A Learning Style Aware Diagnosis Agent for Computer Supported Cooperative Learning

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Abstract

In this study, an intelligent learning style aware diagnosis agent for computer supported cooperative learning is proposed. Learners are first assigned to heterogeneous groups based on their learning styles questionnaire given right before the beginning of learning activities on the e-learning platform. The proposed diagnosis agent then scrutinizes each learner's learning portfolio on e-learning platform and automatically issues feedback messages in case some learner's behavior that is unfitted to his/her learning styles or devious argument on discussion board or wiki is detected. The Moodle, an open source software e-learning platform, is used to establish the cooperative learning environment for this study. The experimental results reveal that the proposed learning style aware diagnosis agent indeed boosts the performance of the learners.

Keywords: e-learning platform, learning style, computer supported cooperative learning, diagnosis, feedback

1. Introduction

In the past few years, developing useful learning diagnosis and assessment systems has become a hot research topic in the literature [1-8]. As the Internet gains wide popularity around the world, e-learning is taken by the learners as an important study aid. In order to help teachers easily analyze students' portfolios in an intelligent tutoring system, many researchers try to transform students' portfolios into some useful information, and hopefully reflect the extent of students' participation in the curriculum activity.

Recently, a lot of e-learning platforms can be used for free on the Internet due to the increasing availability of Open Source software. In this work, we incorporate learning parameter improvement mechanisms into an Open Software e-learning platform, Moodle [9], to verify the feasibility of the proposed algorithms. The most important reason for the choice of Moodle as the pupils' online learning platform is that Moodle is used for free and is designed to support a social constructionist framework of education, such as collaboration, activities, critical reflection, etc. Meanwhile, there are several striking features in Moodle that well suit the pupils' online learning in this work:

- It is suitable for 100% online classes as well as supplementing face-to-face learning
- It supports simple, lightweight, efficient, compatible, low-tech browser interface.
- Most text entry areas, such as resources, forum postings, etc., can be edited using an embedded WYSIWYG HTML editor.
- It allows flexible array of course activities - Forums, Quizzes, Resources, Choices, Surveys, Assignments, Chats, Workshops.
- The teachers can define their own scales to be used for grading forums and assignments.
- It is effortless to proceed with further study and analysis on the learners' profiles as they are comprehensively established.

The synchronous chat tool was used and learners in a small assigned group analyze the problem together. Based on their prior knowledge, they determined the information they already had and what information they were still required to possess and had to learn to solve the problem. During this collaboration, they propose hypotheses to the problem; organize a plan of action required to tackle the generated learning issues and assign group members to conduct defined tasks. Learning takes place in an active and interactive environment, and the learner construct knowledge by formulating ideas into words with these ideas built upon the reactions and responses of others.

Traditional techniques for detecting similarity between long texts documents have focused on analyzing shared words [10]. Such techniques are usually effective when dealing with long texts because similar long texts usually contain a degree of co-occurring words. However, word co-occurrence in short texts may be scarce or even nonexistent mainly because of the inherent flexibility of natural language, which enables people to express similar meanings using quite different sentences in terms of structure and content. Since such word co-occurrence information in short texts is very limited, this problem poses a difficult computational challenge. To tackle this challenge, the focus of this paper is primarily on developing algorithms to compute the similarity between very short texts, and then apply the algorithms to detect the relevance degree between the messages posted on discussion board and wiki and the learning topics. Meanwhile, some proper feedback messages will be issued to the learners in case some abnormal behaviors such as idleness are detected.

It has been proven that teaching the learners according to their learning styles could effectively assist the learners in the learning activities. There have been several learner's learning style models proposed in the literature. Kolb/McCarthy learning cycle [11-14] is based on the assumption that learning involves a cycle of four learning stages, but each learner is likely to feel most comfortable in one of the four stages of the cycle based on his/her preferences along two dimensions of Perception (abstract/concrete) and Processing (active/reflective). There are five learning style dimensions specified in Felder-Silverman learning style model [15-20], which are Perception (sensing/ intuitive), Processing (active/reflective), Input (visual/ verbal), Organization (inductive/ deductive), and Understanding (sequential/ global). Gee [21] examined the influence of student learning style preference on student achievement in course content, course completion rates, and attitudes about learning in an on-campus or distance education remote classroom. Both distance and on-campus groups were taught simultaneously by the same instructor, received identical course content, and both groups met weekly. The Grasha-Riechmann Student Learning Style Scales (GRSLSS) has been used to identify the preferences learners have for interacting with peers and the instructor in the classroom setting [22-24]. The six social learning styles identified by GRSLSS are the Independent, Dependent, Competitive, Collaborative, Avoidant, and Participant. The inventory is made up of 60 items, including six scales, ten items per scale. Learners are asked to judge themselves using a five-point rating scale that ranges from strongly disagreement to strongly agreement. Among the different learning style instruments, the GRSLSS seems to be ideal for assessing student learning preferences in a college-level distance learning setting. First, the GRSLSS is one of the few instruments designed specifically to be used with senior high school and college/university students. Second, the GRSLSS is a relevant scale that addresses one of the key distinguishing features of a distance class, the relative absence of social interaction between instructor/learner and learner/learner. Third, the GRSLSS promotes a desirable learning environment by helping faculty design courses and develop sensitivity to learner needs. Fourth, the GRSLSS promotes understanding of learning styles in a broad context, spanning six categories. Learners possess all of six learning styles, to a greater or lesser extent, and a rationale for pursuing personal growth and development in the underutilized learning style areas is thereby provided.

A brief discussion of each learning style is enumerated below.

- **Independent** students prefer independent study, self-paced instruction, and would prefer to work alone on course projects rather than with other students.
- **Dependent** learners look to the teacher and to peers as a source of guidance and prefer an authority figure to tell them what to do.
- **Competitive** learners attempt to perform better than their peers do and to receive recognition for their academic accomplishments.
- **Collaborative** learners acquire information by sharing and by cooperating with teacher and peers. They prefer lectures with small group discussions and group projects.
- **Avoidant** learners are not enthused about attending class activities and discussion.
- **Participant** learners are interested in class activities and discussion, and are eager to do as much class work as possible. They have a strong desire to meet teacher expectations.

Cooperative learning [25-32] has received increased attention in recent years due to the movement to educate learners with disabilities in the least restrictive environment. It is a relationship in a group of learners that requires positive interdependence, individual accountability, interpersonal skills, face-to-face promotive interaction, and processing. Computer supported cooperative learning (CSCL) [25-37] has grown out of wider research into computer supported cooperative work (CSCW) and cooperative learning. The purpose of CSCW is to facilitate group communication and productivity, and the purpose of CSCL is to scaffold students in learning together effectively. They both are based on the promise that group process and group dynamics are supported and facilitated by computer supported systems in ways that are not achievable by face-to-face.

In this work, questionnaire developed by James and Gardner [24] is used to determine students' learning styles. Meanwhile, learners are grouped to facilitate learning based on Kumar's framework, which examines the relationship of instructional process and information technology to students' learning styles [24].

The remainder of the paper is organized as follows. Section 2 shows the details of the intelligent diagnosis agent. Section 3 reviews and discusses the experimental results. Conclusions and the future work are made in Section 4.

2. Architecture of e-learning platform

There are three major components in the proposed e-learning platform as shown in Fig. 1. They are grouping module, curriculum support module, and learning diagnosis agent. The grouping module is used to group the learners with different learning styles according to the questionnaire of learning styles categorization designed by Kumar [21]. Notably, each learner can be classified into one of the five learning style clusters as shown in Table 1. The curriculum support module as shown in Fig. 2 assists the instructor and the learners in collecting the supplementary learning material and allows the instructor to organize the discussion issues on the discussion board and wiki. The learning diagnosis agent is used to issue the feedback messages to the learners or the instructor in case the transcript posted by the learner is determined to be irrelevant to the learning topics, or some abnormal behaviors of the learner, such as having been idling for some period of time, are detected.

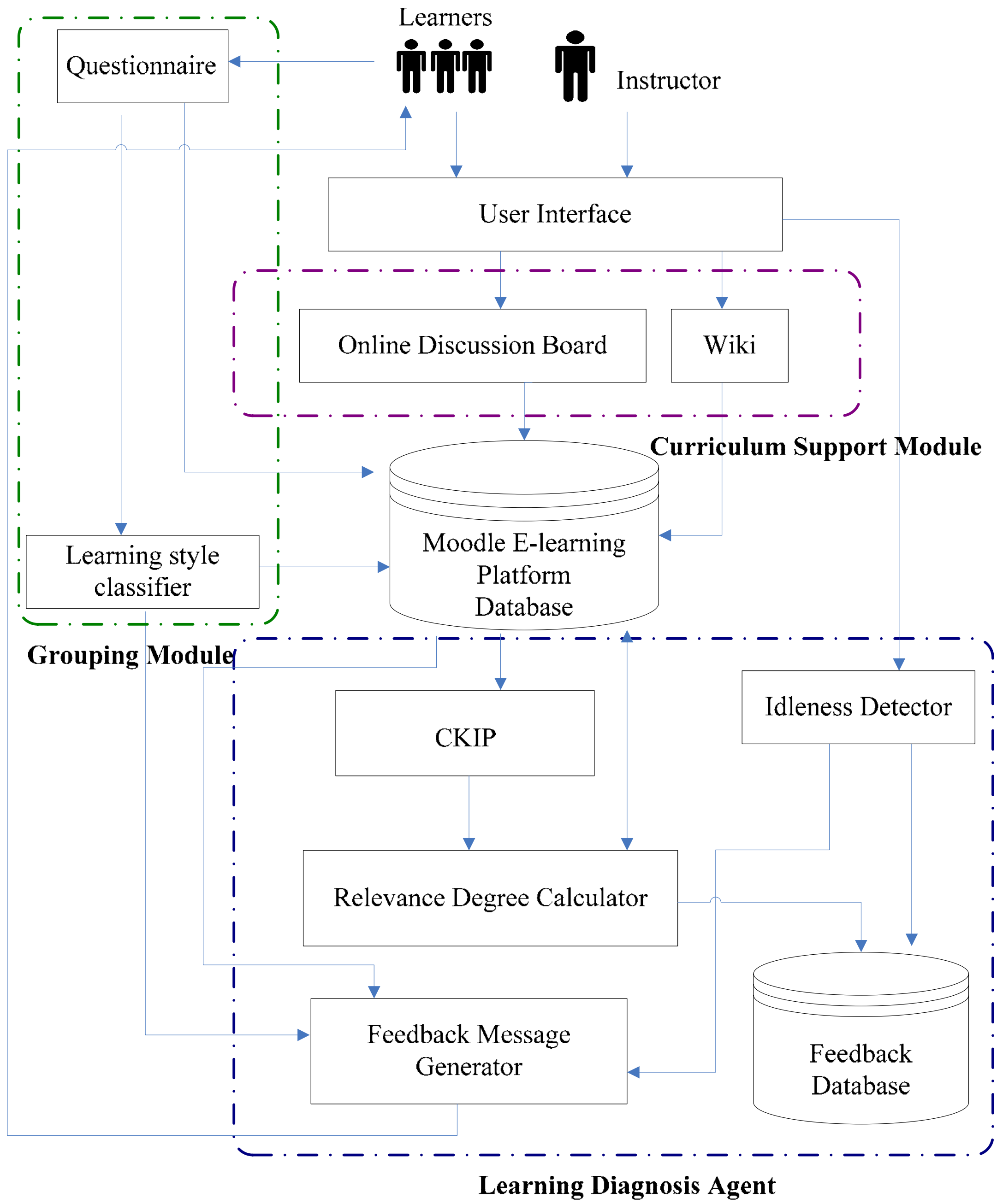

Fig. 1. Architecture of e-learning platform.

Table 1. The five learning style clusters.

	Learning Styles
Cluster 1	Dependent, Participant, and Competitive
Cluster 2	Participant, Dependent, and Collaborative
Cluster 3	Collaborative, Participant, and Independent
Cluster 4	Independent, Collaborative, and Participant
Cluster 5	Avoidant

Fig. 2. Curriculum support module.

2.1. Learning diagnosis agent

The learning diagnosis agent diagnoses learner's behavior in the e-learning platform, and gives appropriate feedback messages if necessary. The most important function of the learning diagnosis agent is to estimate the relevance degree between the posted transcripts and the learning topics on the discussion board and wiki. As shown in Fig. 3, the keyword extractor module is first used to separate the Chinese words. Decision graph is then used to compute the similarity between the learning topic and the content of the transcript posted by learner. Idleness detector module is used to report the abnormal behaviors of the learners. Finally, the Feedback Module gathers all available information in the learning portfolio database and gives learners appropriate feedback messages. The above mentioned modules used in the learning diagnosis agent are elaborated as follows.

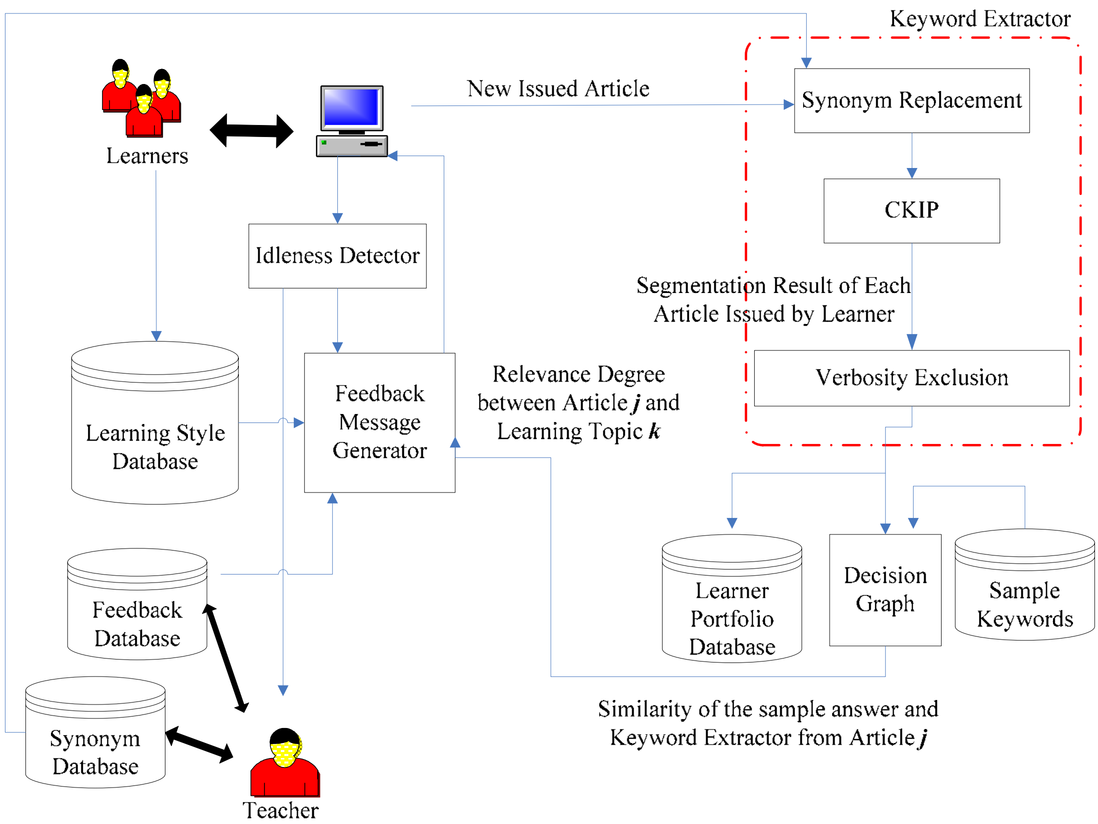

Fig. 3. Learning Diagnosis System.

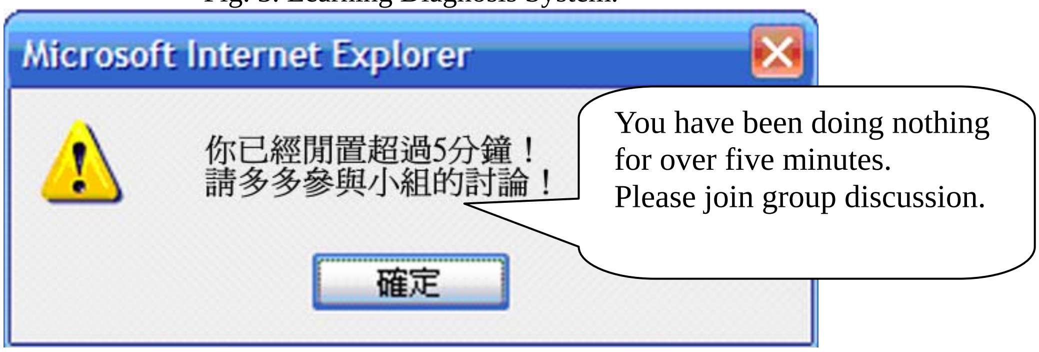

Fig. 4. An example of the message issued by idleness detector.

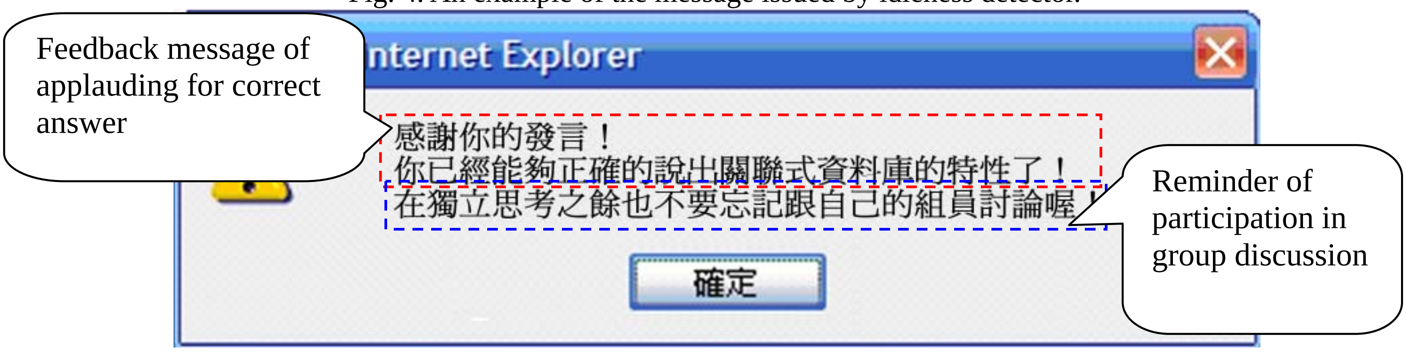

Fig . 5. An example of feedback message for the learners of cluster 3.

2.1.1. Keyword extractor

- **Synonym Replacement**

Since the learner might use a word that has the same meaning as some word used in the sample answers saved in the database, we built a synonym database that can assist us in checking the words used by the learner, and replace them with some appropriate synonym in the database accordingly.

- **CKIP**

Chinese Knowledge and Information Processing (CKIP) system developed by Academia Sinica in Taiwan is used to separate the Chinese words. Meanwhile, verbosity exclusion module is employed to extract verbs and nouns out of the segmentation results for further processing.

2.1.2. Decision graph

Decision graph is an extension of a very well known decision tree representation. Similar to decision trees, a decision graph contains attribute and decision nodes, where attribute nodes contain some kind of test of attributes' values and decision nodes serves to predict the solution. However, the decision graph principle is more flexible and more general than a decision tree. Since it also contains cycles, additional internal variables can be added to process input in a time-series manner, and makes the decision graphs especially appropriate to deal with signals and continuous data.

In this work, decision graph is used to calculate the similarity between two alphabetical string *s* and *s*’. Each string is separated into ordered sub-strings, and each sub-string corresponds to a node in decision graph, which can assist in determining whether there is a similar sub-string in the original string s and s'.

We first construct a matrix $M_{m+1,n+1}$ which is used to describe the decision graph for string *s* and s' as follows,

$$M_{m+1,n+1} = \begin{pmatrix} e_{0,0} & \cdots & e_{0,n+1} \\ \vdots & \ddots & \vdots \\ e_{m+1,0} & \cdots & e_{m+1,n+1} \end{pmatrix}, \tag{1}$$

where *m* and *n* denote the length of alphabetical string *s* and that of alphabetical string s', respectively. Besides, the elements at the first column and the first row in $M_{m+1,n+1}$ are initialized to zeroes.

The value of the element $e_{i,j}$ in $M_{m+1,n+1}$ is determined by,

$$e_{i,j} = \begin{cases} e_{i-1,j-1} + 1 & ,if \quad s_i = s'_j \\ \max(e_{i-1,j}, e_{i,j-1}) & ,if \quad s_i \neq s'_j \end{cases}, \tag{2}$$

where $i = 1 \cdots m$, $j = 1 \cdots n$, s_i is the *i*th alphabetical string *s*, and s'_j is the *j*th alphabetical string s'.

Base on Eqs. (1) and (2), the similarity between two alphabetical string *s* and s’ is derived by,

$$Sim_{s,s'} = \frac{e_{m+1,n+1}}{\frac{m+n}{2}} \times 100. \tag{3}$$

Then the similarity between the posted transcript and the sample transcript that are most similar to the posted transcript can be expressed by,

$$C = \operatorname*{Max}_{i} Sim_{u,s_i}, \tag{4}$$

where *u* is posted transcript, and s_i is the *i*th sample transcript in the database.

2.1.3. Idleness Detector

The idleness detector is used to discover whether the learner has not participated in group discussion for some period of time. Figure 4 shows an example of feedback message that reminds or encourages learners to give their opinions on the discussion board or wiki when the idleness detector finds out the learner has been doing nothing for over five minutes.

2.1.4. Feedback Module

The feedback module may issue messages to the learners/instructor if it is activated by decision graph or idleness detector. A set of feedback rules built in the feedback message database corresponds to the outputs of decision graph and idleness detector. The feedback message can be used either to give advices to the learners that go the wrong direction or to inform the instructor the occurrence of biased group discussion. Meanwhile, different feedback rules for corresponding learning styles are collected in the database with the assistance of the instructor. The example message as given in Fig. 5 applauds the learners of cluster 3, who possess collaborative, participant, and independent learning styles, for their correct answers to the question, and encourage them to keep actively involved in group discussion.

3. Experimental Results

To verify the effectiveness of the diagnosis agent proposed in this work, a freshman course offered at Computer Science department, National Hualien University of Education participated in the experiments. There are 32 students enrolled in this class. A pre-test in the form of question and answer was taken after classroom teaching, and nine students passed the test. Then, the 32 students were divided into heterogeneous discussion groups in the e-learning activity according to their learning styles. After their discussion on the learning topics, each student was asked to take a post-test in the form of question and answer again. It can be observed from the test results, as given in Table 2, that the learners indeed benefited by group discussion held in the e-learning activity.

Table 2. The results of pre-test and post-test.

	Pre-test	Post-test
Pass	28.12%(9/32)	96.87% (31/32)
Fail	71.88%(23/32)	3.13%(1/32)

4. Conclusion and future

In this work, a learning style aware learning diagnosis agent based on machine learning techniques is proposed. Learners' transcripts on discussion board and wiki were examined to detect whether the learners plan wrong solutions. A feedback rule construction mechanism is used to issue feedback messages to the learners in case the diagnosis agent detects that the learners go in the biased direction or they have not been joining the group discussion for some period of time. The experimental results exhibit that the proposed work is effective in assisting the students with different learning styles in learning the database concepts taught at a freshman course.

In the future work, we plan to employ advanced machine learning techniques to access each individual's performance based on the contents of the learners' transcripts. Meanwhile, we will try to automatize feedback message rule construction mechanism to further reduce the instructor's labor work. In addition, more advanced text mining technique will be adopted in our future work to accurately measure the similarity of expected solution and posted transcripts.

Appendix

Learning Style Survey

The following is a Grasha-Riechmann student learning style survey. It has been designed to help you clarify your attitudes and feelings toward the courses you have taken thus far in college. There are no right or wrong answers to each question. However, as you answer each question, form your answers with regard to your general attitudes and feelings towards all of your courses.

1 = strongly disagree | 2 = moderately disagree | 3 = undecided |
4 = moderately agree | 5 = strongly agree

1.	I prefer to work by myself on assignments in my courses.
2.	I often daydream during class.
3.	Working with other students on class activities is something I enjoy doing.
4.	I want teachers to state exactly what they expect from students.
5.	To do well, it is necessary to compete with other students for the teacher's attention.
6.	I do whatever is asked of me to learn the content in my classes.
7.	My ideas about the content often are as good as those in the textbook.
8.	Classroom activities are usually boring.
9.	I enjoy discussing my ideas about course content with other students.
10.	I rely on my teachers to tell me what is important for me to learn.
11.	It is necessary to compete with other students to get a good grade.
12.	Class sessions typically are worth attending.
13.	I study what is important to me and not always what the instructor says is important.

14.	I very seldom am excited about material covered in a course.
15.	I enjoy hearing what other students think about issues raised in class.
16.	I want clear and detailed instructions on how to complete assignments.
17.	In class, I must compete with other students to get my ideas across.
18.	I get more out of going to class than staying at home.
19.	I learn a lot of the content in my classes on my own.
20.	I don't want to attend most of my classes.
21.	Students should be encouraged to share more of their ideas with each other.
22.	I complete assignments exactly the way my teachers tell me to do them.
23.	Students have to be aggressive to do well in courses.
24.	It is my responsibility to get as much as I can out of a course.
25.	I feel very confident about my ability to learn on my own.
26.	Paying attention during class sessions is difficult for me to do.
27.	I like to study for tests with other students.
28.	Trying to decide what to study or how to do assignments makes me uncomfortable.
29.	I like to solve problems or answer questions before anybody else can.
30.	Classroom activities are interesting.
31.	I like to develop my own ideas about course content.
32.	I have given up trying to learn anything from going to class.
33.	Class sessions make me feel like part of a team where people help each other learn.
34.	Students should be more closely supervised by teachers on course projects.
35.	To get ahead in class, it is necessary to step on the toes of other students.
36.	I try to participate as much as I can in all aspects of a course.
37.	I have my own ideas about how classes should be run.
38.	I study just hard enough to get by.
39.	An important part of taking courses is learning to get along with other people.
40.	My notes contain almost everything the teacher said in class.
41.	Being one of the best students in my classes is very important to me.
42.	I do all course assignments well whether or not I think they are interesting.
43.	If I like a topic, I try to find out more about it on my own.
44.	I typically cram for exams.
45.	Learning the material was a cooperative effort between students and teachers.
46.	I prefer class sessions that are highly organized.
47.	To stand out in my classes, I complete assignments better than other students.
48.	I typically complete course assignments before their deadlines.
49.	I prefer to work on class projects and assignments by myself.

50.	I would prefer that teachers ignore me in class.
51.	I am willing to help other students out when they do not understand something.
52.	Students should be told exactly what material is to be covered on exams.
53.	I like to know how well other students are doing on exams and course assignments.
54.	I complete required assignments as well as those that are optional.
55.	When I don't understand something, I first try to figure it out for myself.
56.	During class sessions, I tend to socialize with people sitting next to me.
57.	I enjoy participating in small group activities during class.
58.	I want teachers to have outlines or notes on the board.
59.	I want my teachers to give me more recognition for the good work I do.
60.	In my classes, I often sit toward the front of the room.

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