al., 2013). Aher and Lobo (2013) have presented an e-learning course recommendation system based on machine learning techniques that identify students' behaviors toward their interested courses. Various data mining algorithms are compared, such as classification and association rule algorithm, association rule mining of classified and clustered data, and clustering and association rule algorithm. Results prove that the combination of clustering and classification, and association-rule algorithm is the best one. These approaches consider course enrolment behavior in the recommendation process; however, these rule-based methods may not perform well for new users (Schein et al., 2002).

Huang et al. (2013) calculated the percentage of completed courses of the students and then generated a list of course recommendations. Domain experts were responsible for constructing curriculum program ontology using the protégé tool. This researcher has suggested making an effort in the future to define and check the demand for courses by automatically generating relations among related courses (Huang et al., 2013). Some researchers have worked on predicting grades as students tend to select the courses in which there are higher chances for them to score. Sobecki and Tomczak (2010) suggested that ant colony optimization (ACO) can be used effectively in student grade prediction.

Another study has discussed the combination of association rules and collaborative filtering methods. Collaborative methods can be successfully used to find similar users based on interest. An association rule-mining algorithm is used to extract course association rules. This method recommends courses while calculating their respective grades, as achieving good grades is the usually ultimate goal of students (Al-Badarenah & Alsakran, 2016). Bozyigit et al. (2018) proposed to use collaborative methods with OWA operators to recommend courses. Existing approaches have mainly considered the recent grades in the recommendation process. However, this approach has offered to study students' performance while taking the course multiple times. However, this study lacks other very considerable factors used in existing research, such as the social influence of students on their friends and classmates (Bozyigit et al., 2018). Bendakir and Emsa (2006) used a current user rating along with former student experience and developed a recommendation system. However, this system has some limitations when providing its recommendations. One limitation is that it depends upon student registration data, which is not usually accessible (Bendakir & Esma, 2006). Upendran et al. (2016) considered the previous students' skills and capabilities as a trained data set and used these attributes to recommend courses to new students with similar abilities.

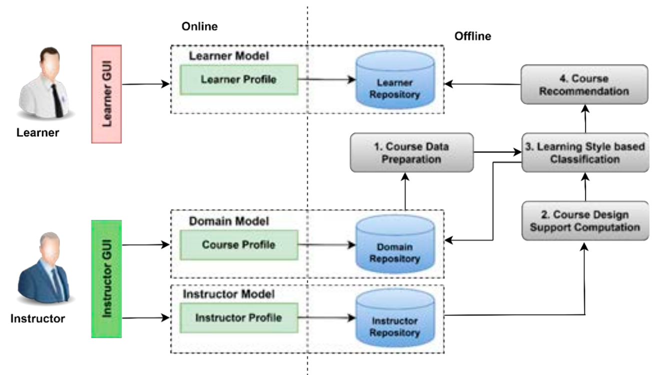
According to Ibrahim et al. (2018), the recommendation process can be more comprehensive and intelligent by including additional user contexts—for example, available student behavior, learning style, and learning interests—in the recommendation process. Unfortunately, almost all methods have been proposed without incorporating the learner's learning style. Vaishali et al. (2016) have given only a theoretical framework to consider learning styles in the recommendation process. El-Bishouty et al. (2018) assessed the course based on learning style. However, course categories can be utilized for the learning style-based course recommendation process, improving the overall e-learning process and helping students choose the courses according to their matching learning styles.

The goal of this paper is to recommend online courses to students considering their learning styles. For this purpose, we have analyzed the courses according to guidelines provided by Felder-Silverman (Felder, 1988). The main contributions of this work are as follows:

1. Inclusion of an instructor's influence metrics by introducing a customized support factor in the course design process. It is a significant step to measure the impact of an instructor's teaching methods. It will substantially help instructors to evaluate and reconsider their courses and shift toward some pre-decided learning style. For this purpose, a course categorization algorithm is designed based on the FSLSM model.
2. A learning-style-based course recommendation framework is proposed. This framework would mainly serve the students to choose the courses based on their matching learning styles. Moreover, instructors can analyze and redesign their courses to meet some specific learning styles.

PROPOSED FRAMEWORK

This section describes the proposed course recommendation framework that can be embedded in any management system to support learning-style-based course recommendations for learners. A framework is illustrated in Figure 2. A graphical user interface (GUI) will help users navigate the program, and it will automatically call the recommendation engine to find the best-recommended courses. The following subsections describe the detail of these models and their interface.



USER INTERFACE

In our proposed framework, there are two user types: learners and instructors. Learners expect the system to generate appropriate recommendations according to their learning style. In contrast, instructors are supposed to use an interface to feed the course information into the system and learn the learning style category of their desired courses. Hence individual interfaces are designed for both kinds of users. The detail of these interfaces is discussed in the section below.

LEARNER INTERFACE

The learner interface will be used to receive recommendation requests, receive the learner's personal information, and retrieve the recommended courses through this display only, as shown in Figure 3. Initially, a user must fill out the registration form and Felder-Silverman Index Learning Style Questionnaire (ILSQ) form. The registration form requires the learner's personal information and the record of previously taken courses. The learning style questionnaire of Felder and Soloman (1988) is comprised of 44 questions and is used to assess learners' learning styles. This information will be used in the recommendation engine to generate the course recommendations.

Figure 3. Learner Interface

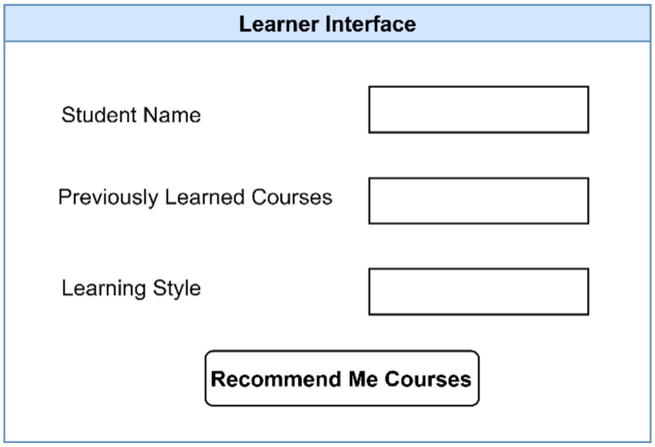
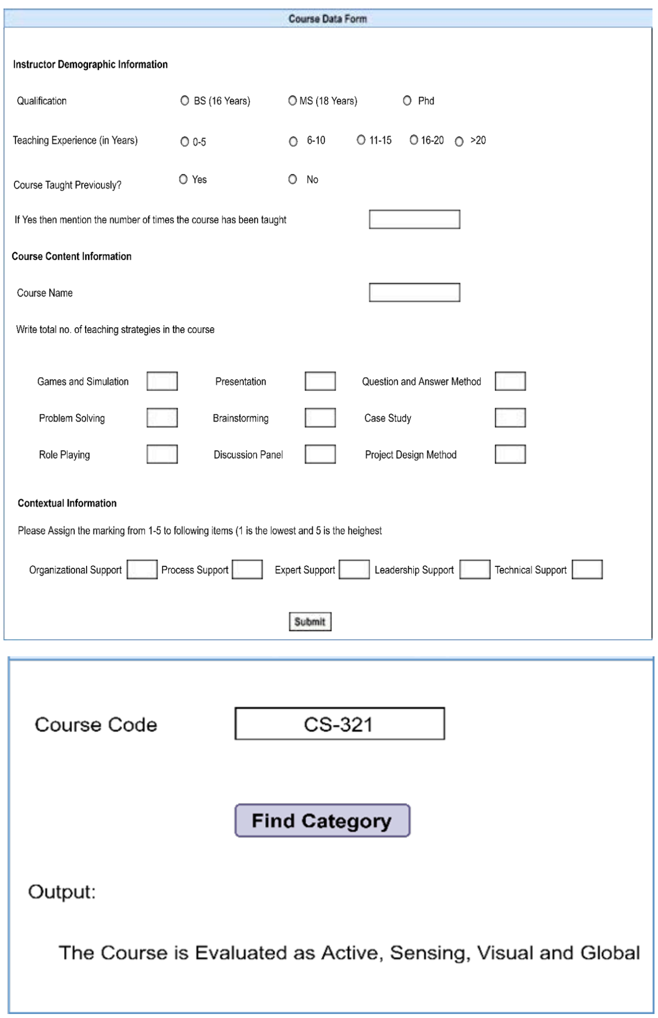


Figure 4. Instructor Interface



INSTRUCTOR INTERFACE

There are two roles of the instructor in this research. First, instructor must enter course design information, which will be stored in the database for defining course categories according to learning style. A course data form is designed to gather course design information intended to be completed by the instructor, as demonstrated in Figure 4. Second, an instructor can find the course category by providing the course code details. It would help the instructor and other stakeholders involved in the design process assess and improve the overall course content. The description of the course design form is given in below.

PROPOSED MODELS

The proposed framework comprises of four main components: Learner Model, Instructor Model, Domain Model, and Recommendation Model. These four models work together to produce the course recommendations suitable for learners' learning styles.

LEARNER MODEL

This module aims at collecting learner details and developing a learner model. The framework requires the learner to fill out the registration form and Index Learning Style Questionnaire (ILSQ) to create a student profile based on learning style. The registration form includes personal information and previously taken courses. The learning process initiates after storing the learner's interests in the learner model.

INSTRUCTOR MODEL

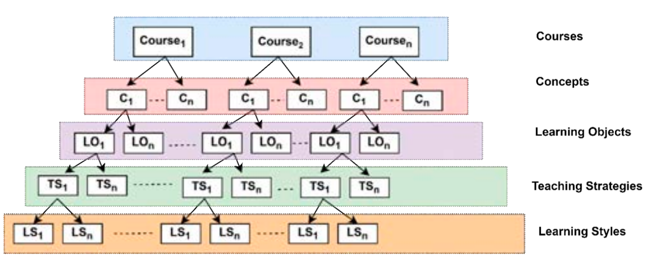
This module aims to gather information about the instructor and create an instructor model. The primary information includes personal information, courses taught, teaching experience, and academic qualifications. This information is required to assess the instructor's influence on the course design process. This information creates an instructor model and is saved in the storage area for further usage. Once a course is added to the database, the instructor can find the category of courses concerning the FSLSM learning style dimension.

DOMAIN MODEL

A domain model includes all the information of a specific discipline. The instructor must provide course information through learning objects and their perspective teaching strategy. Usually, learning objects are represented by their formats (image, audio, video, and others). The learning object format helps support multiple learning concepts, which is a good indicator of learning style (Al-Khanjari et al., 2010). Teaching strategies (TS) are the students' components to promote a thorough understanding of the knowledge. The main objective is to stimulate student learning. FSLSM can support the appropriate learning style for each teaching strategy (Felder, 1988). The recent study presents instructional strategies that could be applied, such as games and simulations, problem-solving, role-playing, presentation, discussion panel, brainstorming, case study, question and answer method, and project design method. These teaching strategies are explored to integrate with potential learning style categories (Franzoni et al., 2008). One central aspect of our research is to assess the whole course based on the possible learning styles of the learning objects, something that has not been explored to the extent that is intended here. There are some contextual factors needed for an effective course design process. A practical method inculcates these variables because teachers sometimes have an insufficient understanding of the design role and need assistance in creating a clear image of what they expect of the process and the product. In this study, five types of support are considered to represent the contextual characteristics of the course designing process, namely organizational, process, expert, technical, and leadership support.

A domain can be modeled by dividing the course into five layers, the first one reflects the category of courses, and each category is divided into numerous courses. Each course is offered with a collection of concepts, and each concept is correlated with different learning objects. Finally, each learning object is connected to potential learning styles. The description of combining learning styles with learning objects can be found in the next section. Figure 5 illustrates the components involved in the course decomposition.

Figure 5. Hierarchical Organization of the Knowledge Concepts



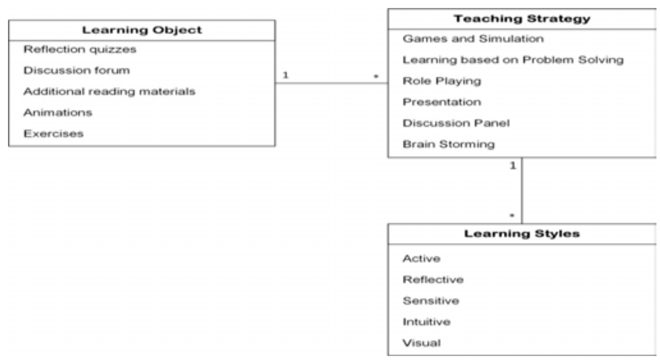
RECOMMENDATION MODEL

Our proposed recommendation model consists of four steps, namely, (a) course data preparation, (b) course design support computation, (c) learning style-based classification, and (d) course recommendation. The detail of these steps is given below.

Step 1: Course Data Preparation

The purpose of this step is twofold. The first is to match the suitable learning styles with the planned teaching strategies for all course learning objects. According to Franzoni et al. (2008), each learning style category can be associated with the teaching strategy. Moreover, a specific learning style can also accommodate more than one teaching strategy. This phenomenon is presented in Figure 6.

Figure 6. *Mapping of Teaching Strategy with Learning Style*



This stage's second goal is to convert the categorical data of teaching strategies into numerical data and handle **the missing values against some learning objects.**

Step 2: *Course Design Support Computation*

This step aims to derive the course design support value used further in the recommendation process. Course design is a collaborative effort involving an expert team and the instructor. This component aims to assess the weight of stakeholder involvement in the process. The instructor's influence can be calculated by considering their attributes (i.e., education and experience) (Boxuan et al., 2019). The estimated value has been used to

$$\mathrm{weight_{II}}(x_i) = \sum[(\mathrm{Value_{Qualification}}(x_i), \mathrm{Value_{experience}}(x_i)]$$

denote the instructor's ability in the course recommendation process. The aim of calculating influence is to assess the teacher's qualities in the course curriculum process.

For instructor influence, their skills have been taken in the course design process in experience and education.

In any process, it is mandatory to normalize the data for consistency. For instance, attribute data can be standardized to fall between small ranges such as 0 to 1. This research has used a min-max normalization method for feature scaling of data (Zhang et al., 2017). The data are converted into forms suitable for mining using the following formula:

$$X = \frac{X - \mathrm{Min}}{\mathrm{Max} - \mathrm{Min}}$$

Contextual influence in the course designing process is represented in support, as explained in the prior section. The responses are calculated on a five-point Likert scale.

$$\mathrm{weight}_{CI}(x_i) = \Sigma\begin{pmatrix}\mathrm{Val}_{Org.Support}(x_i), \mathrm{Val}_{Process.Support}(x_i), \mathrm{Val}_{Expert.Support}(x_i), \\ \mathrm{Val}_{Technical.Support}(x_i), \mathrm{Val}_{Leadership}(x_i)\end{pmatrix}$$

Let x be a course; instructor influence be $\mathrm{weight}_{II}(x_i)$, contextual influence be $\mathrm{weight}_{CI}(x_i)$, the total weight of course design influence can be written as:

$$W_{CDI}(x_i) = \alpha * \mathrm{weight}_{II}(x_i) + \beta * \mathrm{weight}_{CI}(x_i)$$

Where α and β are parameters to control the proportion of weights (Boxuan et al., 2019) (Jing & Tang, 2017). According to researchers, the effect of the sum of these parameters should be 1(Esteban et al., 2018). These parameter values are being set to ½ to have a null effect, i.e., 1. The calculated weight of course design influence has been used to derive the course's net support computation in equation 5.

$$\mathrm{Weight}_{SC}(x_i) = W_{CDI}(x_i) * \mathrm{support}(x_i)$$

Where $\mathrm{support}(x_i)$ can be measured by the number of times the teacher has taught the course.

Step 3: *Learning-Style-Based Classification*

The course data is provided from the data preparation module in a distinct style for all individual learning objects. We have calculated the net support computation value for every course in eq (5), which has been used as minimum support to eliminate the categories from the list having a value less than the calculated threshold. We must analyze the learning object data based on this threshold value to establish the course category. The proof of concept of the proposed algorithm is given below for the reader's clarification.

Input*: learning objects corresponding learning style data, net course support computation (threshold value)*

Output*: Course Category*

begin

retrieve required data

loop *for all data in retrieved data*

if *learning style data count is greater than support computation value*

calculate difference of learning style count with another category of same dimension

save the difference with greater value category name

if *difference is between 1 and 3*

course is well balanced to both dimensions

save into the table

else if *difference is between 5 and 7*

course has moderate preference for greater dimension

save into the table

else if *difference is between 9 and 11*

course has strong preference for greater dimensions

save into the table

else

retrieve next category data

end loop

end

Step 4: *Course Recommendation*

Course recommendation is the primary step in the proposed framework. The learner will provide their learning style and previously studied courses. Initially, courses will be searched from the database according to the learning style of learners. The course dataset is built by mapping learning style dimensions to an item and each course to a transaction. The courses will be used to produce association rules for recommendations by using the fpgrowth algorithm. We can represent item-set as,

$$Item\ set = \{course_1, course_2, \ldots, course_n\}$$

and transaction id as,

$$LS_{active}, LS_{reflective}, LS_{intuitive}, LS_{sensing}, LS_{visual}, LS_{verbal}, LS_{sensing}, LS_{global}$$

Support and confidence are the two parameters generally used to generate association rules. We aim to obtain higher-quality association rules to cover many courses. For association rules of the form A □ B where A and B is sets of courses, support and confidence formulas are respectively defined as:

$$\mathrm{Supp}(A \Rightarrow B) = \frac{\text{no. of records containing both A and B courses}}{\text{total no. of courses}}$$

$$\mathrm{Conf}(A \Rightarrow B) = \frac{\text{no. of records containing both A and B courses}}{\text{total no. of records containing A course}}$$

A balanced trade-off is needed between coverage and accuracy to produce better recommendation results. Rules generated by setting up the minimum support and confidence level are considered strong association rules (Han et al., 2012). In this research, support and confidence are set to be 20% and 70% as standards used in literature, respectively (Boxuan et al., 2019).

We will validate the findings by measuring the coverage and accuracy of the recommendation. Coverage measures the system's ability to generate the courses the student is likely to follow, whereas accuracy measures the system's ability to offer accurate recommendations. These can be defined as follows:

$$Coverage = |R(sk) \cap T(sk)|/|T(sk)|$$

$$Accuracy = |R(sk) \cap T(sk)|/|R(sk)|$$

CONCLUSION

This paper has put forward an automated course recommendation framework to enhance the existing knowledge by addressing students' personalization needs while eliminating the cold start problem. We have addressed the incompatibility issue of teaching methodology with student learning skills, which results in an inefficient learning process by examining the critical factors required in the course design process. Courses are evaluated for potential learning styles at the design level, which was not explored before. There are two significant implications of the envisaged framework. First, the proposed framework can help the learners discover matching courses concerning their learning styles to achieve the learning process. Second, the proposed method can help instructors enhance the course syllabus based on course learning styles assessment. This work is being presented as proof of concept. Future work includes selecting dataset, implementation, and validation of framework in a real environment to assess the quality of the proposed algorithm and method.

DECLARATIONS

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Competing Interests

There are no competing interests in this research.

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