An Intelligent Tutoring System Enhancing Transdisciplinary Problem-finding in Design-led Integrated STEM Education

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Abstract
Globally, Industry 4.0 technologies' rapid development advances the rising role of design-led integrated STEM education in schools. However, the absence of problem-finding abilities among students may make it difficult to carry out the educational program. Adaptive learning with artificial intelligence (AI) can be used to construct and implement a learner-centred intelligent tutoring system, which will enable students to adapt and engage in relevant learning tasks by improving their transdisciplinary problem-finding skills and stocking authentic contextual information designs. In order to solve the research problem, this study explores three significant areas of information: 1) automatic construction of knowledge structures; 2) individual ability values and group classification; 3) adaptive recommendation of review content and assessment tasks. As a result, this study promotes the development of an intelligent tutoring technology framework containing data, algorithms, and services for integrated STEM, thereby enhancing a social atmosphere that values science and encourages innovation.

Keywords: *Integrated STEM education; Design-based pedagogy, Artificial intelligence; Adaptive tutoring, Personalised resource recommendation*

1 INTRODUCTION

The rapid advancement of transdisciplinary Industry 4.0 technology highlights the increasing importance of the role of integrated STEM education in schools. It has been known that the training mode and teaching content of traditional sub-discipline education would make it difficult for students to master and apply cutting-edge scientific and technological knowledge, resulting in their lack of competitiveness in the labour market [3]. This research aims to build an intelligent learning guidance system that helps cultivate learners with problem-finding ability in the transdisciplinary era, thus exploring feasible solutions for the integrated STEM education model driven by artificial intelligence (AI).

Zhou et al. (2020) have proved that Design-based Pedagogy (DBP) can be applied to transdisciplinary curriculum development and relevant project implementation. [13] Only when 'design' is taken as an essential part of the pedagogical framework can the integrated STEM education programs simultaneously realise cross-disciplinary integration, real-world scenario, and problem-solving. Design can generate a shared language for creativity and innovation [8], thus driving transdisciplinary teaching teams to guide students in solving real-world problems [7]. Moreover, design can also place problem-solving processes in real contexts, as designing problems are often individualised [6], which is up to designers themselves [4]. DBP, an educational environment based on teaching scaffolding, can guide students to solve problems through designing practice. It

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also provides a methodological foundation for integrated STEM curriculum development and relevant project implementation [10]. The Solution-based Design Process (SBDP) (see Figure 1) is one of the few frameworks that can generate knowledge based on a transdisciplinary syllabus to solve practical issues [14].

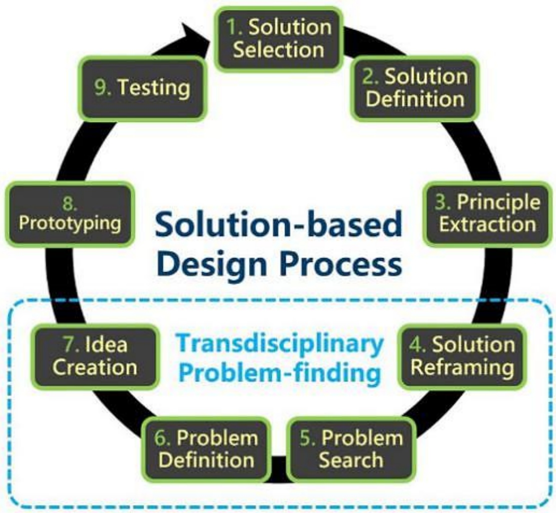

Figure 1: Solution-based design process [14]

The problems that have to be solved in innovation are often vague and complicated, so how to define them will affect the subsequent solutions and processes. Identifying and defining problems is indispensable, which is, nonetheless, often overlooked in China's STEM education. There is a significant positive correlation between problem-finding ability and creativity, which means that students will exercise and improve their creativity during the cultivation of problem-finding ability [1]. Identifying and exploring problems is, therefore, conducive to developing students' design thinking, a cognitive model that is important in the real world [2]. Innovation occurs not only in problem-solving, but also in problem finding, so identifying and defining problems tends to generate enormous innovative value in both engineering and business [9]. In this study, transdisciplinary problem finding corresponds to steps 4 to 7 in the SBDP, namely solution reconstruction, problem search, problem definition, and conceptual creativity. SBDP, a pedagogical framework for integrated STEM, makes problem finding ability concretely characterised as procedural knowledge with divergent thinking, rather than declarative knowledge.

Educational AI, an emerging research field formed by the combination of learning science and artificial intelligence [5] [11], provides a feasible intelligent guidance system for cultivating learners with the transdisciplinary problem-finding ability, which also has a very positive meaning for integrated STEM education. 'Learning models' hereby aim to use artificial intelligence technology to achieve personalised learning based on learners' interests, abilities, knowledge, and so forth [12], which paints a blueprint for a learner-centred AI adaptive learning system for this study. Until now, there has been a lack of research and practice trying to build a learning guidance system using artificial intelligence when it comes to integrated STEM education, let alone using the system to cultivate students with the ability to discover transdisciplinary problems.

2 METHODOLOGY FOR CONSTRUCTING INTELLIGENT TUTORING SYSTEMS

In order to discover transdisciplinary problems in integrated STEM education, a set of theoretical modules for constructing an intelligent tutoring system are established in this study, including a domain knowledge model, a learner ability evaluation model, and a problem finding-oriented learning content and evaluation task recommendation model. The corresponding construction method is as follows:

(1) Automatically create knowledge points for discovering transdisciplinary problems through knowledge graphs, which are then effectively combined with the intelligent system, so that learners can acquire SBDP procedural knowledge to improve their ability to locate relevant problems.

(2) Adopt the Rasch model in the Item Response Theory (IRT) to obtain the responses of the subjects, and then use the relevant relational expressions to estimate the item parameters through modern mathematical iterative methods and the potential abilities of the subjects, so as to help teachers evaluate the students' beginning behaviours, plan instructional activities, and diagnose students' learning difficulties to provide feedback.

(3) The learning content and evaluation task recommendation must be based on the previous evaluation results, and relevant content needs to retain the upstream and downstream information regarding knowledge points, that is, the overall presentation of knowledge points in steps 4 to 7 in SBDP; the learning content and evaluation task recommendation also need to be updated dynamically so as to accurately match the personalised requirement.

3 INTELLIGENT TUTORING SYSTEM FOR ENHANCING TRANSDISCIPLINARY PROBLEM-FINDING

Figure 2 below shows the work-flow to build an intelligent learning guidance system, including how to automatically construct the knowledge structure for transdisciplinary problem finding in integrated STEM education, how to build models to evaluate learners' problem finding ability, and how to develop adaptive recommendation for relevant learning content and evaluation. The corresponding system functions are as follows:

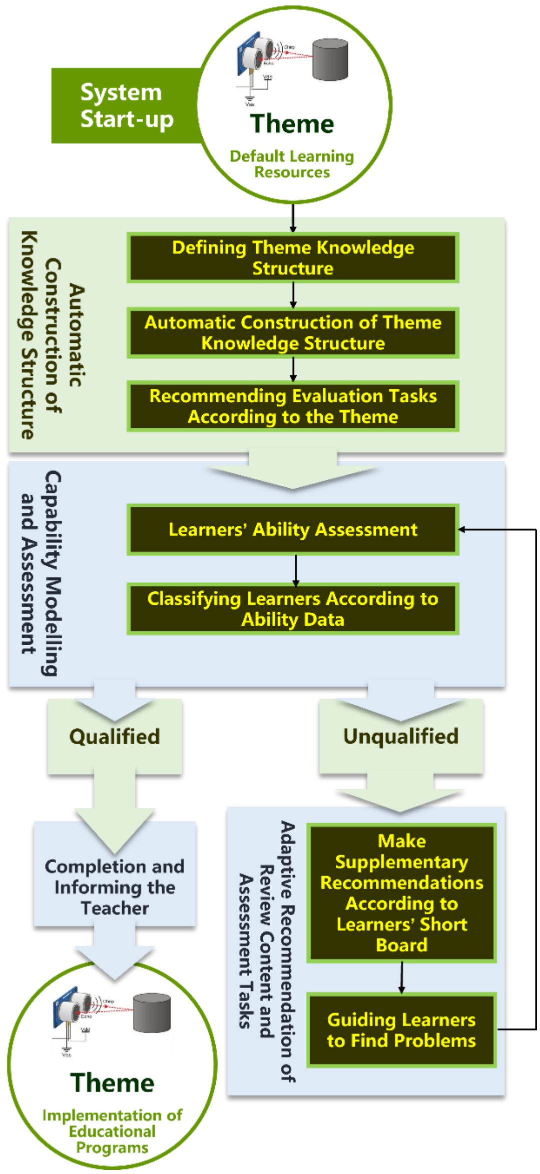

Figure 2: Work-flow of the intelligent tutoring system

(1) The system uses the probabilistic topic model Latent Dirichlet Allocation (LDA) to obtain the subject headings of relevant knowledge points and introduce the co-occurrence frequency statistical matrix. Besides, the discovery of domain tacit knowledge is realised by combining the system with the Apriori algorithm. By identifying the shareable first principles (corresponding to 'Solution Reframing' in SBDP) and application scenarios (corresponding to 'Problem Search') between procedural knowledge points, the system can determine the correlation between them according to the core text data obtained from the knowledge points. Afterward, the relevant knowledge points will be embedded into the knowledge graph of transdisciplinary problem finding, thus generating a knowledge structure conducive to improving the learners' ability to discover problems.

(2) The system adopts IRT to build a model with transdisciplinary problem finding ability. Introductory and formative assessments are required to analyse learners' relevant abilities, including objective questions regarding selection, construction, and sequential multiple-choice. The system can generate a probability model of correct answers based on IRT according to the performance of the learners, which is then used to reflect and predict their potential ability, thereby characterising their ability to find transdisciplinary problems.

(3) In the system, the adaptive recommendation content comprises learners-oriented personalised knowledge resources and problem-finding ability evaluation tasks. After learners master the required learning resources and complete the introductory assessment to start the recommendation function, the system will combine the learners' relevant abilities with the knowledge structure according to the assessment results based on the previously constructed transdisciplinary problem finding ability model. If the evaluation result is negative, the system will automatically recommend learning content (containing relevant information about the upstream and downstream of SBDP) suitable for his or her current ability. This kind of learning content-adaptive recommendation must have a self-circulation mechanism; that is, it can perform an iterative evaluation of the learner's ability based on the dynamic analysis to ensure dynamic updates and achieve accurate individualization with different degrees of difficulty as well.

4 TECHNOLOGY ROADMAP OF THE INTELLIGENT TUTORING SYSTEM

As shown in Figure 3, the study proposes appropriate technical routes based on the intelligent tutoring system to realise algorithms related to automatic construction of knowledge structure, ability modelling and evaluation, and adaptive learning content and evaluation task recommendation for transdisciplinary problem finding in integrated STEM education.

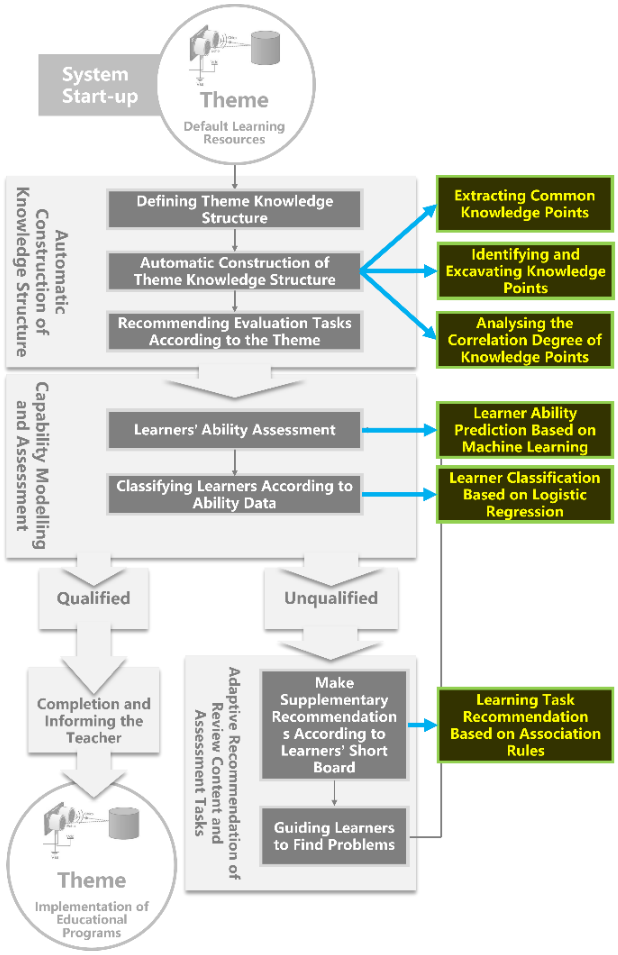

Figure 3: Related technologies for the intelligent tutoring system

4.1 *Technical Route for Automatic Construction of Knowledge Structure*

Based on Table 1, the minimum knowledge unit is defined in the knowledge database as $\pi = \{T, S, C\}$ in the study. It is a carrier for cultivating students with the ability to discover relevant problems and also can be used to build a knowledge structure library for improving this ability. Knowledge topic construction is the basis of personalised learning, which in turn depends on the identification of topic words and the analysis of the relevance of knowledge points. Therefore, this study adopts an LDA-based topic model to construct a knowledge association framework through frequent item mining.

Table 1: Structured definition of knowledge points

Items	Definitions
Knowledge topic: T	Knowledge topics for Integrated STEM educational programs focus on equipment (such as sensors) related to Industry 4.0 technology
Sub-knowledge point: S	Various first principles (corresponding to 'scheme reconstruction' in SBDP) as minimum units under the knowledge topic
Problem scenario: C	A variety of application scenarios (corresponding to 'question search' in SBDP) that a single first-principle sub-knowledge point may be suitable for

(1) Keyword finding algorithm based on the LDA model:

The route performs word segmentation on the data set, which is vectored to generate a word bag. Then, a corpus is generated to train the LDA topic model, and the LDA model is used to complete the knowledge topic classification for new documents or data. The route initialises the topic $z = \{z_1, z_2, \ldots, z_m\}$ according to the content of documents, treating a document or data set in the database as a sequence of words $d = \{w_1, w_2, \ldots, w_x\}$ to construct a corpus W. Each document in the corpus corresponds to a multinomial distribution with T topics based on the given methods, such as trial and error, which is recorded as θ. Each topic, in turn, corresponds to a multinomial distribution (denoting as φ) derived from V words in the corpus. For a newly-added document, its topic distribution can be estimated by running the above LDA model again based on the LDA model, thereby updating the knowledge topic corpus. A complete set of T, S, and C is thus constructed through the construction of the LDA model and the analysis of the original data and updates using the LDA model.

(2) Knowledge point correlation analysis in transdisciplinary problem finding:

It requires building a Frequent Pattern (FP) tree and mining it to establish the association of S and C. The route finds the knowledge state set of all sub-knowledge points and application scenarios by building an FP tree of the data-set to form a richer 'question search' basis for SBDP. It first builds a database of application scenarios corresponding to S, in which each application scenario constitutes an item set $I(Item)$, the minimum support degree is defined as $\min\_supp$, and the minimum confidence degree is defined as $\min\_conf$. Then, the data set is scanned to calculate the occurrences and support of each application scenario, and the items in the original data set are sorted in descending order of support. A second scan is performed to create a head pointer table (head), and an FP tree is built based on the item header table. For each item, its conditional pattern base is found to build a conditional FP tree, and infrequent items are filtered through recursively call until a single path is formed. Finally, all strong association rules are determined by merging and screening in the frequent item set already found, by which the association between the corresponding sub-knowledge points and application scenarios is determined, thus establishing a knowledge state set.

4.2 Technical Route for Ability Modelling and Evaluation

The study adopts two dimensions of integrated STEM, namely learning knowledge level and learning skills, to represent the learners' ability model. Although the relevant knowledge level can be accurately assessed according to the knowledge structure of transdisciplinary problem finding and the learners' task completion, the learning skills need to be obtained by comparing the performance of other learners on the same task. Therefore, the relevant skill level is determined in the study from the performance distribution of the individual on the whole, and the level is characterised by the efficiency and accuracy of task completion. The skill level is:

$$\Pi = \{(b, \eta, \mathrm{r}) \mid \mathrm{b} \in \pi, \eta \in [0,1], \mathrm{r} \in [0,1]\} \tag{1}$$

Among them, b represents the knowledge status of students, η represents the efficiency of students' task completion, and r represents the accuracy of students' task completion. The task completion efficiency is the relative position of the time spent by a student compared to the whole by all students. Assuming that the distribution probability function of all students completing a task is $f(x)$, and the time spent by the student is t, the task completion efficiency is:

$$\eta = \int_t^{\infty} f(x)\,dx \Big/ \int_0^{\infty} f(x)\,dx \tag{2}$$

(1) Construct the weight and dimension of transdisciplinary problem finding ability:

This route corresponds to the evaluation dimensions of the individual capabilities in steps 4 to 7 in SBDP. The setting of the test task x focuses on examining a specific ability dimension, or the comprehensive ability with weight. For each ability dimension s_i, the score is determined mainly based on the knowledge difficulty b, efficiency η, and accuracy rate r of the relevant tasks. This study adopts the partial assignment Rasch model to improve the scoring standard, and its mathematical expression is:

$$\ln\left(\frac{P_{nik}}{1-P_{nik}}\right) = B_n - D_{ik} \tag{3}$$

Among them, k represents the score, D_{ik} represents the difficulty of task i on a score of k, and P_{nik} represents the probability of a subject with an ability of B_n to get a score of k in task i.

(2) Predict learners' ability values and make classification:

The route implements group classification based on learner competency values with the help of automated procedures. This classification obeys the Bernoulli binomial distribution with a small feature space, and the learners will generate a large amount of new data during the evaluation process. Therefore, it chooses Logistic Regression to classify learners according to the ability data. It is found that the classification type of 0 - problem is characterised by low competence, while that of 1 - problem by high competence; it is proposed to add a regularization term to Loss Function in order to avoid the problem of overfitting. It first imports data K, including learner characteristics and skill indicators, and the characteristics of a certain student are recorded as $k = \{s_1, s_2, s_3, s_4\}$. Then, data pre-processing, including feature bias processing and normalization processing, is performed; classifier training is further conducted, probability parameter θ is determined through the maximum Likelihood estimation, parameters are updated by using stochastic gradient descent or Newton method, and overfitting is prevented by adding regularization; finally the classifier is run, and the type of learner is outputted according to the returned probability.

4.3 Technical Route for Adaptive Learning Content and Evaluation Task Recommendation

(1) Adaptive learning content recommendation based on ability evaluation:

Only learning tasks that can match both learners' transdisciplinary problem-finding abilities and their challenge expectations can meet individualised learning needs. The combined recommendation method is adopted to stack the recommended algorithms based on collaborative filtering and association rules to generate more accurate recommendations. Firstly, the route constructs a link task according to the learning knowledge topic z and the strong knowledge association rules based on mining in the FP tree algorithm, thus forming a preliminary recommendation result R. In this process, tasks are arranged in descending order of support, and those with the same support are selected synchronously. Secondly, according to the preliminary recommendation result R , it adopts the recommendation algorithm based on collaborative filtering to take the highest difficulty of task completed by the learners with similar ability distribution as the recommendation level and select the task closest to this level to add it to the learning content sequence. Finally, the above two steps are repeated. With the accumulation of students' learning content sequence and the continuous improvement of their ability in classification, the system will make more and more accurate recommendations.

(2) Adaptive evaluation task recommendation based on multiple algorithms

The adaptive evaluation task recommendation should be conducted on the basis of the results from the previous round of evaluation, with the goal of using as little content as possible to complete a new round of evaluation of the learner's ability to solve relevant problems. The route firstly develops algorithms based on recommendations in terms of content, collaborative filtering, and association rules, and then calculates the efficiency and average accuracy rate of learners' problem finding according to the evaluation results. Then, an evaluation scheme is built, that is, a link task based on strong knowledge association rules according to the FP tree algorithm mining, in which the tasks are arranged in descending order of support, and those with the same support are selected. The constructed evaluation structure is further screened. If the corresponding knowledge point sets overlap, only the evaluation tasks with the lowest degree of difficulty are retained according to the accuracy and efficiency expectations; the sub-optimal spanning tree is adopted to select tasks, and the evaluation status k is obtained in a loop. The learners' benchmark ability is $\Pi = \{(b, \eta, r)\}$, in which b is the knowledge structure level mastered by them at that time. Finally, the knowledge structure is switched according to the students' degree of task completion, and the above four steps are repeated to select suitable tasks for subsequent tests.

5 CONCLUSIONS

In conclusion, this study promotes the development of an intelligent tutoring technology framework containing data, algorithms, and services, thereby enhancing a social atmosphere that values science and encourages innovation through integrated STEM education. This study specifically develops subject word discovery algorithms and conducts knowledge point relevance analysis to complete the automatic construction of knowledge structures for transdisciplinary problem-finding; relevant problem-finding ability subdivisions and assessment weights and dimensions are proposed to enable the mechanism to predict individual ability values and classify groups based on regression analysis results, namely learner ability modelling and assessment; recommendation algorithms are applied based on content, collaborative filtering, and association rules to achieve adaptive recommendation of review content for learning relevant problem-finding and tasks for assessing the ability.

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