IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 3 March 2023, accepted 16 April 2023, date of publication 26 April 2023, date of current version 10 May 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3270804

RESEARCH ARTICLE

Agent-Based Personalized Assessment Tasks Recommendation Considering Objective and Subjective Factors

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This work was supported in part by the National Natural Science Foundation of China under Grant 62006090, and in part by the Research Funds of Central China Normal University (CCNU) under Grant 31101222211 and Grant 31101222212.

ABSTRACT In traditional education, there is not much difference between assessment tasks designed for learners. However, learners' learning performance may vary due to a number of factors, e.g., learning ability, academic emotion, and learners' and teachers' academic expectations. Considering those factors, accurately recommending personalized assessment tasks for each learner is challenging. To overcome the limitations in the current work, this paper proposed an autonomous-agent-based approach to recommend personalized assessment tasks considering multiple factors. Contributions of the proposed approach contain three aspects: (1) Considering objective factors, the proposed approach involves dynamically adjusting the assessment tasks recommended for students by applying both item response theory and the proposed academic emotion influence model. (2) Considering subjective factors, the proposed approach can dynamically predict learners' learning performances by applying autonomous agent-based negotiation. (3) The proposed recommendation algorithm based on discrete linear programming can effectively address the issue of cold start in typical recommendation algorithms. The experiments conducted in this paper demonstrate that the proposed approach effectively recommends assessment tasks for learners by considering both objective and subjective factors. The results indicate that this approach generates better recommendation outcomes than traditional content-based and collaborative filtering recommendation algorithms. Furthermore, the experiments reveal that the teacher's personality is the primary factor affecting the recommendation results, while the degree of similarity between the teacher's and learner's personality also plays a role.

INDEX TERMS Personalized recommendation, learning performance, academic emotion, academic expectation, autonomous agent negotiation.

I. INTRODUCTION

In traditional learning, learning objectives, processes, and contents often fully depend on teachers, i.e., there is very little difference between learning resources available for each learner. Typically, teachers develop learning resources relying on their personal experience and do not consider learners' individuations, which cannot generate appropriate learning outcomes for all learners. With the development of information technologies, personalized teaching provides customized learning resources considering learners' individual preferences and personalities to maximize learning effectiveness. As one of the most commonly used types of evaluations in teaching and learning, the quality of assessment tasks greatly impacts the learning outcome. To maximize the learning outcome, the recommendation of personalized assessment tasks is well worthy of study.

In personalized learning, a learner's learning outcome is impacted by objective and subjective factors, e.g., learners' ability, learners' emotions, and learners' and teachers' expectations. Obviously, considering various learning abilities, learners should be provided with different assessment tasks

The associate editor coordinating the review of this manuscript and approving it for publication was Pasquale De Meo.

regarding levels of difficulty and the coverage of knowledge items in personalized learning. Also, a learner's academic emotion [1] greatly impacts his/her learning outcome, where positive emotion can generate positive learning performance while negative emotion decreases learning performance [2]. In this study, we define learning ability and academic emotion as objective factors.

Moreover, to motivate learners to progress, the learner and his/her teacher may have their own academic expectations in the teaching and learning process. For example, a learner might have a preference for learning content and the corresponding difficulty regarding his/her own learning goal. Similarly, a teacher also has his/her preference for the teaching goal, i.e., the coverage of knowledge items and their corresponding difficulty according to the predefined subject outline. To maximize the outcome of personalized teaching and learning, it is challenging to coordinate and handle the conflicts between learners' learning expectations and teachers' teaching expectations [3]. In this study, we define learners' and teachers' academic expectations as subjective factors. From the analysis mentioned above, it can be concluded that it is challenging to provide a solid solution to the personalized assessment tasks recommendation considering multiple subjective and objective factors.

There are many personalized learning recommendations based on learners' characteristics. Dwivedi and Bharadwaj recommend learning materials considering learners' learning styles and ability [4]. Shi et al. introduce academic emotion in the assessment tasks recommendation algorithm [5]. Saito and Watanobe develop personalized learning paths for learners based on the mastery of knowledge items, which is evaluated by historical data [6]. Furthermore, learners' characteristics also include other factors. Christian indicates that academic achievement is influenced by learners' and teachers' expectations, i.e., it is practical to consider learners' and teachers' expectations in the personalized assessment tasks generation [7]. The above literature shows that the majority of current researchers focus on recommending personalized assessment tasks considered learning ability. However, the current work cannot provide effective solutions to solving the personalized assessment tasks recommendation, especially considering multiple factors, e.g., the learner's ability, the learner's emotion, the learner's and teacher's academic expectations of the learning outcome, etc.

To overcome the limitations in the current work, this paper proposes a personalized assessment tasks recommendation approach considering multiple factors. In detail, this paper has the following contributions. The proposed approach can (1) dynamically adjust the recommended assessment tasks considering a learner's ability and his/her changing academic emotion, (2) dynamically predict a learner's learning performance considering the learner and teacher's academic expectations by applying autonomous agent negotiation [8], and (3) handle the problem of cold start in the research of typical recommendation algorithms. In this study, several experiments are conducted to evaluate the performance of the proposed approach, and the experimental results show that the proposed recommendation approach can effectively recommend assessment tasks to learners considering objective and subjective factors.

The paper is organized as follows. Section II provides a discussion of related work. Section III introduces the proposed approach for assessment tasks recommendation. Section IV provides experimental settings and experimental results. Section V concludes the paper.

II. RELATED WORK

In the research of personalized teaching and learning, most current work considers the learner's learning ability as the major factor when generating personalized assessment tasks. Wei et al. control the difficulty of assessment tasks matching learning ability to motivate learners to achieve higher achievement [9]. Tang applies collaborative filtering to select learning materials matching learning ability [10]. However, the above papers do not dynamically adjust recommended learning materials considering changing learning ability.

Emotions in the learning process are fundamental and can critically impact learners' learning performance [11]. Zhang et al.'s [12] and Pekrun et al.'s [13] work show a relationship between academic emotions and academic performance. Their work shows that positive academic emotions can improve learners' learning performance. Hayat et al. reveal that effective monitoring and intervention of academic emotions can help learners achieve better academic achievement [14]. An optimized recommendation for personalized teaching and learning assessment tasks should consider academic emotion. Shi et al. recommend learning materials based on learners' academic emotions to maintain positive academic emotions [5]. However, this paper only introduces academic emotion in the recommendation framework but does not analyze the relationship between learning performance and academic emotion.

Moreover, learners' and teachers' academic expectations also have great impacts on personalized teaching and learning [15], [16]. Wang et al. conclude that there is a strong link between teachers' expectations and learners' achievement [17]. However, the teacher's expectation sometimes performs inaccuracy with biased. Urhahne et al. indicate that teachers tend to overestimate learners' achievement [18]. Therefore, learners' academic expectations are introduced to reduce the influence of potentially biased teacher expectations. Fu et al. conclude that learners' expectations and performance are mutually influential [19]. Scholtens et al. show that positive learners' expectations positively affect future academic achievement [20]. However, few studies discuss and analyze the academic expectations of learners and teachers in generating personalized assessment tasks.

For personalized assessment tasks generation considering factors, there are various recommendation algorithms. By capturing learners' preferences, Huang and Lu adopt the content-based recommendation algorithm to personalize course recommendations to improve learning

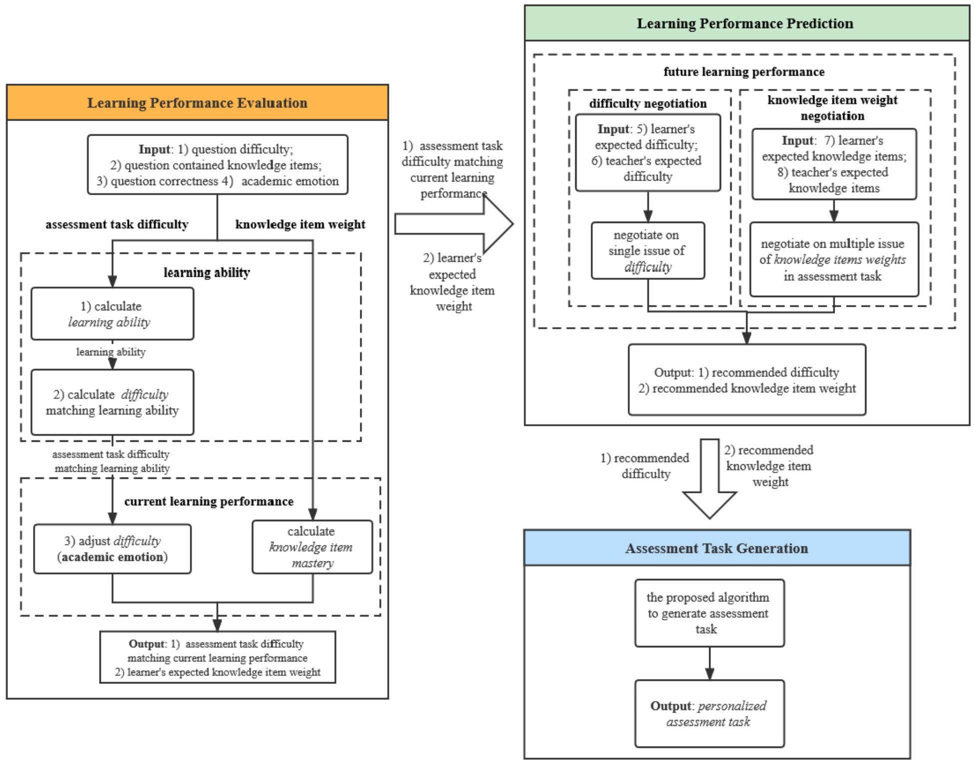


FIGURE 1. The process of the proposed personalized assessment tasks recommendation approach.

effectiveness [21]. Wang and Fu propose a dynamic, collaborative filtering algorithm to filter personalized learning resources based on learners' characteristics in real-time [22]. However, content-based and collaborative algorithms often face cold start problems when only a small amount of historical data information is available. Meanwhile, the accuracy of content-based and collaborative filtering algorithms is not accurate in the recommendation process considering multiple factors.

In summary, current research on assessment task recommendation primarily focuses on learners' academic ability and overlooks their academic emotions and the academic expectations of both learners and teachers. This research addresses this gap by considering all four factors, i.e., objective and subjective factors, and clarifying their interconnection in the assessment task recommendation process. By doing so, personalized assessment tasks can be recommended to learners, helping them achieve better academic achievement.

III. PROPOSED APPROACH FOR PERSONALIZED ASSESSMENT TASKS RECOMMENDATION

This paper aims to dynamically generate personalized assessment tasks with appropriate difficulty and knowledge items considering objective and subjective factors. Firstly, considering objective factors (i.e., learning ability and academic emotion), the proposed approach evaluates current learning performance to obtain learning preferences for each learner in the following two steps: (1) evaluating the difficulty of assessment tasks matching learner's learning ability; (2) evaluating the mastery of knowledge items and dynamically adjusting the difficulty of assessment tasks according to learner's academic emotion. Then, based on subjective factors (learners' and teachers' academic expectations), the proposed approach predicts future learning performance, i.e., goals to achieve higher learning performance, to motivate learners to have better academic achievements. Then, the proposed approach can predict the proper difficulty and knowledge items of an assessment recommended for a learner. Finally, the proposed recommendation algorithm generates personalized assessment tasks according to the predicted learning performance of a learner. Figure 1 shows the process of the proposed personalized assessment tasks recommendation approach, which contains the following three steps: 1) learning performance evaluation, 2) learning performance prediction, and 3) assessment tasks generation.

1) **Learning performance evaluation**: During the learning process, a learner's learning performance not only depends on his/her learning ability but also on a number of factors, e.g., learners' emotions. Therefore, to accurately evaluate a learner's learning performance, his/her learning ability has to be evaluated first. Then, based on the evaluated learning ability, the difficulty of assessment tasks matching the learning ability can

be obtained. Also, the learner's mastery of knowledge items can be obtained accordingly. Besides, the difficulty of recommended assessment tasks can be dynamically adjusted considering dynamic changes in learners' academic emotions.

2) **Learning performance prediction**: This step predicts learners' future learning performances based on the current learning performance acquired in **Step 1**. It is a fact that teachers' and learners' expectations are effective indicators for predicting future learning performances [17], [19]. Based on the above fact, the difficulty of an assessment task and recommended knowledge items for a learner considering teachers' and learners' expectations academic expectations can be acquired by applying the theory of autonomous agent negotiation.
3) **Assessment tasks generation**: Based on the recommended difficulty of an assessment task and knowledge items to be covered acquired in **Step 2**, the proposed approach generates personalized assessment tasks for each learner by applying Discrete Linear Programming (DLP) [23].

A. LEARNING PERFORMANCE EVALUATION CONSIDERING OBJECTIVE FACTORS

Considering objective factors, i.e., learning ability and academic emotions, this subsection aims to evaluate the difficulty and mastery of knowledge items of assessment tasks matching current learning performance.

1) DIFFICULTY DEFINITION

In the process of evaluating learning ability, question difficulty is usually an essential factor. To accurately recommend personalized assessment tasks with appropriate difficulty, this subsection provides definitions of question difficulty and assessment task difficulty.

The question difficulty can be defined as follows by (1). Based on similarity, knowledge items are divided into different knowledge categories, e.g., two-digit addition belongs to the addition category, and two-digit multiplication belongs to the multiplication category. As shown in (1), a question difficulty is the average of maximum difficulty values in each category.

$$d_q = \frac{\sum_{i=1}^{n_c} max(d_{K_{i,j}})}{n_c} \tag{1}$$

In (1), d_q refers to question difficulty; n_c refers to number of knowledge categories; $d_{K_{i,j}}$ refers to difficulty of knowledge item j in Category i; $max(\cdot)$ refers to a function to calculate the maximum difficulty of knowledge items in each category.

Usually, an assessment task contains a number of questions. Hence, based on the question difficulty d_q acquired from (1), the difficulty of an assessment task can be obtained by (2).

$$d_a = (\sum_{i=1}^{n_q} d_{q,\,i})/n_q \tag{2}$$

In (2), d_a refers to the difficulty of an assessment task; $d_{q,\,i}$ refers to the difficulty of Question i; n_q refers to the number of questions in an assessment task.

2) RECOMMENDING PROPER DIFFICULTY CONSIDERING LEARNING ABILITY

This subsection introduces the process of evaluating learning ability and acquiring difficulty of assessment tasks matching learning ability, which contains two steps: 1) Based on the difficulty and correctness of questions, the learning ability is acquired by item response theory [24]. 2) The difficulty of assessment tasks matching the learning ability can be calculated through the proposed method.

In the process of **learning ability evaluation**, as a basis for evaluating current learning performance, it is necessary to acquire the learning ability of each learner. Learners' responses to questions with different difficulties can be adopted to evaluate learners' abilities. This paper applies the one-parameter logistic model [24] to evaluate learners' ability, as shown in (3).

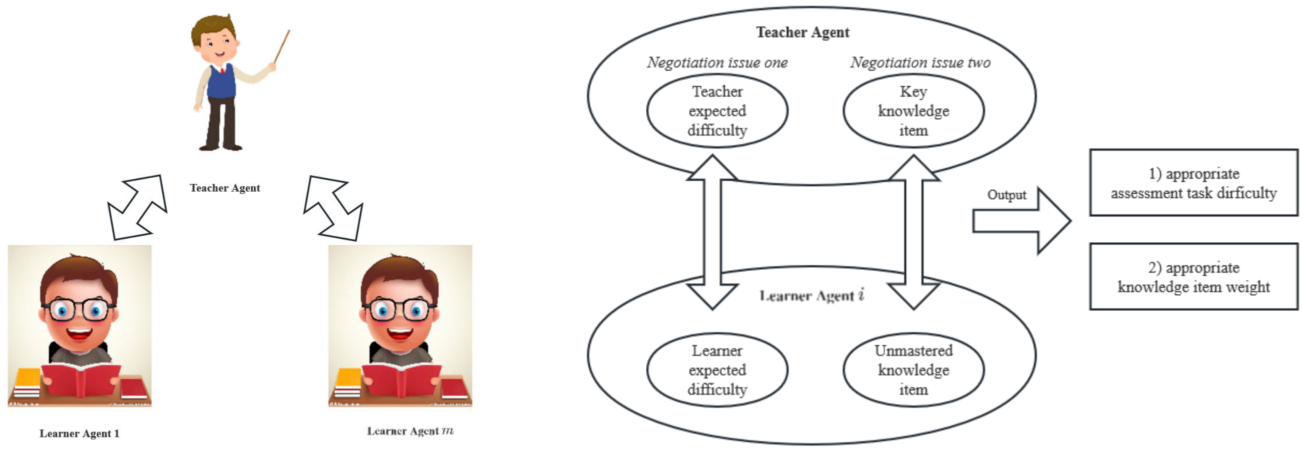
$$\begin{aligned} f_o = \sum_{i=1}^{n_q} u_i \log\left(\frac{e^{(\theta - d_{q,\,i})}}{1+e^{(\theta - d_{q,\,i})}}\right) \\ + (1-u_i)\log\left(1-\frac{e^{(\theta - d_{q,\,i})}}{1+e^{(\theta - d_{q,\,i})}}\right) \end{aligned} \tag{3}$$

In (3), $u_i \in \{0, 1\}$ refers to whether the learner's response to Question i is correct or not; n_q refers to the number of questions in the assessment task; θ indicates the learning ability; $d_{q,\,i}$ refers to the difficulty of Question i. To **acquire the difficulty of assessment tasks matching the learning ability** acquired through (3), this paper proposes Algorithm 1 to show the relationship between the learning ability and the difficulty of assessment tasks.

Algorithm 1 Construction of Mapping Function

Input: $d_{q,\,i}, \theta_i, n_f$
Output: $map(\cdot)$
for *each* $i \in [1, n_f]$ **do**
  $d_i^{cor} = d_{i-1}^{cor} + (min(d_{q,\,i}) - min(d_{q,\,i}))/n_f$;
  $\theta_i^{min} = \theta_{i-1}^{min} + (max(\theta_i) - min(\theta_i))/n_f$;
  $\theta_i^{max} = \theta_{i-1}^{max} + (max(\theta_i) - min(\theta_i))/n_f$;
  $map(\theta_i^{min}, \theta_i^{max}) = d_i^{cor}$;
end

In Algorithm 1, the mapping function ($map(\cdot)$) between the difficulty of assessment tasks ($d_{min}^{l,\,int}$) and learning ability (θ) is constructed. Firstly, the inputs are specified as difficulty of question i ($d_{q,\,i}$), learning ability (θ_i), and the number of different learning ability (n_f). The idea of the algorithm is that



(a) Negotiation between teacher and learner (b) Negotiation issues between a teacher agent and a learner agent

FIGURE 2. **Negotiation framework between a teacher agent and learner agents.**

when the learning ability belongs to the interval [minimum learning ability i (θ_i^{min}), maximum learning ability i (θ_i^{max})], the difficulty of assessment tasks matching learning ability $d_{min}^{l,\,int}$ is equal to the corresponding difficulty i (Line 5).

3) RECOMMENDING PROPER KNOWLEDGE ITEMS AND DIFFICULTY CONSIDERING LEARNING PERFORMANCE

This subsection introduces the process of evaluating learners' learning performance considering academic emotions. In the process of evaluating **knowledge items mastery matching learning performance**, the recommended assessment tasks should contain unmastered knowledge items to facilitate learners' progress. This subsection introduces the evaluation of knowledge items mastery. The error rates of knowledge items are an essential criterion for evaluating the mastery of knowledge items. Equation (4) shows the mastery of knowledge item j.

$$W_{l,j}^{int} = \frac{n_{j,\,wrg}}{n_{j,\,all}} \tag{4}$$

In (4), $W_{l,j}^{int}$ refers to the mastery of knowledge item j matching current learning performance in the assessment task; $n_{j,\,wrg}$ refers to the number of errors for knowledge item j in the assessment task; $n_{j,\,all}$ refers to the total number of the knowledge item j contained in the assessment task.

To recommend the proper **difficulty of an assessment task considering the effect of academic emotion**, an Academic Emotion Influence (AEI) model is proposed in this paper, shown by (5).

$$d_{min}^{l} = (1 + \frac{\xi_1}{1+e^{-\alpha}} + \xi_2) \cdot d_{min}^{l,\,int} \tag{5}$$

According to the influence of academic emotions, the difficulty of assessment tasks matching current learning performance, i.e., d_{min}^{l}, is acquired, as shown in (5), ξ_1 and ξ_2 refers to scaling constants; α shows the academic emotion value; $d_{min}^{l,\,int}$ refers to the difficulty of assessment tasks matching learning ability.

B. LEARNING PERFORMANCE PREDICTION CONSIDERING SUBJECTIVE FACTORS

Considering subjective factors, i.e., learners' and the teachers' academic expectations, this subsection aims to predict future learning performance based on current learning performance acquired from Subsection III-A. However, the teacher's and learner's expectations are usually not aligned, e.g., learners' unmastered knowledge items and key knowledge items emphasized by teachers might not be aligned. As one effective technique for resolving such a conflict between the teacher's expectations and the learner's expectations, the method of autonomous agent negotiation is applied to reconcile teachers' and learners' academic expectations. By applying multi-agent system theory, a teacher and students can be modelled as autonomous agents. Figure 2(a) shows the negotiation containing a teacher agent and m learner agents, where learner agents are mutually independent. This subsection introduces the proposed approach of learner's learning performance prediction considering both learner's and teacher's academic expectations by applying the theory of autonomous-agent-based negotiation.

As shown in Figure 2(b), two issues are negotiated between a teacher agent and a learner agent: 1) recommended difficulty of assessment tasks and 2) recommended weights of knowledge items in the assessment tasks. Firstly, through the autonomous agent negotiation, the learners' and the teachers' academic expectations for difficulty and mastery of knowledge items are modelled, where Table 1 shows symbols and meanings of academic expectations. The maximum or minimum expectations of the agent a are used to represent learners or teachers with different personalities, e.g., the gap between the maximum expectation and the minimum expectation represents different personalities (e.g., aggressive or conservative teacher/learner). Specifically, to promote learner progress, the learner's minimum expected difficulty (d_{min}^{l}) is set as the difficulty matching current learning performance, which can be acquired from Subsection III-A3.

TABLE 1. Symbols and meanings of academic expectations.

Symbol	Meaning
h	teacher agent
l	learner agent
d	difficulty of assessment tasks
w	one value representing all knowledge items
$\mathrm{c}_{\mathrm{b}}^{\mathrm{a}}$	maximum or minimum expectation of agent a, where $\mathrm{a} \in \{\mathrm{l}, \mathrm{h}\}$, $\mathrm{b} \in \{\max, \min\}$, $\mathrm{c} \in \{\mathrm{d}, \mathrm{w}\}$

TABLE 2. Symbols and meanings of negotiation protocol and strategy.

Symbol	Meaning
$\mathrm{A}^{\mathrm{h}}(\cdot)$	function to make negotiation
$\mathrm{c}_{\mathrm{h}\to\mathrm{l}}^{\mathrm{t}}$	agent l receives an offer from h at time t, $\mathrm{c} \in \{\mathrm{w}, \mathrm{d}\}$
β_{a}	concession rate for agent a, which is a factor indicating personalities
$\mathrm{t}_{\max}^{\mathrm{a}}$	deadline for agent $\mathrm{a} \in \{\mathrm{h}, \mathrm{l}\}$, when deadline reaches, negotiation ends
$\mathrm{u}^{\mathrm{a}}(\mathrm{t})$	utility value (i.e., rewards), which agent a have acquired at time t
$\mathrm{W}_{\mathrm{b}}^{\mathrm{a}}$	the set of minimum or maximum expected weights of knowledge items, for agent a, $\mathrm{a} \in \{\mathrm{h}, \mathrm{l}\}$ $\mathrm{b} \in \{\min, \max\}$
ϖ_{i}	weight coefficient of knowledge item i in the negotiation
n_{k}	the number of knowledge items in the negotiation
$\mathrm{W}_{\mathrm{l}}^{\mathrm{int}}$	mastery of knowledge items matching learners' current learning performance
$\mathrm{W}_{\mathrm{t}}^{\mathrm{int}}$	weights of knowledge items matching teachers' expectations
W_{re}	recommended weights of knowledge items
d_{re}	recommended difficulty of assessment tasks
r_{h}	reserved utility for agent h, i.e., minimum expectation of agent h
r_{l}	reserved utility for agent l, i.e., maximum expectation of agent l
$\alpha^{\mathrm{a}}(\mathrm{t})$	concession value at time t for the agent a

Usually, autonomous agent negotiation consists of three basic components: negotiation procedure, negotiation protocol, and negotiation strategy [25]. The negotiation procedure specifies how to address issues. The negotiation protocol shows how to get a consensus, i.e., mutually acceptable results. The negotiation strategy denotes the way of changing tactics over time. For the negotiation procedure, the negotiation of recommended difficulty contains only one dimension, so the *single-issue* negotiation [26] is applied in this paper. Besides, the negotiation of knowledge item weight includes multiple dimensions, i.e., various knowledge items in the assessment task. Hence, the *package deal* negotiation [27] is applied in the proposed approach. The following two subsections introduce negotiation protocol and negotiation strategy for the difficulty of assessment tasks and weights of knowledge items.

1) NEGOTIATION PROTOCOL

In the proposed approach, the difficulty of the assessment task and the weights of knowledge items are the issues covered in the "offer" negotiated between the teacher agent and the learner agent. The negotiation protocol specifies how to exchange offers in the negotiation process. The negotiation protocol is symbolized, as Table 2 shows.

Equation (6) shows a protocol for negotiating difficulty and weights of knowledge items for assessment tasks [26]. The negotiation ends if the negotiation reaches the deadline or $u^a(t) \geq u^a(t')$, $u^a(j)$ refers to utility value, if $u^a(t) \geq u^a(t')$, which means that agent a gains more rewards at t than rewards at t', the negotiation ends. Otherwise, agent a retains the modified expected values.

$$A^h\left(t', c_{h\to l}^t[j]\right) = \begin{cases} \text{Quit} & \text{if } t_{max}^a \\ \text{Accept} & \text{if } u^a(t) \geq u^a(t') \\ c_{h\to l}^{t'}[j] & \text{otherwise} \end{cases} \tag{6}$$

In (6), $A^h(\cdot)$ refers to the function to make negotiation; t_{max}^a refers to the deadline for agent a; $c_{h\to l}^t$ refers to agent l receives an offer from agent h at time t; $u^a(t)$ refers to utility value, which agent a have acquired at time t.

The calculations for $u^a(t)$ about the difficulty of assessment tasks and weights of assessment tasks are shown in (7), at the bottom of the next page. In (7), $c \in \{w, d\}$ represents difficulty of assessment tasks or one value representing all knowledge items, respectively; $u^a(t)$ refers to the utility value for agent a has acquired at time t; $c_{\max}^a$ refers to the maximum expectation of agent a; $d_{\min}^a$ refers to the minimum expectation of agent a; r_a refers to the reserved utility for agent a; β_a refers to the concession rate for agent a; t_{max}^a refers to the deadline for agent a.

2) NEGOTIATION STRATEGY

This subsection introduces the negotiation strategy applied to generate recommended difficulty and knowledge items weights in recommended assessment tasks. Equation (8) [26] shows the concession value, which represents changes in the concession value.

$$\alpha^a(t) = r_a + (1 - r_a)\left(\frac{\min\left(t, t_{max}^a\right)}{t_{max}^a}\right)^{\frac{1}{\beta_a}} \tag{8}$$

In (8) $\alpha^a(t)$ refers to concession value at time t for the agent a; r_a refers to the reserved utility for the agent a; β_a refers to the concession rate for the agent a, and the concession rate indicates a learner or a teacher with different personalities in the negotiating process, e.g., the large value of concession rates means aggressive people; t_{max}^a refers to the deadline for agent a. Algorithm 2 shows the negotiation strategy for generating recommended difficulty of assessment tasks and weights of knowledge items.

In Algorithm 2, recommended difficulty of assessment tasks (d_{re}) and recommended weights of knowledge items (w_{re}) are acquired. Firstly, the inputs are specified as reserved utility (r_l and r_h), concession rate (β_l and β_h), deadline (t_{max}^l and t_{max}^h), the expectation for the difficulty of assessment tasks (d^l_{min}, d^l_{max}, d^h_{min}, and d^h_{max}), the learner's and the teacher's expectation for weights of knowledge items (W^{int}_l and W^{int}_t), number of knowledge items in the negotiation (n_k), and weight coefficient of knowledge item i (denoted as ϖ_i). Next, in each loop, the smaller value in W^{int}_l and W^{int}_t are put in the W^l_{min}, the bigger value in W^{int}_l and W^{int}_t are put in the W^h_{max} (Lines 1-4). Then, the value representing all knowledge items of w^l_{min} and w^h_{max} are calculated (Lines 5-8). For assessment tasks difficulty negotiation, negotiations continue when t is smaller than the deadline of agent h or agent l and $u(t) \leq u(t')$ (Line 9). As a result, the recommended difficulty of assessment tasks can be required (Lines 9-15). Similarly, the recommended weights of knowledge items for all knowledge items are calculated (Lines 16-22). Then, after negotiations, it updates weights of knowledge items based on the $W^{l,i}_{min}$, and stores in the set W (Lines 23-25). Finally, the updated weights of knowledge items are normalized to acquire the set of recommended weights of knowledge items W_{re} (Lines 26-28).

C. AGENT-BASED ASSESSMENT TASKS GENERATION APPLYING DISCRETE LINEAR PROGRAMMING

In traditional recommendation algorithms, such as collaborative filtering algorithms, the cold start problem is usually encountered, usually due to the lack of historical data of items as a reference, resulting in poor accuracy of recommendations. Therefore, this research method attempts to design a recommendation algorithm that does not require historical data, i.e., relying solely on the learner's learning status to be able to accurately find suitable questions from the database. This subsection shows the process of assessment tasks generation. Firstly, the recommendation algorithm is introduced based on recommended weights of knowledge items (W_{re}), and difficulty of assessment tasks (d_{re}) are acquired through Algorithm 2. In this paper, recommendation approaches for personalized assessment tasks can be modelled as the process of solving linear programming equations for optimal solutions. Firstly, the number of recommended knowledge items contained in the recommended assessment task is calculated in (9).

$$num_i = n^r_q W_{re,i} \tag{9}$$

In (9), num_i refers to the number of recommended knowledge item i contained in a generated assessment task; n^r_q refers to the number of questions in a recommended assessment task; $W_{re,i}$ refers to the recommended weight of knowledge item i.

To generate a personalized assessment task containing the recommended number of knowledge items with recommended difficulty, the process is transformed into a DLP problem as shown in (10). The number of knowledge items for recommendation obtained from (9) is set as to *constraints*. The difficulty of recommended assessment tasks closest to the recommended difficulty of assessment tasks is regarded as the *objective function*.

$$\begin{aligned} &\min |d_{re} - d_a| \\ &\text{s.t.} \begin{cases} \lfloor num_i \rfloor \leq \sum_{j=1}^{n_q} x_{i,j} \leq \lfloor num_i \rfloor + 1 & i \in [1, n^r_k] \\ k_i \in K_{re} \end{cases} \end{aligned} \tag{10}$$

In (10), d_{re} refers to the recommended difficulty of the assessment task; d_a refers to the recommended difficulty of assessment tasks; num_i refers to the recommended number of knowledge items i appearing in the recommended assessment task; n^r_k refers to the number of recommended knowledge items; n_q refers to the number of questions in the recommended assessment task; $x_{i,j}$ refers to the number of knowledge item i in the question j; K_{re} refers to the recommended knowledge items.

Algorithm 3 generates the personalized assessment tasks for learners (a_{per}) considering objective and subjective factors. Firstly, the inputs are specified as the number of questions in the assessment task (n_q), the number of knowledge items in the assessment task (n_k), correctness for question i (u_i), the difficulty of question i ($d_{q,i}$), scaling constants in AEI (ξ_1 and ξ_2), academic emotion value (α), and question i in the dataset (q_i). Then, the learner's expected weight of each knowledge item (W^{int}_l) is evaluated (Lines 1-9). Next, based on the difficulty and correctness of the completed assessment tasks, the learner's learning ability θ can be acquired through the least-square method [28] (Lines 10-13). According to Algorithm 1 and learning ability θ, the assessment tasks difficulty matching learning ability $d^{l,int}_{min}$ can be acquired (Line 14). Then, based on the learner's academic emotion, the learner's minimum expected difficulty d^l_{min} can be calculated (Line 15). Then, Algorithm 2 calculates recommended difficulty of assessment tasks d_{re} and a set of recommended weights of knowledge items W_{re} (Line 16). Then, the number of each recommended knowledge item appearing in the generated assessment task num_i is calculated (Line 18). Based on the recommended difficulty of assessment tasks and sets of knowledge items, the recommendation algorithm applying DLP is applied to generate recommended personalized

$$u^a(t) = \begin{cases} \left(c^a_{\min} + \left((1-r_a)\left(\dfrac{\min(t, t^a_{max})}{t^a_{max}}\right)^{\frac{1}{\beta_a}} + r_a\right)(c^a_{\max} - c^a_{\min})\right) - c^h_{\min} & \text{for agent } h \\ c^a_{\max} - \left(c^a_{\min} + \left(1 - \left(r_a + (1-r_a)\left(\dfrac{\min(t, t^a_{max})}{t^a_{max}}\right)^{\frac{1}{\beta_a}}\right)\right)(c^a_{\max} - c^a_{\min})\right) & \text{for agent } l \end{cases} \tag{7}$$

Algorithm 2 Negotiation Strategy for Generating Recommended Difficulty Value and Knowledge Items Weights

Input: $r_l, r_h, \beta_l, \beta_h, t^l_{max}, t^h_{max}, d^l_{min}, d^l_{max}, d^h_{min}, d^h_{max}, W^{int}_l, W^{int}_t, n_k, \varpi_i$
Output: d_{re}, W_{re}

for *knowledge item* $i \in [1, n_k]$ **do**
  $W^{l,i}_{min} = min\{W^{int}_{l,i}, W^{int}_{t,i}\}$;
  $W^{h,i}_{max} = max\{W^{int}_{l,i}, W^{int}_{t,i}\}$;
end
for *knowledge item* $i \in [1, n_k]$ **do**
  $w^l_{min} += \varpi_i \, W^{l,i}_{min}$;
  $w^h_{max} += \varpi_i \, W^{h,i}_{max}$;
end
while $t \le t^a_{max}$ *and* $u(t) \le u(t')$ *for difficulty (refers to (6) and (7))* **do**
  if *agent l launches the negotiation* **then**
    $d_{re} = d^l_{\min} + \alpha^l(t)\left(d^l_{\max} - d^l_{\min}\right)$;
  else
    $d_{re} = d^h_{\min} + \left(1 - \alpha^h(t)\right)\left(d^h_{\max} - d^h_{\min}\right)$;
  end
end
while $t \le t^a_{max}$ *and* $u(t) \le u(t')$ *for weights of knowledge items (refers to (6) and (7))* **do**
  if *agent l launches the negotiation* **then**
    $w_{re} = w^l_{\min} + \alpha^l(t)\left(w^l_{\max} - w^l_{\min}\right)$;
  else
    $w_{re} = w^h_{\min} + \left(1 - \alpha^h(t)\right)\left(w^h_{\max} - w^h_{\min}\right)$;
  end
end
for *knowledge item* $i \in [1, n_k]$ **do**
  $W_i = (1 + (w_{re} - w^{h,i}_{max})/w^{h,i}_{max})\, w^{h,i}_{max}$;
end
for *knowledge item* $i \in [1, n']$ **do**
  recommended weights of knowledge items, $W_{re,i} = W_i / \sum_{i=1}^{n'} W_i$;
end

Algorithm 3 Negotiation Strategy for Generating Recommended Difficulty Value and Knowledge Items Weights

Input: $n_q, n_k, u_i, d_{q,i}, \xi_1, \xi_2, \alpha, q_i$
Output: a_{per}

1 **for** *knowledge item* $j \in [1, n_q]$ **do**
2   **for** *question* $i \in [1, n_q]$ **do**
3   the total number of knowledge item j, $n_{j,all} = n_{j,all} + 1$;
4   **if** $u_i == 0$ **then**
5   the number of errors for knowledge item j, $n_{j,wrg} = n_{j,wrg} + 1$;
6   **end**
7   **end**
8   calculate weights of knowledge items $W^{int}_l(j)$ (refers to (4)) ;
9 **end**
10 **for** *question* $i \in [1, n_q]$ **do**
11   construct one-parameter logistic model (refers to (3)) ;
12 **end**
13 apply least-square method to calculate θ ;
14 apply $map(\cdot)$ acquired from **Algorithm 1** to obtain $d^{l,int}_{min}$;
15 calculate d^l_{min} (refers to (5)) ;
16 d_{re} and W_{re} are acquired from **Algorithm 2** ;
17 **for** *recommended knowledge item* $i \in [1, n^r_k]$ **do**
18   $num_i = n_q \, W_{re,i}$, (refers to (9)) ;
19 **end**
20 **for** *question* j *in*$[1, n^r_q]$ **do**
21   **for** *knowledge item* $i \in [1, n^r_k]$ **do**
22   **if** *knowledge item i exists in question j* **then**
23   the number of knowledge item i in the question j, $x_{i,j} = x_{i,j} + 1$
24   **end**
25   **end**
26   $\lfloor num_i \rfloor \le x_{i,j} \le \lfloor num_i \rfloor + 1$;
27   $d^{all}_q = d^{all}_q + d_{q,j}$;
28 **end**
29 set an objective function $\min |d_{re} - d_a|$;
30 generate personalized assessment tasks (refers to (10));

assessment tasks (Lines 20-30), where constraints are set in Lines 20-28, and the objective function is set in Line 29.

Based on the learner's current and future learning performance, the recommendation algorithm customizes the personal assessment tasks, which controls difficulty and contains knowledge items to facilitate learners to achieve higher academic achievements. The current learning performance is dynamically adjusted according to learning ability and academic emotion. Also, agent-based negotiations are introduced to a good balance between the learner's individualization and the teacher's teaching goal (i.e., the learners' academic expectation and the teachers' expectation in this paper). Finally, by applying DLP, the proposed recommendation approach generates personalized assessment tasks, where the cold start problem can also be solved when data is sparse.

IV. EXPERIMENT

A. EXPERIMENTAL SETTING

To evaluate the effectiveness of the proposed approach, this paper conducts simulations for several recommendation scenarios involving one teacher and various learners in the environment. This subsection provides an overview of the experimental setting from four aspects: 1) conducted experiments, 2) dataset, 3) measurement metric, and 4) parameter settings.

1) CONDUCTED EXPERIMENTS

Three following experiments are conducted to evaluate the performances of the proposed approach. Considering various factors, we simulate different types of learners, with 100 learners in each type.

- **Experiment 1**: To show the impact of academic emotions on learning performance, this experiment measures the impact of the recommended difficulty of assessment tasks on different types of academic emotions over time.
- **Experiment 2**: To demonstrate the impact of academic expectations, this experiment measures the learning performances of learners with or without considering academic expectations. Furthermore, **Experiment 2** considers the different personalities of both learners and teachers to show the further impact of academic expectations on learning performance.
- **Experiment 3**: To evaluate the effectiveness of the proposed recommendation algorithm, **Experiment 3** compares with traditional collaborative filtering and content-based approaches by applying different methods of similarity calculations, i.e., Euclidean distance [29], Manhattan distance [30], and Cosine similarity [31] when the historical dataset contains a small size of samples.

2) DATASET

For this study, we use a dataset consisting of mathematical questions for third-grade primary school students. The dataset includes two types of questions: fill-in-the-blank and application questions, which can better test learners' learning performance. All the questions in the dataset are crawled from a widely-used app called Ape Search [32]. After de-noising the data, e.g., by removing duplicate questions, 1587 questions in the experiments are selected, containing 804 fill-in-the-blank questions and 783 application questions. According to knowledge items defined in this study, experiments in this paper adopt 62 knowledge items [33] in total, i.e., 49 traditional knowledge items, 11 mathematical rules (e.g., commutative law), and two mathematical reasoning (i.e., inductive reasoning and deductive reasoning). According to the similarity of knowledge items, knowledge items are classified into seven categories: time, statistical tables, addition and subtraction, position and direction, multiplication and division, decimals, and measurement.

3) MEASUREMENT METRIC

This subsection introduces the measurement metrics used in the experiments to evaluate the performance of the proposed approach. These metrics include accuracy and knowledge item coverage. A higher accuracy indicates a smaller difference between the actual value and the recommended value obtained by the proposed approach, while a higher coverage indicates a greater diversity of recommended knowledge items.

Difficulty accuracy measures the average value of precision between the recommended difficulty of assessment tasks and generated difficulty of assessment tasks.

$$acc_d = 1 - (\sum_{i=1}^{n_l} \frac{|d_{r,i} - d_{a,i}|}{d_{r,i}})/n_l \tag{11}$$

In (11), acc_d refers to the difficulty accuracy; n_l refers to the number of learners; $d_{r,i}$ refers to the recommended difficulty of assessment tasks for learner i; $d_{a,i}$ refers to the difficulty of the generated assessment tasks for learner i; n_l refers to the number of the learners.

Knowledge items accuracy measures the precision between recommended knowledge items and appeared knowledge items in the generated assessment tasks. Equation (12) calculates the average value of all learners' knowledge items accuracy.

$$acc_k = 1 - (\sum_{i=1}^{n_l} \frac{|n^k_{r,i} - n^k_{a,i}|}{n^k_{r,i}})/n_l \tag{12}$$

In (12), acc_k refers to the knowledge items accuracy; $n^k_{r,i}$ refers to the number of total recommended knowledge items for learner i; $n^k_{a,i}$ refers to the number of recommended knowledge items in the generated assessment task; n_l refers to the number of the learners.

Knowledge items coverage means the percentage of recommended knowledge items to all knowledge items. Equation (13) defines the knowledge items coverage as the average of all learners' coverage.

$$cov_k = (\sum_{i=1}^{n_l} \frac{n^k_{r,i}}{n^k_t})/n_l \tag{13}$$

In (13), cov_k refers to the knowledge items coverage; n^k_t refers to the number of total knowledge items; $n^k_{r,i}$ refers to the recommended knowledge items for learner i; n_l refers to the number of learners.

4) PARAMETER SETTINGS

Firstly, this subsection presents the parameter settings for Experiment 1 (academic emotion). In Frenzel A C's study [34], academic emotions are classified into the following five categories: enjoyment, pride, anxiety, anger, and shame. Enjoyment and pride are considered positive academic emotions, while anxiety, anger, and shame are negative academic emotions. Based on Frenzel A C's study, different values are assigned to academic emotions (i.e., enjoyment, pride, anxiety, anger, shame) in this study, which are 2, 1, -1, -2, and -3, respectively, where positive values indicate positive academic emotions and negative values represent negative academic emotions. Finally, the least-squares method [35] is applied to calculate the parameters of (5) based on the influence of academic emotion on learning performance. Table 3 shows parameter settings for the AEI model.

To comprehensively test the impact of academic emotions on learning performance, five types of learners' academic emotions are taken, as shown in Table 4.

TABLE 3. Parameter settings for AEI model.

Parameter	Setting
academic emotion value (α)	$[-3, 3]$
scaling constant one (ξ_1)	1.505
scaling constant two (ξ_2)	-0.774

TABLE 4. Types and settings for academic emotion.

Types	Settings for academic emotions
Type 1	positive all the time
Type 2	negative all the time
Type 3	regularly fluctuating
Type 4	from positive to negative
Type 5	from negative to positive

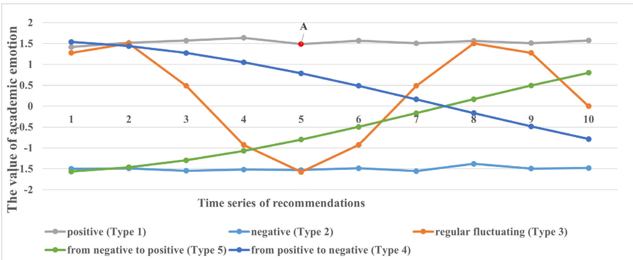


FIGURE 3. Parameter settings of academic emotions for five types of learners.

There are five types of learners considered in this study based on their academic emotions. Type 1 learners maintain a high level of enthusiasm for studying, which leads to sustained positive academic emotions. Type 2 learners have little interest in studying, resulting in sustained negative academic emotions. Type 3 learners can control their academic emotions in a range over a period of time. Type 4 learners are losing interest in learning, leading to a change in academic emotions from positive to negative. Type 5 learners are gaining interest in studying, resulting in a change in academic emotions from negative to positive. These five types of learners cover most learners with various types of academic emotions in real life.

Figure 3 presents the detailed average values of academic emotions for each type of learner. The vertical axis of the graph represents the average values of academic emotions, and the horizontal axis represents the time series of recommendations. For example, Point A in the figure denotes that in the fifth assessment tasks recommendation, the mean value of academic emotions of all Type 1 learners is 1.5. As shown in Figure 3, the values of academic emotions in the experiments align with five types of academic emotions.

Next, we present the parameter settings for Experiment 2 (academic expectation). In this study, we utilize autonomous-agent negotiation theory to resolve the conflict between a learner's academic expectations and a teacher's academic expectations. The specific parameter values for academic

TABLE 5. Parameter settings for negotiation of difficulty and weights of knowledge items.

Parameter	Setting
agent l with maximum expectation ($\mathrm{c}^{\mathrm{l}}_{\mathrm{max}}$)	$\alpha_1(\mathrm{c}^{\mathrm{h}}_{\mathrm{max}} + \mathrm{c}^{\mathrm{l}}_{\mathrm{min}}) + \alpha_2(\mathrm{c}^{\mathrm{h}}_{\mathrm{max}} - \mathrm{c}^{\mathrm{l}}_{\mathrm{min}})$, $\alpha_1, \alpha_2 \in (0, 1)$
agent h with minimum expectation ($\mathrm{c}^{\mathrm{h}}_{\mathrm{min}}$)	$\alpha_1(\mathrm{c}^{\mathrm{h}}_{\mathrm{max}} + \mathrm{c}^{\mathrm{l}}_{\mathrm{min}}) - \alpha_2(\mathrm{c}^{\mathrm{h}}_{\mathrm{max}} - \mathrm{c}^{\mathrm{l}}_{\mathrm{min}})$, $\alpha_1, \alpha_2 \in (0, 1)$
reserved utility for agent a ($\mathrm{r_a}$)	random in $[0.3, 0.4]$
concession rate for agent a (β_a)	random in $(0, 20)$

TABLE 6. Types and settings for academic expectations (flexible or stringent).

Types	Settings for academic expectations
Type i	flexible learners and flexible teachers
Type ii	stringent learners and stringent teachers
Type iii	stringent learners and flexible teachers
Type iv	flexible learners and stringent teachers

expectations derived from applying autonomous-agent negotiation are listed in Table 5. The scaling factors α_1 and α_2 are included in the table to indicate different levels of academic expectations.

To better test the impact of academic expectations on learning performance, we consider different types of personalities (i.e., flexible or stringent, and aggressive or conservative), and the following types of participants are taken in the experiment. Firstly, Table 6 outlines the different personality types (flexible or stringent) involved in the experimentation process of academic expectations. The difference between flexible and stringent people can be reflected by the difference between the values of maximum academic expectation and minimum academic expectation, where a big difference indicates flexible people and a small difference represents stringent people.

Then, Table 8 shows the different personality types (aggressive or conservative) involved in the experimentation process of academic expectations. The difference between aggressive and conservative people can be reflected by the different concession rates of their academic expectations, where a large concession rate indicates aggressive people and a small concession rate represents conservative people. In the experiment, to clearly distinguish people's personalities, the concession rate $\beta_a \in (10, 20)$ is applied to represent aggressive people, while the concession rate $\beta_a \in (0, 1)$ is utilized to represent conservative people.

B. EXPERIMENTAL RESULT

Firstly, **results of Experiment 1 (academic emotion)** are shown. To show the impact of academic emotions on learning performance, results of **Experiment 1** are shown in Figure 4, where the vertical axis represents the average recommended

TABLE 7. Results of the recommending process with and without consideration of academic expectations.

Factors	Difficulty		Knowledge Items		Correctness	
	Average value	Accuracy	Coverage	Accuracy	Baseline	Average value
with academic expectations	0.670	95.3%	54.8%	94.7%	61.1%	80.1%
without academic expectations	0.483	92.7%	41.4%	98.8%		91.4%

TABLE 8. Types and settings for academic expectations (aggressive or conservative).

Types	Settings for academic expectations
Type v	conservative learners and conservative teachers
Type vi	aggressive learners and conservative teachers
Type vii	conservative learners and aggressive teachers
Type viii	aggressive learners and conservative learners

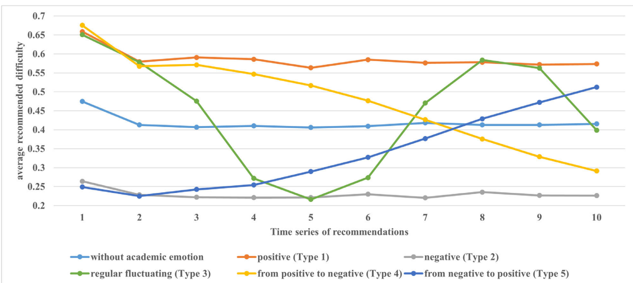


FIGURE 4. Changes in recommended difficulty over time with academic emotions.

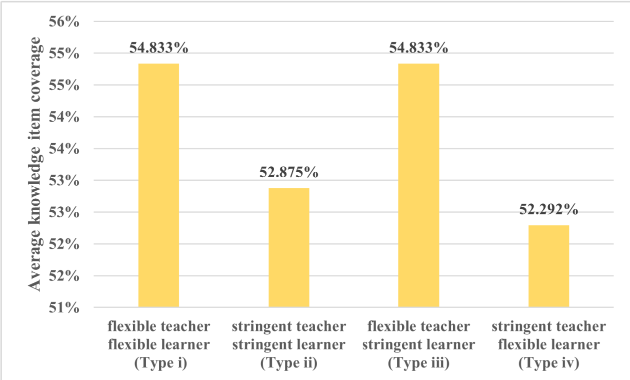
difficulty of assessment tasks and the vertical axis represents the time series of recommendations.

In Figure 4, the light blue line stays in the middle representing learners without considering academic emotions, and it is utilized as the benchmark for comparisons. Figure 4 shows that the recommended difficulty by the proposed approach for Type 1 learners is higher than the benchmark due to learners with positive academic emotions, while for Type 2 learners, the recommended difficulty is lower due to their negative academic emotions. The recommended difficulty for Type 3 learners fluctuates around the light blue line as their academic emotions fluctuate, and the recommended difficulty for Type 4 learners gradually decreases and ultimately is below the benchmark because the learner's academic emotion is positive at the beginning but then changes to negative. Conversely, the recommended difficulty for Type 5 learners gradually increases and is ultimately higher than the benchmark as the academic emotions change from negative to positive. The experimental results show the proposed assessment tasks recommendation approach effectively reflects the impact of learners' academic emotions on their learning performance.

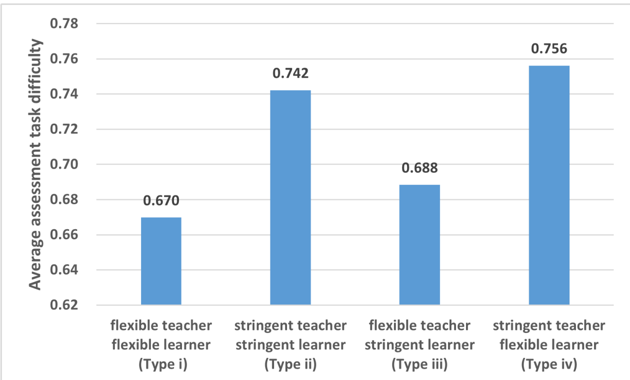
Then, **results of Experiment 2 (academic expectation)** are displayed. To demonstrate the impact of academic expectations on the learning expectation, results of **Experiment 2** are shown in Table 7 regarding difficulty, knowledge items, and correctness of the assessment task.

In Table 7, although the recommendation without academic expectation generates a bit higher knowledge items accuracy than the recommendation with academic expectations, the values by applying the proposed assessment tasks recommendation approach considering academic expectations generate better outcomes regarding difficulty and knowledge items in the assessment tasks recommendation. It can be seen that all values are effectively improved except for the average value of correctness. For correctness, the recommendation with academic expectation has a closer probability of acquiring correct questions to the baseline (80.1% is closer to 61.1% than 91.4%). The closer probability indicates the predicted number of correct results in the recommended assessment tasks is closer to the expected value, which means the recommendation considering academic expectations can help learners achieve higher academic achievements, i.e., if recommending an assessment task without considering academic expectations, learners cannot effectively improve their learning performance through a high probability of getting correct results. In conclusion, the proposed assessment tasks recommendation approach effectively reflects the impact of academic expectations on learning performance and can improve learners' learning performance regarding various academic expectations of teachers and learners.

To further demonstrate the impact of varying levels of academic expectations on learning performance, different types of teachers and learners are adopted in this experiment, denoted as Types i, ii, iii, iv. The results of Experiment 2 are presented in Figure 5. Figure 5(a) compares the coverage of knowledge items among individuals with different personalities, i.e., flexible or stringent. The vertical axis of the graph indicates the value of knowledge items coverage, while the horizontal axis represents the four types of negotiations with different personalities. Furthermore, Figure 5(b) illustrates the comparison of recommended difficulty among individuals with different personalities, i.e., flexible or stringent. The vertical axis of the graph represents the value of recommended difficulty, and the horizontal axis represents the four types of personalities.

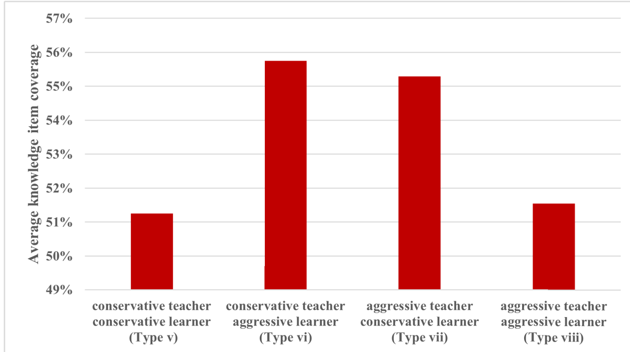


(a) Comparison of knowledge items coverage

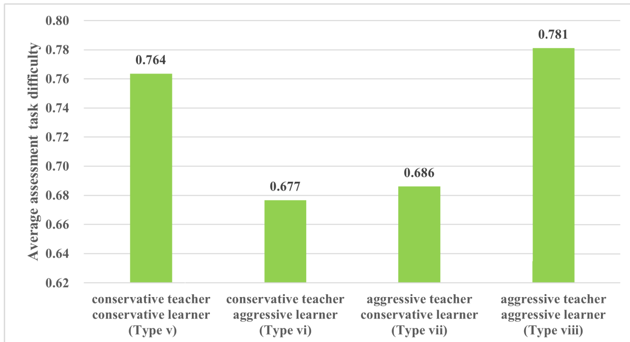


(b) Comparison of recommended difficulty

FIGURE 5. Comparison of academic performance with different personalities (flexible or rigorous).



(a) Comparison of knowledge items coverage



(b) Comparison of recommended difficulty

FIGURE 6. Comparison of academic performance with different personalities (aggressive or conservative).

In Figure 5, some interesting results can be found. For the same personality of teachers and different personalities of learners (i.e., Type i vs. Type iii, and Type ii vs. Type iv), there are not many differences between values of recommended difficulty and knowledge items coverage. However, for the same personality of learners and different personalities of teachers (i.e., Type i vs. Type iv, and Type ii vs. Type iii), there are great differences between values of recommended difficulty and knowledge items coverage. We can conclude that, for participants with flexible and stringent personalities, the teacher's personality might have a higher impact on the recommended difficulty and knowledge items coverage than the learner's personality in the assessment tasks recommendation. Moreover, stringent teachers prefer higher difficulty, while flexible teachers prefer higher coverage of knowledge items in the assessment tasks recommendation (i.e., Type ii vs. Type iii, and Type i vs. Type iv).

To further examine the impact of different concession rates of academic expectation among teachers and learners on learning performance, an experiment is conducted with different types of teachers and learners (Types v, vi, vii, viii). The experimental results are presented in Figure 6. Specifically, Figure 6(a) compares the coverage of knowledge items among individuals with conservative and aggressive personalities, with the vertical axis representing the value of knowledge items coverage and the horizontal axis indicating the four types of negotiations with different personalities. Additionally, Figure 6(b) illustrates the comparison of recommended difficulty among individuals with different personalities, with the vertical axis representing the value of recommended difficulty and the horizontal axis indicating the four types of personalities.

Figure 6 shows that the teachers and the learners having similar personalities (i.e., both are conservative and both are aggressive in Type v and Type viii) prefer higher difficulty in assessment tasks. However, teachers and learners who have different personalities (i.e., one is conservative and the other is aggressive in Type vi and Type vii) prefer higher coverage of knowledge items. Furthermore, for teachers and learners who have the same personalities (i.e., Type v and Type viii), aggressive people prefer higher difficulty than conservative people. In general, learners and teachers with similar personalities believe the difficulty is more important than the knowledge items coverage, while learners and teachers with different personalities prefer knowledge items coverage as more important than difficulty in the assessment tasks recommendation.

Finally, **results of Experiment 3 (recommendation algorithm)** are displayed. To show the effectiveness of the proposed assessment tasks recommendation approach, we carry out a comparison between some commonly-used recommendation algorithms when the historical dataset contains

TABLE 9. Comparison of the proposed recommendation algorithm with collaborative filtering and content-based approaches.

Recommendation algorithm	Similarity calculation	Difficulty accuracy	Knowledge items accuracy	Knowledge items coverage
content-based approaches	Eucledian Distance	88.83%	73.07%	26.29%
	Manhattan Distance	94.26%	72.80%	28.13%
	Cosine Similarity	36.61%	76.01%	20.06%
collaborative filtering	Eucledian Distance	53.43%	44.94%	16.63%
	Manhattan Distance	57.01%	81.68%	35.42%
	Cosine Similarity	58.38%	84.80%	38.13%
proposed recommendation algorithm	/	92.40%	95.05%	53.42%

only 200 records. Table 9 shows results of **Experiment 3**, which measures the performance of three recommendation algorithms regarding difficulty accuracy, knowledge items accuracy, and knowledge items coverage.

In Table 9, compared with content-based and collaborative filtering algorithms, the proposed assessment tasks recommendation approach has the highest difficulty accuracy, knowledge items coverage, and knowledge items accuracy. This indicates that the proposed approach can accurately generate assessment tasks that match the learner's learning performance while considering various academic emotions of learners and academic expectations of both teachers and learners. Table 9 shows that the content-based and the collaborative filtering recommendation algorithms do not perform well when the historical dataset contains only a small size of samples, while the proposed recommendation approach can well handle the cold-start problem when data is sparse. Overall, the proposed assessment tasks recommendation approach can effectively recommend assessment tasks according to the learner's academic emotions and the teacher's and learners' academic expectations regarding difficulty accuracy, knowledge items accuracy, and knowledge items coverage.

In conclusion, from the above experimental results, it can be seen that the proposed assessment tasks recommendation approach can 1) accurately and effectively recommend assessment tasks for learners with different types of personalities regarding academic emotions and academic expectations and 2) generate a better recommendation outcome regarding difficulty accuracy, knowledge items accuracy, and knowledge items coverage compared to the traditional content-based and collaborative filtering recommendation algorithms. Moreover, the experimental results also reveal some other interesting points:

1) For participants with flexible or stringent personalities, the teacher's personality is the leading factor in the assessment tasks recommendation, and it has a higher impact on the recommended difficulty and knowledge items coverage.
2) For participants with aggressive or conservative personalities, teachers and learners with similar personalities believe the difficulty is more important than the knowledge items coverage, while learners and teachers with different personalities prefer knowledge items coverage as more important than difficulty in the assessment tasks recommendation.

V. CONCLUSION

Personalized assessment tasks recommendation is a hot research problem in education. This paper proposes an agent-based assessment tasks recommendation approach to recommend personalized assessment tasks considering objective and subjective factors. The process of recommendation involves the following steps, (1) dynamic evaluation of learning performance considering learning ability and academic emotion; (2) real-time prediction of learning performance considering the learners' and the teacher's academic expectations; (3) accurate recommendation of personalized assessment tasks with reasonable difficulty and knowledge items. This study also tests learners with various learning abilities, academic emotions, and expectations in experiments. The experimental results show that the proposed assessment tasks recommendation approaches are feasible and effective in recommending assessment tasks matching learners' learning performance considering learners' academic emotions and teachers' and learners' academic expectations. In future research, deeper investigations will be conducted on the applications of multi-agent technologies for the rational allocation of educational resources. For example, the focus will be on optimizing the allocation of teachers' time to enhance their influence on the academic performance of the class through personalized tutoring and support.

DATA AND CODE AVAILABILITY

The initial data sets are gained from a widely used and open-sourced app called Ape Search (https://www.yuantiku.com). The processed data sets and codes (in Matlab) are publicly available as a GitHub repository (https://github.com/Mercccy/agent-based.git).

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