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An Adaptive Feedback System to Improve Student Performance Based on Collaborative Behavior

MUHAMMAD AWAIS, UME HABIBA, HINA KHALID, MUHAMMAD SHOAIB, AND SHAZIA ARSHAD

Department of Computer Science, University of Engineering and Technology at Lahore, Lahore 54890, Pakistan

Corresponding author: Muhammad Awais (awais.hassan@uet.edu.pk)

ABSTRACT With advancements in educational technologies, e-learning platforms have evolved to provide learning environments to the privileged and under-privileged population so that they can learn at their own pace. The success of these systems relies on engaging experience and timely and accurate feedback to the students on their performance. Still, these systems suffer from high student dropouts, often due to a lack of personalization in student interactions. While students show different collaborative behavior, i.e., some students are social, and like discussions, while others are self-oriented and do not participate in any collaborative activity, the feedback and interactions with students are generally not customized based on their type of collaborative behavior. This research aims to develop a method that provides adaptive feedback to each student according to their type of collaborative behavior and preferred gamification elements. Two experiments were performed to evaluate the system, and the results show that the system, with adaptive feedback, significantly improved student performance.

INDEX TERMS Computer aided instruction, collaborative work, distance learning, feedback, knowledge based systems.

I. INTRODUCTION

In the last few years, the e-learning platforms have expanded exponentially, which makes them a cost-effective, space independent, and time-saving alternate resource for learning [1]. These platforms contributed a lot towards educating people in underdeveloped areas, where the instructional and technical resources are rare, but these platforms are experiencing a considerable drop-out ratio [2]. There are several factors for the increased drop-out ratio of students, but the lack of feedback, absence of an instructor, and lack of interactions among the learners are the important ones [3], [4]. The interactions between instructor-student and student-student result in collaborative learning. Collaborative learning, also known as social learning, directly influences the academic achievement, consistency, and positive attitudes of the learners [5]. Students with self-learning capabilities make autonomous decisions, including the choice of goals, learning materials, and learning strategies. Students in online learning courses possess different collaborative learning behaviors; some students possess self-learning abilities, while others tend to have collaborative learning abilities.

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Feedback is defined as "the information about how the student's present state relates to his goals and interests" [6]. The experiment found [7] that the learning of students increases when they are more engaged and interested in the learning process. A student's engagement in any learning activity is significantly increased by providing feedback about the performance and current actions of the student [8]. In traditional classrooms, the teacher forwards feedback messages to the students regarding their strengths and weaknesses. Based on the feedback and assessment, the teacher guides students to take the steps [6] and if students act accordingly, their chance to succeed increases. Various architectures exist for the specific assessment of and provision of feedback to students [9]–[13]. Most of these feedback techniques are defined for traditional classrooms, within which it is difficult to tailor the feedback to each student individually based on the type of collaborative learning behavior, i.e., self or social learning. In our opinion, this is the primary drawback of these architectures because students in a classroom have different collaborative learning behaviors, and their engagement preferences are also different. This issue becomes more significant in an online learning environment where the students come from very different demographics and possess varying collaborative learning behaviors and preferences. However,

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in the e-learning domain, it is possible to design specific and targeted feedback to each student's collaborative learning behavior.

Some of the existing studies have provided feedback to students about their performance [9], [14], but the feedback did not consider the type of collaborative learning of students or whether they tended to learn in groups or preferred self-study. Due to the different collaborative learning behaviors of the students in online learning settings, there is a need for an architecture that can give feedback to learners based on their kind of collaborative learning behavior and performance status. The goal of this paper is to design an intelligent adaptive feedback system in the e-learning environment, so it increases the performance of the learners.

A. RESEARCH QUESTIONS

1) How can we provide feedback adaptive to the collaborative learning behavior of the students?
2) How can adaptive feedback increase the performance of the students in e-learning environments?

This paper contributes a method in the literature that develops adaptive feedback for each student based on their learning tendency and gamification preference.

II. LITERATURE REVIEW

Ross et al. proposed an online learning platform of adaptive quizzes to elevate engagement, motivation, and learning outcomes [14]. The system provides instant and informative feedback to the students about their performance, but the feedback did not adapt according to the individual's collaborative behavior type.

Karin & Annette [9] presented a framework, which provided feedback about the grammar errors while composing a German sentence. The system used visualizations of the pedagogical agents with animations to highlight feedback errors. The system provided the same feedback to all students, which was only related to their performance and did not focus on adaptive feedback. However, according to Ruofei et al., feedback adaptive to the collaborative learning type of student is necessary for improved performance [15].

Serge *et al.* [10] provided adaptive feedback to the students in a virtual learning environment. This feedback system informed the students about the errors that they had made during each mission, and they got more detailed feedback if they failed to improve over a series of missions. The authors divided control groups into two categories: one that received detailed feedback after completion of each task and the other that received general feedback. Results showed that detailed feedback significantly improved the performance of the students.

Tempelaar *et al.* [11] showed the implementation of Shum & Crick's theoretical framework of learning analytics infrastructure. The authors showed that the learning disposition data, along with the data extracted through formative assessment techniques, have a positive impact on the performance of the student. Shannon and Kathryn [12] proposed the architecture to engage students in online courses by providing face-to-face interactions with the students. Gwendolyn & Demetria presented the idea of video feedback for increasing efficiency and value for the feedback process in e-learning environments [13]. This study showed that video feedback is a better way of exchanging emotions and conveying the instructor's personality to the students of online learning platforms.

Tsai et al. suggested two different types of feedback in a gaming environment, which includes immediate, elaborated feedback (IEF) and non-immediate, elaborated feedback (no-IEF) [16]. The experiment showed that IEF enhanced the students' knowledge-acquisition abilities. Alvarez *et al.* [17] analysis of the effects of the feedback given to the online learners showed that student discussion increases the responses of students to a significant extent.

Wu *et al.* [18] determined the effects of instructors' positive and negative feedback on the learning outcomes of students. The authors also examined the impact of the source of feedback by providing independent feedback from both instructors and computers. The results showed that instructors should always offer positive feedback to students rather than negative feedback. They also found that in the absence of any facial expression, negative feedback aroused feelings of frustration in the students.

Awofeso and Bamidele [19] performed a survey to show that feedback improves the performance of the student as well as instructors and helps instructors to improve themselves and their instructional methodologies. However, the survey had two shortcomings: 1) the survey was conducted on a small group (66) of students; 2) the survey did not contain any open-ended questions, so the students were not independent in the choice of more accurate answers. Onah and Sinclair [20] proposed a framework that suggested instructional material to a student according to that student's profile. Their recommendations were also based on the objectives and preferences of the student. Bendou *et al.* [21] presented the specifications of an active online pedagogical agent "PAOLE" (Pedagogical Agent for Online Learning Environment). The authors listed "feedback" as one of the primary characteristics of a pedagogue as well as a motivating strategy for students.

Weltman *et al.* [22] proposed the concept of an adaptive tutorial capable of engaging students, providing interactive learning, and adaptive feedback. The adaptive feedback provided the information, whether the answer to a question as provided by a student is correct or not. It also consisted of hints which explain why a response may be wrong and the exact calculations upon the second attempt of the question. Vijayakumar *et al.* [23] proposed SQL Quizbot: a chatbot for providing immediate and cumulative feedback to the students. The chatbot offers feedback based on the performance and the confidence level of the student, but this system did not utilize the feedback to suggest activities to students so their performance may be improved.

TABLE 1. Comparison between existing studies for providing feedback and the proposed work.

	Feedback based on performance	Feedback according to the collaborative learning behavior of students	Feedback based on the engagement of learners	The suggestion of activities based on the feedback
Tsai (2015)	×	×	✓	×
Gwendolyn 2016	✓	×	×	×
Manli (2017)	✓	×	×	×
Niyi (2017)	✓	×	×	×
Vijay Kumar 2018	✓	×	×	×
Proposed work	✓	✓	✓	✓

An ontology-based personalized feedback generator (OntoPeFeGe) [24] provided feedback to the students that were according to the characteristics of the students and type of question. The authors employed Bloom's taxonomy for assessing the kind of question and provided five different kinds of feedback. Bimba *et al.* [25] reviewed various techniques for adapting feedback based on different characteristics of students, i.e., means, goals, targets, and strategies. The study did not contain any literature for adaptive feedback based on assessing the collaborative behavior type of student that can improve his or her performance [25]. Table 1 presents a comparison between existing studies on feedback and the proposed system.

III. METHODOLOGY

The proposed system consists of three components: 1) concept level determinant 2) behavior examiner and 3) feedback designer. As a course consists of multiple concepts, the "concept-level-determinant" identifies the student level of understanding for each concept. At the second step, the behavior examiner identifies the type of activities performed by the students and classifies them into self or social types of activities. Finally, the feedback designer takes input from both components and gives feedback to the student based on the type of activities performed by students repeatedly and their understanding level of the concept. Fig 1. represents an abstract architecture of the proposed system.

A. CONCEPT LEVEL DETERMINANT

The module determines the concept understanding level of a student based on her responses to the questions. The performance (marks) of a student in the concept-relevant-questions help to determine the level of a concept. The concept understanding level is logged against the concept name in the "concept-level log." The marks and the scaled value of each question are used to calculate the score of the student. If the score of a student is less than the threshold value, the concept is marked as weak concepts for the student.

Let for a subject C, S and Q are the sets that represent the concept of the subject, enrolled students with the subject, and questions of the subject, respectively.

$$C = \{c_1, c_2, c_3 \ldots, c_n\}; \quad S = \{s_1, s_2, s_3, \ldots\ldots., s_m\}; \quad Q = \{q_1, q_2, q_3, \ldots.., qo\}$$

Let QC is a set of ordered pairs of question and related concepts of a subject such that:

$$QC = \{(c, q) | c \in C \text{ and } q \in Q\}$$

Each Concept $c \in C$ is related to one or more questions $q \in Q$.

1) IMPORTANCE LEVEL (ImpLevel) FUNCTION

Let ImpLevel: $QC \rightarrow \mathbb{R}$ is a function that returns a scaled value between 0-1 that shows how the question q is related to concept C, while 0 is being the lowest and 1 is the highest w.r.t importance of the concept.

2) SCORE OF A QUESTION

The function QScore: $Q \times S \rightarrow \mathbb{R}(q, s)$ returns the score of a student in a question such that:

$$QScore\ (q,s) = \begin{cases} +1, & R(q, s) = ActualResponse\ (q) \\ -1, & R(q, s) \neq ActualResponse\ (q) \\ 0, & R(q, s) = 0 \end{cases} \quad (1)$$

where $q \in Q$, $s \in S$.

The function R (q, s) returns the response of student s, on question **q**. The function ActualResponse(q) returns the correct answer to the question q. The function QScore returns 1 when the response of student R (q, s) is equal to the ActualResponse(q) of the question been asked. QScore has a negative value of −1 if the response provided by the student doesn't match the actual response of the question. Zero value of QScore indicates that the student has not given any response to the question, i.e., R (q, s) is equal to zero.

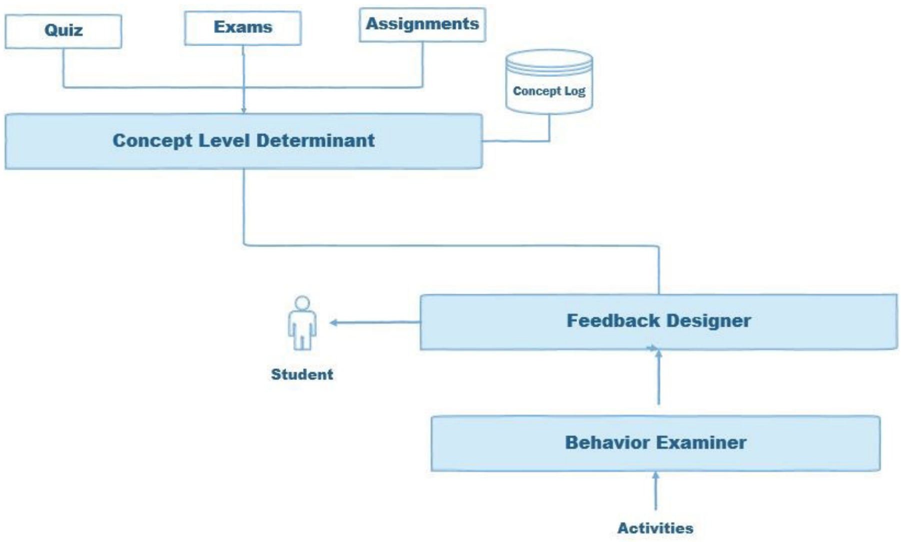

FIGURE 1. Layered architecture of the proposed system.

3) DETERMINING ALL QUESTIONS RELEVANT TO A CONCEPT

From the relation QC, the function question: C ⇾ Q returns the set of questions that are related to a particular concept c €C.

4) DETERMINING CONCEPT UNDERSTANDING LEVEL

Let CScore: S × C→ ℝ is the score of a student s S for concept c defined as:

$$\text{CScore}(s, c) = \sum\nolimits_{i=1}^{m} QScore\ (q, s) \times ImpLevel(q, c) \qquad (2)$$

where q € C Question (c) and m is the total number of questions of a concept c. Where q ϵ CQuestion (c) and m is the total number of questions of a concept c. The product of the importance level of the question and student response determines the score of question of the concept. The total score of the concept is calculated by summing up of all these scores. The concept level determinant module uses the following algorithm for identifying the concepts in which a student is weak.

Algorithm 1 Weak Concepts Identification

Input: Concepts [], Student
Output: WeakConcepts []
1: **For each c in Concepts [] do**
2: *Score* ← *CScore(s, c)*
3: **if** *score* < *threshold* **do**
4: WeakConcepts.add(c)
5: endif
6: end for
7: Return WeakConcepts []

B. CONCEPT LOG

All concepts in which a student is weak are stored in concept log, against his student id. The log Table 2. helps to examine the level of student's understanding of a concept. This component provides valuable information to feedback designer module.

C. BEHAVIOR EXAMINER

For each student, a profile is maintained that keep track of the engagement level, a list of preferred incentives, and a set of the most attempted activities by the student. After analyzing the profile, the behavior examiner classifies the activities attempted by a student as self-activities or social-activities. This component examines activities of a student Table 3. to construct the learning profile.

5) DETERMINING THE PREFERRED INCENTIVE

When a student performs an activity, she always gets some (point, badge, reward) of incentives that motivate a student to repeat the activity. Based on the achieved incentive and the type of activities, the behavior examiner marks the student as self or social player. A self-player mostly attempts an activity for self-learning or satisfaction, whereas a social player attempts those activities based on social interaction, discussion, or help.

D. PLAYER TYPE IDENTIFIER

Player-type
identifier assists behavior examiner in classifying the player type as self or social player. The identifier takes the activities attempted by the student, and time spent on them as input and returns the player type of the student. Player-Type stores the output of the player type identifier.

TABLE 2. Instance of log.

Student-Id	Concept	Level of understanding
DB-2018-XYZ	Database normalization	Weak
DB-2018-XYZ	Outer Joins	Strong
DB-2018-XYZ	Inner Joins	Strong
DB-2018-XYZ	Transactions	Weak

TABLE 3. Activities incentives and corresponding classification.

Activity Incentive	Activity type
Points	Self
Levels	Self
Badge (Helper)	Social
Badge (Socializer)	Social
Quests	Self
(Leaderboard)	Social
Reward (Gifts)	Social
Badge (Explorer)	Self

1) SET OF AVAILABLE ACTIVITIES, AND TIME SPENT ON ACTIVITIES

Let A be the set of activities available in the system such that:

$$A = \{a_1, a_2, a_3 \ldots\ldots\ldots\ldots a_p\}$$

Each activity is associated with only one player type. Let I be the incentives obtained after performing the activities from A such that:

$$I = \{I_{A1}, I_{A2}, I_{A3}, \ldots . I_{An}\}$$

Let SAk be the set of activities performed by a student K, where SAk ⊂ A. Let ActivityType is a function which takes Activity as input and return its type. The ACounter is a function which returns the total number of activities of input activity type.

ACounter(player type) = $\sum a$ iff ActivityType (a)= player-type and a ∈ SAk.

$$PlayerType\,(SA_k) = \begin{cases} Social, & Acounter\,(SA_k, Social) > Acounter(SA_(k), Self) \\ Self, & Acounter\,(SA_k, Social) > Acounter(SA_(k), Self) \end{cases} \quad (3)$$

E. FEEDBACK DESIGNER

This component designs feedback for a student based on his performance, type of preferred incentive, and classified player type. Feedback consists of three portions:

- The first portion of feedback contains the player type of the student as identified by the behavior examiner.
- The second portion asks the student to perform an activity that can help to increase his performance. His preferred activities help to choose the activity to be presented to the student.

The third portion of the feedback presents the incentive to the student for motivating him to perform the activity. The incentive is selected based on the player type. Table 4. presents some instances of feedbacks generated by the proposed system.

IV. EXPERIMENTS

A. EXPERIMENTAL SETUP

The experiments were performed on first-year undergraduate students in the computer science department. All students were randomly selected and were an average age of 21 years. The selected students were divided into two sections: A & B. Two-hundred-and-eighty students were enrolled in section A, while two-hundred-seventy were in section B. The authors recorded their names, ages, sections, interests, and pre-requisites studied. Only 1% of the students had studied the course previously or had some background knowledge of the subject. All the other students were taking the course for the first time.

B. EXPERIMENT (I): WITHOUT ADAPTIVE FEEDBACK

In Experiment (I), the students from section (A) enrolled in an e-learning course on database management system (DBMS). For section A, we offered a system that shows the same feedback, in terms of the progress bar, irrespective of the student's learning dimensions. The system does not show the adaptive feedback with incentives. In this way, students can view the marks they have obtained for quizzes, exams, and assignments. Furthermore, the feedback system is passive rather than active, which means that students view the feedback instead of it being shown to them by the system from time to time. The students were free to use the discussion

TABLE 4. Sample feedback generated by the proposed system.

Learning assessment component	Concept	Performance Level	Player-type	Preferred incentive	Feedback
Quiz	Stack	Poor	Self	Points	Hi Tony! You can watch the video lectures for stack data structure by Thomas Edison. He has used various animations and infographics for explaining stack. If you attend the full lecture and reattempt the quiz, you will have an extra 50 points in your account. You can also clear your ambiguities by discussing with the instructor and in the discussion forum.
Exam	Round robin scheduling algorithm	Average	Social	Badges	A round robin is a form of preemptive scheduling algorithms. You can excel in this concept by first getting the idea about what is preemptive scheduling. There is also a complete series of lectures on preemptive scheduling. It would be helpful to you. In the case of watching each video lecture, and then discussing it with your friend, you will be awarded the badges.
Assignment	Database normalization	Excellent	Self	Levels	John, you have stood second in the class in normalization assignment. Although your performance is exceptional, you have to maintain it to retain your position of "master of database normalization." You can read the pdf lectures available on the course site. You will only be able to move to the next concept if you complete concept at the previous level. At each level, you will get a reward.

forum to share ideas. However, the system logged all of the activities and the time spent on these activates by the students.

C. EXPERIMENT (II): WITH ADAPTIVE FEEDBACK

During Experiment (II), the students from section (B) were asked to enroll in an online DBMS course. The contents of the course were the same as in Experiment I, but this course was equipped with an intelligent instructor. The intelligent instructor (bot) provides adaptive feedback to students according to the proposed method. The intelligent instructor indicates the areas in which students are weak. It also presents certain activities to the students, along with incentives for each activity.

V. RESULTS AND DISCUSSION

For both experiments, we calculated the performance of students from their marks in questions relevant to concepts. There are four categories of the students based on the grades assigned to them, as shown in Table 5.

A total of 550 students was enrolled in the course on database management systems. Of these, 280 students were enrolled in section A, and the remaining 270 students were enrolled in section B. The grades achieved by the participants, with and without adaptive feedback, are listed in Table 6.

As the learning profile of each student also contains the activities performed by the student and time spent of each

TABLE 5. Grade-marks scale.

Marks	Grade
85-100	A
70-85	B
40-70	C
<40	F

activity, so this information is used for estimating engagement time of the student Table 7. Engagement time is the average of all time intervals spent by the group on multiple activities.

A. QUANTITATIVE COMPARISON OF PERFORMANCES OF THE EXISTING AND PROPOSED SYSTEM

Karin & Annette 9] percentage of performance was increased from 52% to 67% showing an increase of 28.84% while the proposed system showed that the average performance was increased up to 39.052% than the legacy system. Serge et al. found that feedback about the performance in missions didn't provide any significant difference in performance [10]. Supanc *et al.* found that different types of feedback to

TABLE 6. Results of students with and without adaptive feedback.

Grade	Without adaptive feedback		With adaptive feedback	
F	109	(38.9%)	77	(28.51%)
C	84	(30.0%)	66	(24.44%)
B	54	(19.2%)	75	(27.77%)
A	33	(11.78%)	52	(19.259%)
Total	280		270	

TABLE 7. Average time spent by students on the E-learning platform.

T_{avg} (Without adaptive feedback) (per week)	T_{avg} (With adaptive feedback) (per week)
10 hours	15 hours

students didn't influence their knowledge acquisition rate as two-way ANCOVA showed that no interaction existed between the two factors of the learning environment and feedback type [15].

In this research, the proposed system provides feedback to the students based on their kind of behavior. The system analyzes the students' performance for each concept and logs the information to provide the feedback. The system offers the students customized feedback that had three primary parts: 1) player type based on the collaborative behavior of the student; 2) incentive to be presented as the result of performing that action; 3) activity preferred by the student. The system selects an action that best matches the student's player type and frequently performed activity. To motivate the students, the system offers an incentive that is a favorite of the student, and the student mostly performs the activity that tends to provide this incentive. For example, if a student prefers self-study and attempts the assignments regularly, he would be awarded points. Conversely, if a student often performs the activities, returns the badge and discusses the quiz after attempting, the student will be awarded badges.

The adaptive feedback significantly improved the performance of the students. The number of students who get A and B grades in the proposed system is 19.259%, 27.77% higher than the number of students who get A and B grades in the legacy system. Similarly, the percentage of the students who get the lower grades of C and D decreased to 24.44% and 28.51% respectively in the proposed system. Also, the average number of hours spent by the students within the proposed system has increased to 15 hours. These figures indicated that the adaptive feedback based on students' collaborative behavior type has a considerable impact on the performance of the student.

VI. CONCLUSION

To reduce students' drop-out ratio from e-learning platforms and bridge the gap of an instructor, we have proposed a framework containing an integrated intelligent instructor to provide adaptive feedback. The intelligent instructor provided feedback that was adaptive to the collaborative behavior of the students, as students may have different collaborative tendencies, i.e., social or self. The results of the experiments performed showed that the adaptive feedback based on the collaborative behavior of the students enhanced both their performance and engagement level. In the future, the system may be improved by incorporating artificial techniques such as supervised and reinforcement learning techniques.

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