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A Bayesian-based knowledge tracing model for improving safety training outcomes in construction: An adaptive learning framework

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ABSTRACT

Safety training plays a pivotal role in effectively reducing unsafe behaviors in the construction industry. Despite the numerous effort to improve safety training, existing studies lacked consideration of trainees' different learning characters, nor did they adapt the suitable training materials to trainees' mastery of safety knowledge. Against this contextual backdrop, this research proposes a Bayesian-based Knowledge Tracing (BKT) model to recommend personalized training materials according to trainees's learning progress. The proposed BKT model tracks and predicts trainees' performance with their cognitive characters, abilities, and historical training records. It also adjusts trainee's probability of mastering safety knowledge concepts for determining future training sessions. In this way, the safety training is adaptive and personalized, thus more effective. An exploration study is conducted in the laboratory environment to validate the effectiveness and feasibility of the proposed BKT model. The research results showed that 83.33% of the respondents felt gained safety knowledge after the training, and 66.67% of the respondents affirmed the effectiveness of the BKT model-based training system in improving the effectiveness of training. The results demonstrated that the proposed model performed well at educating safety knowledge and reducing unsafe behavior.

1. Introduction

Despite decades of research effort and practice innovation to improve safety performance, construction remains as one of the most dangerous industries, with accidents and fatalities pervasive worldwide (Zou and Sunindijo, 2015;Jin et al., 2019; Fang et al., 2020; Fang et al., 2021). For example, more than 20% of all work-related fatal accidents occurred in the European Union were associated with construction in 2017 (Vignoli et al., 2021). In China, 802 workers were killed in the construction industry in 2021, and 793 workers in 2020 (MOHURD, 2022). Unsafe behavior is a leading contributor to accidents in construction (Carrillo-Castrillo et al., 2017; Ding et al., 2018 Love et al., 2019). It is well recognized that through safety training and safety awareness enhancement, the behavioral safety performance can be improved (Namian et al., 2016; Love et al., 2017; Hussain et al. 2018; Xu et al., 2019a, 2019b ; Vignoli et al., 2021).

The traditional approach to safety training mainly occurred in the classroom settings, leveraging different materials such as case studies, rules and regulations readouts, and videos (Love et al., 2017). This traditional approach is not as practical as on-the-job training (Barriuso et al., 2021) because of the following reasons:

➢ People possess different cognitive, mental, and experiential capabilities, and thus safety training should be able to respond to individual learning characters and needs and be organized in a way relatable to daily jobs (Xu et al., 2019a, 2019b);
➢ Prompt feedbacks on the learning results help learners learn better and quicker, and safety training should be able to track their learning results and provide adjustment to their future training plans (Wu 2019);
➢ On-site safety training should be innovatively attractive to improve learners' motivation and engagement.
➢ The trainees are mainly adults, so that andragogy training approach may be more suitable (Zou and Sunindijo 2015).

Therefore, it is urged that the safety training approach be modified to accommodate individuals' requirements dynamically and adaptively with prompt feedback, which is recognized as adaptive learning in

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educational research. Development and advancement in digital technologies introduced innovation to adaptive learning in professional training (Wang et al., 2018). Cutting-edge information and communication technologies (ICT) provide people with web-based or mobile-supported training approaches (Bhandari et al., 2019; Martin et al., 2020). The learners have access to the prestored training resources, allowing them to undertake personalized training anywhere at any time. However, currently, in self-administered online training, the resources are usually provided to individuals in a predefined way, without prompt feedback on their learning results; It also lacks clear differentiation of trainees' learning characters, scenario-based and easily-related presentation of safety knowledge, nor the accurate adaption of trainees' mastery of knowledge concepts.

Against this contextual backdrop, the research aims to address the following question: *How can scenario-oriented training match peoples' learning characteristics to help them better understand and actively engage in safe work practices?* To answer this question, the research proposes an adaptive learning framework that adapts to individual learning characteristics, cognitive styles, and mastery of safety knowledge with a Bayes-based knowledge tracking approach, targeting trainees' learning characters, cognitive abilities, and historical training records. Adaptive training approaches are underpinned by tailor-made techniques that can improve people's motivation, engagement, satisfaction, and safety performance (Barla et al., 2010; Ross et al., 2018; Martin et al., 2020). The BKT model tracks trainees' cognitive status to understand their mastery of knowledge and predict their future training performance.

The contributions of this research lay in developing a Bayesian-based knowledge tracking (BKT) model that can dynamically describe people's learning knowledge cognitive status for the personalized and accurate recommendation of training materials. Our research commences by reviewing the extant literature on safety training in the construction industry and adaptive learning application. Then, the framework is presented. The effectiveness and feasibility of the proposed framework are next described. The research contributions, limitations, and the need for future research are presented in the conclusion.

2. Safety training and learning in construction

Safety training improves workers' awareness and skills and ensures construction safety performance (Loosemore and Malouf, 2019). Training delivers essential knowledge to people, guarantees specific task proficiency required to prepare people for trade settings, and instills a positive risk-sensitive attitude and safe climate in the workplace (Shin et al., 2014; Hou et al., 2017). Research indicates that frequent jobsite rotation, unfamiliar work environments, and production pressure can prevent people from receiving adequate and effective safety training (Fang et al., 2016). Traditional classroom training materials have been improved by incorporating photo-type questions and video-based materials to educate people about being safe (Xu et al., 2019a, 2019b). As a result, positive behavioral changes have manifested (Xu, 2014) Advanced visualization techniques such as virtual reality (VR) and augmented reality (AR) have also been applied to enhance learners' cognitive capability and kinetic-motor skills to improve workplace safety (Bosché et al., 2016; Li et al., 2018). Safety training also seeks to improve workers' participation (Namian et al. 2016) by involving supervisors as exemplars to their co-workers and developing more scenario-based approaches (Lin et al., 2018), as well as tailored training sessions and materials for Hispanic migrant workers (Lin et al., 2018; Vignoli et al., 2021).

Construction safety learning falls in the field of andragogy, and the learners are adults, self-directing, and are more interested in the problem-centered approach that help them relate to the practical situations in their daily work environment (Zou and Sunindijo, 2015). Therefore, developing effective safety training techniques and methods lies in understanding the characteristics of people and that the needs of people with different characteristics can be better accommodated. For instance, using experiential and kinaesthetic-centered learning may better construct learners' situational awareness and context (Jeschke et al., 2017; Bhandari and Hallowell, 2017) than using old-fashioned textbook materials. Research has confirmed that it is essential to formulate personalized safety training (Tang et al., 2019), and provide different training materials that cater to unique styles, needs, and expectations (Xu et al., 2019a, 2019b).

2.1. Adaptive learning-based approach for safety training

Adaptive learning delivers customized learning experiences that address an individual's unique needs through just-in-time feedback, plans, and resources. It usually requires trainees to complete the learning process with electronic devices, such as personal computers or mobile phones. As a kind of personalized learning, adaptive learning digs the learning characteristics of learners through their performance data in the learning process and builds a learner-centered learning model (Chrysafiadi and Virvou, 2013; Tang et al., 2019).

Existing research has designed and evaluated several adaptive approaches for safety training. For example, Cen et al. (2006) suggested displaying different interfaces to coal miners according to their individual training needs. Tang et al. (2019) developed a safety guidance system to deliver safety orders based on people's on-site positions. Guo et al. (2019) recommended using different training materials for various trades in different construction processes. However, effective adaptive learning depends on how safety knowledge is organized and displayed, whether learners' characters' descriptions are accurate, whether the recommended approach is targeted, and descriptions of trainees' learning characters with accurate measuring of their mastery levels are in great need.

Learner models are built to describe people's learning characteristics. Existing research on self-administered online learning discovered that users' background, learning styles, cognitive styles, learning interests, learner's previous experience, learner's preference for training contents and display, and learning motives were used in various learner models to describe learners' characters (Brusilovsky and Millán, 2007; Thalmann, 2008; Nakic et al., 2015). Mourlas et al. (2009) found that learning styles, gender, working memories, existing knowledge, and anxiety also influenced online learning. Vandewaetere et al. (2011) identified learners' characters with gender, meta-cognitive abilities, and cognitive, affective, and behavioral characters. The key concept is to describe learners' characters with dynamic records of their learning history. Therefore, our current research considers a learner's (trainee's) characteristics and cognitive level, learning preferences, learning motives, and emotions during safety training to examine the mastery of safety knowledge.

2.2. Knowledge tracing

Knowledge tracing is one of the typical models to track the mastery of knowledge (Yudelson et al., 2013a, 2013b), which was introduced to intelligent education by Corbett and Anderson (1994) and became a fundamental approach to adaptive learning with online systems (Pardos et al., 2013) . In online systems, learners are usually required to learn a series of knowledge concepts, which refer to an exercise, a skill, or a concept (Liu et al., 2021). In self-directed learning, learners can experience fluctuations in their learning behavior, cognitive state, and emotional factors, which leads to unpredictable learning results. Therefore, knowledge tracing approaches monitor learners' mastery of knowledge concepts to determine their future learning processes. Since the knowledge tracing models were introduced and showed the effectiveness (Pardos et al., 2013) in the performance improvement in online learning, many efforts have augmented the knowledge tracing models by introducing item difficulties (Pardos and Heffernan, 2011), forgetting behavior, learning sequence, and information types into consideration (Nagatani et al., 2019).

Existing knowledge tracing models can be divided into three categories:static tracing models, dynamic tracing models, and deep tracing models. The first developed static knowledge tracing (Cen et al., 2006) often used regression models, and dynamic knowledge tracing includes Bayesian knowledge tracking (BKT) (Corbett and Anderson, 1994) to establish the dynamic relationship between learners and knowledge concepts to achieve better performance. Bayesian knowledge tracing infers a learner's history of responses to problems and predicts the learner's future performance.

Later, Piech et al. (2015) brought up a deep knowledge tracing (DKT) model to improve traditional BKT models, by applying recurrent neural network (RNN) in knowledge tracing problems to enable the model to raise prediction accuracy without tagging the relationship of questions and knowledge concepts. However, DKT models depend highly on a large volume of data to feed the neural network, and they are most suitable in MOOCs with a large quantity of training records.

Commonly used recommendation algorithms included the content-based algorithm and the collaborative filtering algorithm (Park et al., 2012, ,). They are effective in preference prediction but not necessarily applicable in adaptive learning. The learning objective is not recommending questions to workers with similar interests but somewhat similar mastery of safety knowledge concepts. Therefore, the knowledge tracing model was introduced in this study to infer people's grasp of the knowledge concepts based on individual similarities and differences.

3. The proposed adaptive training framework

Our research proposed an adaptive safety training framework based on the BKT method for construction workers that identify their learning characteristics and match them to safety knowledge schemes. The research framework is shown in Fig. 1.

The framework is consisted of:

- ➢ *Safety knowledge schemes*, which contain sorted training resources and classify them effectively, and display informal safety knowledge towards construction scenarios to provide construction workers with adaptive training content.
- ➢ *Learner features identification*, which collects and stores information, such as learners' age, length of service, education experience, job trades, and positions, learning styles, learning motivations, and roles in the group.
- ➢ *Knowledge tracing model*, which generates the recommendation algorithm to match construction workers' features with training materials with safety knowledge schemes.

3.1. Safety knowledge database

Many laws, regulations, and regulatory documents set standards and requirements to ensure people's safety and health in the construction industry. For example, the *Construction Safety Operation Regulation* has 525 items, covering 14 types of work, 20 kinds of plants, and technical disclosure; likewise, the *Standard for Construction Safety Inspection* includes 19 inspection template forms, 188 safety inspection items (120 guarantee items, 68 general items), and 771 inspection requirements. However, there are many regulations and many overlapping clauses among those regulations. It is necessary to rationally screen, sort, and integrate scattered and overlapping safety knowledge to form a systematic and logical knowledge system. The extracted unsafe behaviors are conducive to more efficient training of people. Unsafe behaviors can be captured by the on-site camera or recorded by managers using mobile phones during daily safety inspections. Many photos on the construction site together reflect the actual working status of workers during the construction.

Firstly, we selected the safety standards *Safe Operation Regulations for Construction* and *Construction Safety Inspection Standard* as references, extracting items related to behavioral safety. Secondly, combined with on-site photos and weekly safety reports, a preliminary list of unsafe behaviors was formed, considering the classification index, job trades, and accident types. The list of unsafe behaviors was further modified and adjusted through expert review and confirmation.

Next, the safety knowledge concepts were identified with construction scenarios. People, plants, materials, structural components, and the environment were seen as the core concepts, and the relationships between the core concepts were established with statue and action

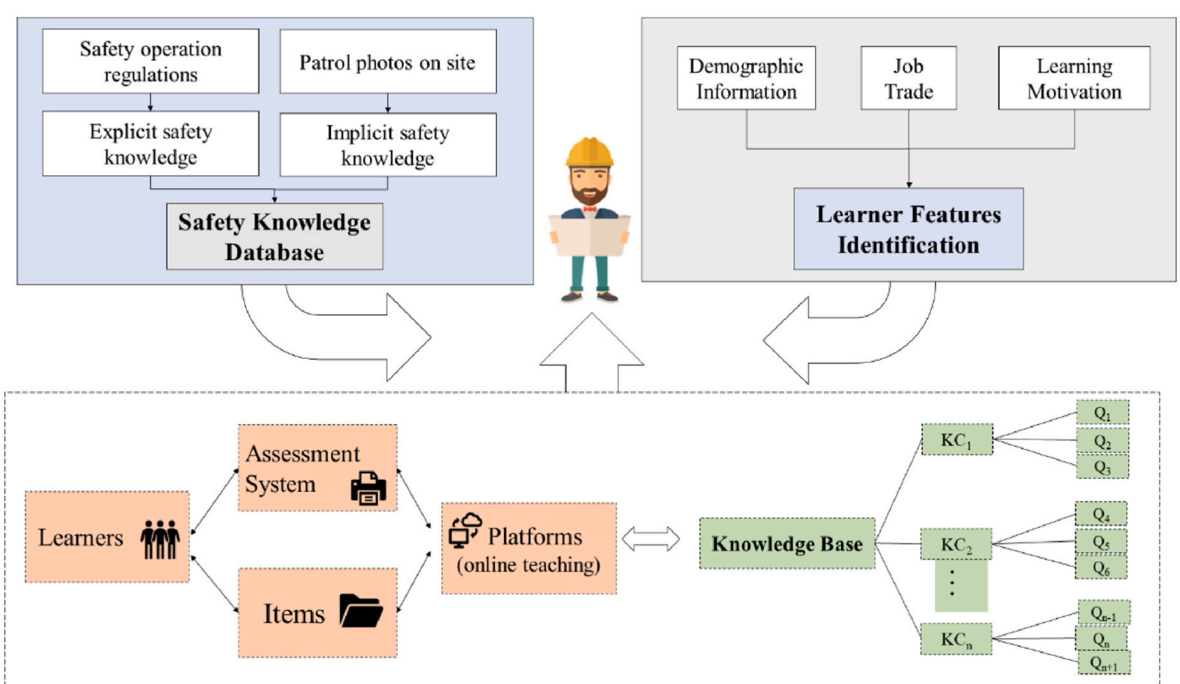

Fig. 1. Framework of adaptive training.

descriptions. Therefore, the safety knowledge could be expressed as (core concept) (scene description) (interrelationship) (core concept) to explain the interrelationships between core concepts and the scene of unsafe behavior. For example, one of the site photos showed that a worker was climing the scaffold, and it could be expressed as the relationship of "climbing" between two core concepts, the worker and the scaffold, which could then be related to the behavioral safety knowledge concept 2-9-1 stated that "no special passage for people to climb up and down the scaffold". Table 1 presents examples of extracting and manifesting the safety knowledge concepts by combining photos with regulations.

The next step was to develop training questions related to the knowledge concepts. More than 800 questions were developed for safety training with at least one knowledge concept related. Those questions were presented graphically to be easily understood and memorized. The test question bank included general questions for all job trades and particular questions for 11 trades. Examples of questions are presented in Table 2.

3.2. The learner model

Learners' characteristics could be modelled by their existing knowledge, skills, and capabilities. *IEEE 1484* (IEEE, 2007) provides a primary taxonomy of learners by their demographic information, preference, performance, safety, and relationships in e-learning. The standard *CELTS-11* used demographic information, security, relationship, performance, education information, preference, and exercise to classify learners. However, these characteristics cannot be fully applied to most trainees in the construction industry, considering that they are adult learners with low literacy and specific requirements on occupational safety knowledge. Therefore, the following information was used to describe the learning characters: demographic information, job trades, learning motivation, learning motivation, group role, and pre-existing safety knowledge (Chen and Jang, 2010).

Table 1
Extraction and matching implicit safety knowledge.

Photos	Expression Pattern	Behavioral Safety Knowledge Concepts
	Workers (core concept) smoke (core concept) on-site (scene description)	1-4-7 no-smoking allowed in the construction site
	Workers (core concept) climb (interrelationship) the scaffold (core concept)	2-9-1 no special passage for people to climb up and down the scaffold
	Workers (core concept) do not use (interrelationship) safety belts (core concept) working at height (scene description)	12-1-3, the operator did not fasten the safety belt or didn't fasten as required
	Workers (core concept) lash (interrelationship) rebars (core concept) standing on steel cages (scene description)	18-4-4 stand on the steel framework and climb up and down the framework when binding the steel bar of column and wall
	Workers (core concept) do not wear (interrelationship) protective goggles or gloves (core concept) during welding (scene description)	18-5-10 the workers did not take safety protection measures during electric welding

- ➢ *Demographic information*: People must provide their basic information at the beginning of safety training, including gender, age, length of service, job trade, and education level.
- ➢ *Job Trade*: People in each job trade must grasp a particular pack of safety knowledge. Examples of unsafe behaviors and trades are shown in Table 3.
- ➢ *Learning Motivation:* Learning motivation is the personal knowledge acquisition needs for training. We categorized people's motivation for safety training into safety needs, work needs, and value orientation. Intrinsic motivation is more autonomous and lasting with higher value, while rewards and punishments induce extrinsic motivation.

We designed four questions for each motivation and measured them with a 5-concept Likert scale, as shown in Table 4. Different weights were assigned to the three learning motivations: safety requirements accounted for 0.5, work requirements accounted for 0.2, and value orientation accounted for 0.3. The final scores of all the questions were used as the scores of the learning motivation test. If learners with scores under six were considered low in learning motivation, learners with scores between 6 and 10 were considered average in learning motivation, and learners with scores higher than ten were considered as high in learning motivation.

4. Bayes-based knowledge tracing model

In this research, a Bayes-based knowledge tracing model was developed to recommend safety training content for people in construction. The knowledge tracing model is shown in Fig. 2. The model's input is the score of trainee i answering questions on n knowledge concepts at Time t. The scores are sent in Bayes networks (for BKT) or neural networks (for DKT) to evaluate their knowledge level and predict future performance. BKT model assumes that learners' knowledge learning has two states. Each knowledge concept is in the "mastered state" or "not mastered state". The learning status of knowledge concepts can be transferred from "not mastered" to "mastered" through learning. However, the learning state of knowledge concepts will not be transferred from the "mastered state" to the "not mastered state" in this research, which means that it is assumed that the mastered knowledge will not be forgotten.

The knowledge tracing model tracks every knowledge concept separately. Therefore, knowledge concepts are organized and connected with hierarchical relationships. When the knowledge concepts are in the mastered state, learners may still make the wrong answer due to mistakes; in contrast, learners may guess the answer correctly when the knowledge concepts are not mastered. Therefore, the mastery of every knowledge concept is designated with four indicators. *Prior Probability P* (L) and *Transition Probability P*(T) are the learning parameters, while *Guess Probability P*(G) and *Slip Probability P*(S) are the performance parameters. The indicators of the BKT model used to calculate learners' knowledge mastery probability are as follows:

- ➢ *Prior probability* (*P*(L)) indicates the learner's initial probability of mastering the knowledge concepts before learning.
- ➢ *Guess probability* (*P*(G)) indicates the probability that learners guess correctly without mastering knowledge concepts.
- ➢ *Slip probability* (*P*(S)) indicates the probability that learners will answer incorrectly when they master the knowledge concepts.
- ➢ *Transition probability* (*P*(T)) indicates the probability a learner who does not currently know the skill will know it after the next practice opportunity.

Therefore, the knowledge tracking model is a special hidden Markov model (HMM). According to Fig. 3, the question node Q is observable in the knowledge tracking model. By inputting the known question performance, we can analyze the learners' mastery of potential knowledge

Table 2
Examples of questions.

Questions	Level of difficulty	Knowledge Concept	Options	Analysis
1) Is the behavior shown below feasible at rest? 	Easy	1-4-7	A Yes. B No.	A special smoking place shall be set up on the site and smoking at will is strictly prohibited.
What are the safety risks in the figure below? 	Medium	10-1-1, 10-5-1, 12-1-1	Workers do not wear safety helmets. B The up and down pathways of the foundation pit are not safe. C All of the above.	Workers should wear safety helmets correctly when entering the construction site. The foundation pit should be provided with a special up and down pathway meeting the safety requirements.
What are the common security risks in the following two pictures?  	Hard	10-1-1, 12-1-1, 12-4-1	A fall from height B no safety helmet on site C no protective measures around the deep foundation pit	Workers should correctly wear safety helmets when entering the construction site and keep good edge protection during foundation pit construction. When working at height, they also should take protective measures.

Table 3
Examples of unsafe behaviours and trades.

Unsafe behavior description	Safety risks	Related trade
Workers throw objects down at height.	Object strike	plasterer, scaffolder, formwork worker, etc
Irrelevant personnel enter the hoisting area.	Hoisting	tower crane driver, gantry crane driver, material hoist driver
No warning or personnel monitoring for the excavators' working radius.	Machinery harm	excavator driver
The welders do not wear gloves and insulating shoes.	Machinery harm	electric welder
The scaffold board is not fully paved or the laying is not firm or stable.	Fall from height	scaffolder
workers do not wear helmets on site.	Personal Safety Protection	all

concepts and predict their performance when they reencounter this knowledge concept. Every time the trainees take the quiz, the BKT model updates their knowledge mastery status. When P(G) and P(S) are both equal to 0, the results reflect the actual status of the trainees; when P(G) and P(S) are both higher than 0.5, it indicates that the probability of slips and guessing is too high for the model to reflect the actual status.

In BKT applications, the four indicators are calculated first, then the individual's knowledge is inferred from their responses. There are two circumstances during the inference process when a correct response is observed: (1) they have mastered the knowledge concepts and have no mistakes; (2) they have not mastered the knowledge concepts but have guessed correctly in doing the questions. Therefore, the probability of the learner correctly answering the question is the sum of the two, as shown in Eq. [1].

$$P(correct) = P(L_{n-1}) \times (1 - P(S)) + (1 - P(L_{n-1})) \times P(G) \qquad \text{Eq. [1]}$$

Table 4
Questions for measuring learning motivation.

Measurement of learning motivation (with weights)	Question
Safety requirements 0.5	1 Safety training will directly or indirectly affect the construction activities, and it is very important to ensure our personal safety. 2 Safety training can improve our safety behavior, which is of great significance to us. 3 I prefer to follow my foreman to learn on-site operation. I don't think safety training is necessary. 4 It is generally believed that safety training is a mere formality and a waste of time.
Job demand 0.2	5 The purpose of participating in the pre-construction safety training is to get the job. 6 The main reason for participating in safety training is job demand. 7 Part of the reason for participating in safety training is job demand, but mainly because it can improve my working abilities. 8 I participated in safety training because I think safety training is very important for safe construction, rather than job demand.
Value orientation 0.3	9 If everyone is willing to participate in safety training, so am I. 10 I am willing to participate in safety training for approval from my manager. 11 Safety training contributes to the establishment of a good safety climate for the team. 12 If there is no supervision, I will also attend safety training on time.

Similarly, there are also two circumstances in which learners answer questions incorrectly: (1) they have mastered the knowledge concepts but made mistakes in answering questions; (2) they have not mastered the knowledge concepts and guessed wrong in doing the questions.

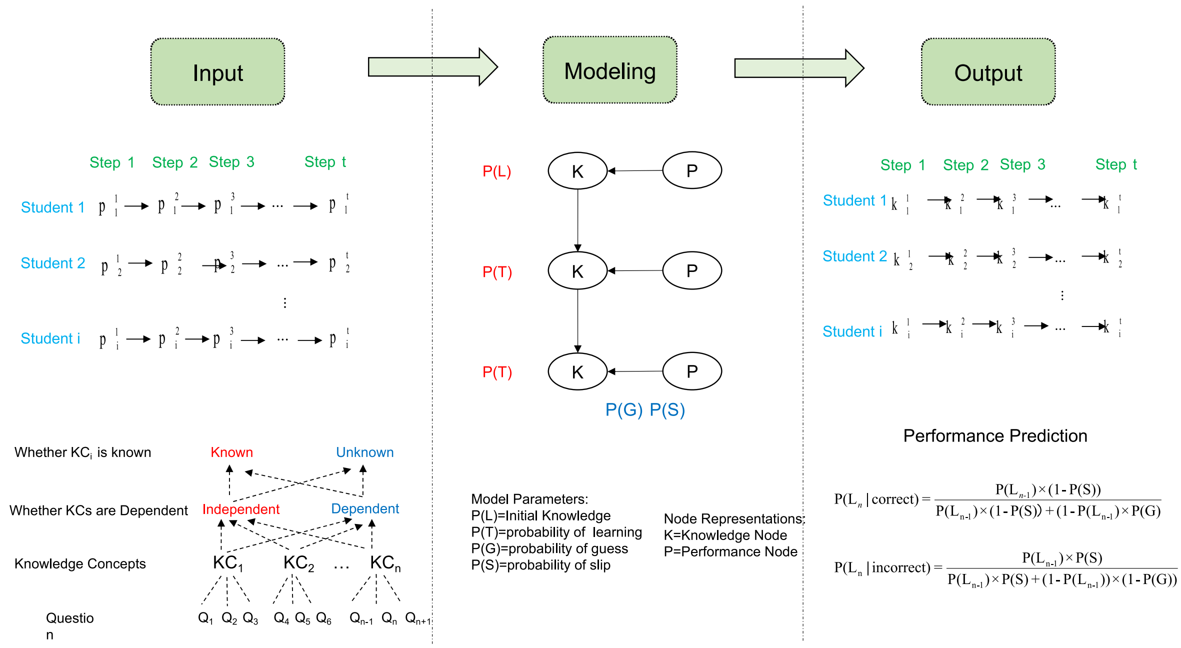

Fig. 2. Knowledge tracing model.

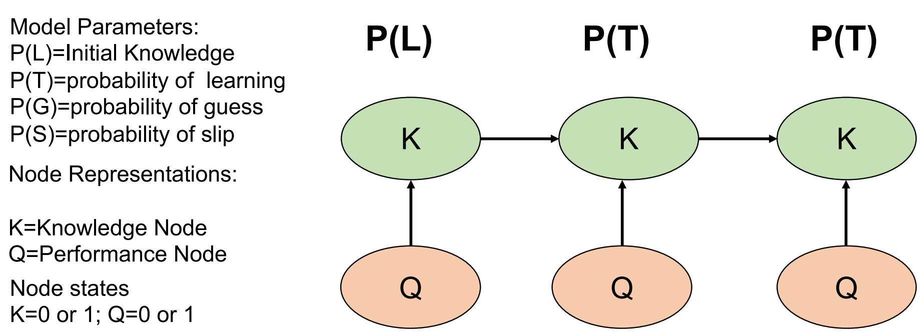

Fig. 3. Bayes-based Knowledge tracing model (Adopted from (Pardos et al., 2013).

Therefore, the probability of learners' wrong answer is the sum of the two, as shown in Eq. [2].

$$P(incorrect) = P(L_{n-1}) \times P(S) + (1 - P(\ )) \times (1 - P(G)) \quad \text{Eq. [2]}$$

According to the Bayesian formula, the probability that a learner has mastered the knowledge when he (she) answer the questions correctly can be obtained by Eq. [3].

$$\mathrm{P}(\mathrm{L}_n|\mathrm{correct}) = \frac{\mathrm{P}(\mathrm{L}_{n-1}) \times (1 - \mathrm{P(S)})}{\mathrm{P}(\mathrm{L}_{n-1}) \times (1 - \mathrm{P(S)}) + (1 - \mathrm{P}(\mathrm{L}_{n-1})) \times \mathrm{P(G)}} \quad \text{Eq. [3]}$$

The probability of mastering knowledge in case of answering incorrectly can be computed by Eq. [4].

$$P(L_n|incorrect) = \frac{P(L_{n-1}) \times P(S)}{P(L_{n-1}) \times P(S) + (1 - P(L_{n-1})) \times (1 - P(G))} \quad \text{Eq. [4]}$$

Then, the learner's mastery of knowledge concepts can be obtained by the following Eq. [5]:

$$P(L_n) = P(L_n|correct) \times C_i + P(L_n|incorrect) \times N_i \quad \text{Eq. [5]}$$

Where, $C_i = {}^{a}/_{n}$, $N_i = {}^{b}/_{n}$. C_i represents the correct answer rate of a knowledge concept of the learner, N_i represents the wrong answer rate of a knowledge concept, n is the total number of questions answered by the learner on the specific knowledge concept, a is the number of correctly answered questions on the knowledge concept, and b is the number of incorrectly answered questions on the knowledge concept. The solution to the mastery probability of knowledge concepts is a continuous iterative process.

5. Experiments and results

In this research, we conducted an experiment to validate the proposed adaptive training framework based on BKT in laboratory. We applied the proposed BKT model in recommending proper questions to trainees, and their performance in the safety tests was recorded as well as their satisfaction with the adaptive safety training approach. At the same time, we built the safety knowledge database from safety regulations to organize the safety knowledge concepts and related them to safety patrol photos from construction sites for the purpose of generating safety questions for training. The research also built the learner model to describe the learning characters and preferences to differentiate learning styles.

5.1. Experiment design

To validate the effectiveness and feasibility of our proposed framework, an experiment was conducted. Twelve senior-year undergraduate students were recruited in the experiment to test if the proposed framework could recommend personalized knowledge concepts to them and improve their safety knowledge level. Our previous research identified core concepts in more than 1000 photos so that those photos could be related to construction scenarios to visually express the safety knowledge. In this research, we used the question bank for scaffolders, which include 139 test questions on 35 knowledge concepts. The trainees had learned the fundamentals of construction processes and safety management but had not been taught specific behavioral safety knowledge as scaffolders. Therefore, it is reasonable to assume that they had no pre-acquired knowledge of the test but the ability to understand the concepts.

Firstly, the basic steps to use the system were explained to the participants, and privacy protection was also clarified. Then the participants completed registration and finished the questions about learning style and motivation. The experiment used the BKT model to calculate participants' knowledge concept mastery probability, then pushed the training questions based on the knowledge concept mastery probability. The recommendation algorithm generated a list of recommended questions that were most helpful in improving the target participant's safety knowledge. In the recommended questions list, questions were sorted by the probability of the target people grasping the knowledge concepts associated with the question. A greater probability showed the target people have mastered the knowledge concept, and a smaller possibility showed that the knowledge concept needed to be further trained. In this way, the algorithm reflected the subtle differences in the degree to which participants have mastered knowledge concepts and improved the reliability of the recommendation results.

Considering there was no historical learning data in the first session, the participants were asked ten randomly selected questions with ten different knowledge concepts in the first session. In the following sessions, they were asked ten questions generated by the BKT model, respectively. Every time a participant completed a test, the system collected the test results and calculated the user's mastery probability of each knowledge concepts. Table 5 shows the user's test question score matrix after the first round of training.

Adaptive recommendation considered both question difficulties and the grasping possibility of the knowledge concepts of the target worker. The target participant's weak knowledge concept could be judged by setting the knowledge concept threshold. When the knowledge concept mastery probability of target participant w_i was less than or equal to the knowledge concept threshold μ_{w_i}, the ability of target participant w_i to master the knowledge concept was considered weak, and more test questions containing this knowledge concept were recommended by the safety training system. The knowledge concepts' threshold of target worker w_i is shown in Equation (6).

$$\mu_{w_i} = \frac{\sum_{g=1}^{N} x_{w_i}^{r_g}}{N} \qquad \text{Eq.[6]}$$

On the other hand, for participants with different learning motivations, the threshold can be adjusted by evaluating the target participant's learning motivation. When the learning motivation of the target participant was low (motivation score of [0, 6) according to the evaluation method of Table 4), μ_{w_i} was then reduced to include test questions with low difficulties, so that more questions were recommended to consolidate the mastery of weak knowledge concepts. When the learning motivation was average (motivation score of [6, 10)), μ_{w_i} was set as the benchmark threshold. When the learning motivation of the target participant was high (score [10,16]), μ_{w_i} was then increased to select only difficult test questions (thus less questions) to promote participants to grasp knowledge concepts better and improve the learning effectiveness of target participants.

If the grasping probability of a certain knowledge concept of worker w_i was less than or equal to μ_{w_i}, the knowledge concept was added to a list D_{w_i} as the list of unfinished test questions for target worker w_i, as follows:

$$Q_{w_i}^{\varphi} = \left[q_{w_i}^{\varphi_1}, q_{w_i}^{\varphi_2}, \cdots, q_{w_i}^{\varphi_\theta}\right](\theta \in 1, 2, \cdots, M) \qquad \text{Eq. [7]}$$

Next, the recommendation system combined the list $ER_{q^{\varphi_\theta}}$ of knowledge concepts containing the questions $q_{w_i}^{\varphi_\theta}$ not answered and the list D_{w_i} of knowledge concepts with weak mastery probability. In this way, the system collected the serial No. Of all weak knowledge concepts from the target participant w_i's unfinished test questions. The recommendation degree $P_{w_i q^{\varphi_\theta}}$ of the target participant w_i's unfinished test questions $q_{w_i}^{\varphi_\theta}$ is shown in Equation (8).

$$P_{w_i q^{\varphi_\theta}} = \frac{\left|ER_{q^{\varphi_\theta}} \cap D_{w_i}\right|}{\left|D_{w_i}\right|} \qquad \text{Eq. [8]}$$

Therefore, the recommended priority $P_{w_i q^{\varphi_\theta}}$ in $Q_{w_i}^{\varphi}$ could be calculated. Then, the recommending priority vectors $P_{w_i} = [P_{w_i q^{\varphi_1}}, P_{w_i q^{\varphi_2}}, \cdots, P_{w_i q^{\varphi_\theta}}]$ of all the unfinished questions for w_i were obtained and the top N questions with higher recommendation degree were pushed to the target people.

In this way, the unmastered knowledge concepts were located through the recommendation method based on the knowledge concept mastery probability. The method prioritised the test questions related to the user's weak knowledge concepts. As shown in Table 6, with the respondents first training session data, the method recommended different questions for each respondent in the second session.

5.2. Results analysis

The learning style and learning motivation test results are shown in Table 7. It showed that different users varied in their learning preferences and learning motivations. In this research, most of the respondents (41.67%) were reading users, followed by kinesthetic users (33.33%). The highest score in learning motivation was 8.7, which was more than double the lowest score. 75% of the respondents' learning motivations were medium (from 6 to 10), but a small number of respondents (25%) showed low learning motivation (below 6).

The experiment stopped after ten sessions to examine the performance. Statistics of learners' mastery probability of the knowledge concepts were obtained. Every participant finished 100 tests questions, including all 35 knowledge concepts. Numbers of questions for every knowledge concepts in the question bank were different, yet the proposed BKT method provided diversed recommendations for heterogeneous learners. As shown in Table 8, the performance on 74.3% of all knowledge concepts (26/35) was improved, and the performance on 54.3% (19/35) knowledge concepts was improved more than 50%. Knowledge Concept 12 showed 93% of improvement, which was the greatest.

Fig. 4 shows several important knowledge concepts of representative users were selected to illustrate the changes in training performance. The results showed that the probability of mastering knowledge concepts fluctuated during the training process. Still, an overall upward trend could be observed, indicating that the learners improved their mastery level of knowledge concepts through the proposed safety

Table 5
Learners' knowledge concept mastery probability.

Learner No.	KC1	KC2	KC3	KC4	KC5	KC6
1	0.426	0.426	0.338	0.485	0.375	0.455
2	0.447	0.447	0.311	0.496	0.204	0.439
3	0.615	0.615	0.437	0.577	0.278	0.434
4	0.518	0.518	0.351	0.557	0.234	0.432
5	0.42	0.42	0.337	0.459	0.154	0.334
6	0.523	0.523	0.443	0.516	0.241	0.426
7	0.524	0.524	0.35	0.53	0.348	0.45
8	0.413	0.413	0.351	0.414	0.23	0.238
9	0.425	0.425	0.385	0.425	0.085	0.34
10	0.429	0.429	0.346	0.426	0.165	0.245

Table 6
Recommendation Results in Session 2 of the training.

No.	Recommended Questions									No.	Recommended Questions								
1	55	107	106	105	103	102	101	100	99	54	**7**	5	43	41	42	54	55	100	101	102	56
2	23	120	54	59	112	27	25	111	21	20	**8**	25	73	71	72	66	63	33	32	114	27
3	20	106	107	30	19	116	117	119	120	121	**9**	69	68	27	30	25	23	21	20	73	19
4	56	62	60	59	57	52	47	46	115	61	**10**	25	100	107	133	33	32	29	27	23	21
5	6	78	83	137	116	117	119	77	128	130	**11**	49	130	127	126	124	122	121	120	33	46
6	29	74	42	43	41	112	116	117	78	23	**12**	21	116	20	19	117	119	120	122	121	71

Table 7
Results of learning styles and level of learning motivation.

User number	Learning styles	Learning motivation scores	User number	Learning styles	Learning motivation scores
1	kinesthetic	7.5	7	reading	6.7
2	reading	8.4	8	visual	4
3	auditory	8.2	9	reading	8.7
4	reading	6.1	10	kinesthetic	7
5	auditory	5.7	11	reading	6.8
6	kinesthetic	5.2	12	kinesthetic	6.6

training approach.

Due to the small sample in this research, no questions were recommended twice, but the same knowledge concept could be examined more than once with different questions. It should also be noted that correct answers in the first few sessions did not necessarily indicate the high grasp probability of the knowledge concepts, because the Guess probability (P(G)) could be high in the first few rounds.

5.3. User satisfactory evaluation

The user satisfaction survey was also conducted after all training sessions were completed. All twelve participants provided responses to the survey. The responses are shown in Table 9. It showed that 91.67% of the respondents thought the training questions were understandable and fun, 83.33% of the participants felt that they had gained new knowledge after the training, and 66.67% of the respondents affirmed the effectiveness of the training system in improving the pertinence of training. In general, 83.33% of the respondents were satisfied with the training. Meanwhile, 8.33% of the respondents felt the training questions were relatively unitary and more complicated for adaptive learning.

6. Discussions

Conventional safety training failed to place explicit safety knowledge in the construction site scenes, describe people with their learning characteristics or recommend safety knowledge concepts according to trainees' grasp level of the knowledge. The development of an adaptive learning-based safety training framework, which was based on BKT, was presented in this paper to provide context-oriented training materials with a distinguished description of people's training motivation, cognitive styles, and safety experience, which can address the shortcomings in conventional safety training in the construction industry. The proposed adaptive learning-based safety training framework (system) enables site management to educate and modify unsafe behavior.

Firstly, the proposed framework integrated explicit safety knowledge specified in regulations and implicit safety knowledge in images/videos. By extracting and manifesting photos and correlating them to rules, this research aligned the explicit and implicit safety knowledge concepts to reflect on-site scenarios. In addition, our proposed framework describes the people's learning characteristics. As a result, our proposed framework can provide accurate and distinguished descriptions of trainees to receive personalized recommendations.

Secondly, applying the knowledge tracing model provided an approach to tracing, analyzing, and predicting people's mastery of the knowledge concepts. Conventional methods include a content-based recommendation that matches people's job trades to knowledge concepts without dynamic evaluation of their mastery and collaborative filtering that matches similar people and lack of cognitive explanation. The knowledge tracing method proposed in this research provides the dynamic evaluation and predictions of trainees' cognitive levels. As a result, it is a promising method to improve the adaptive safety training with information technologies.

Dispite the above research outcomes, there are two limitations of the research. Firstly, the proposed framework is a preliminary study executed and evaluated using a conceptual experiment. The proposed framework has only been verified with undergraduate students, and has

Table 8
Knowledge Concepts and their Improvement.

Knowledge Concept	Numbers of Questions	Improvement	Knowledge Concept	Numbers of Questions	Improvement
1	5	60%	19	4	77%
2	1	78%	20	2	79%
3	9	74%	21	4	−17%
4	3	64%	22	6	86%
5	5	−6.10%	23	2	89%
6	1	−4.88%	24	4	39%
7	3	23%	25	8	−1.88%
8	2	63%	26	3	78%
9	2	78%	27	6	65%
10	3	−2.50%	28	3	40%
11	6	87%	29	5	85%
12	5	93%	30	1	−1.40%
13	8	−11%	31	5	−2.30%
14	7	40%	32	1	81%
15	11	67%	33	3	51%
16	1	40%	34	3	−13.30%
17	1	26%	35	2	72%
18	4	28%			

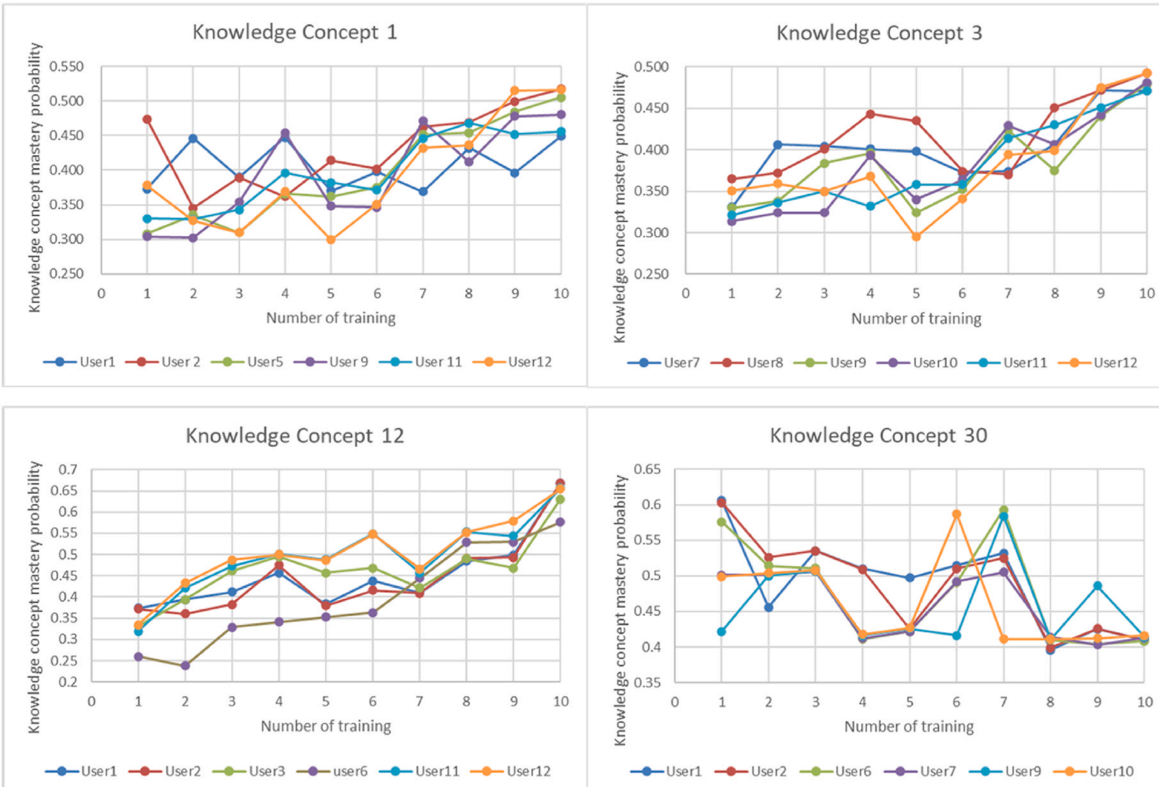

Fig. 4. Grasping probability of knowledge concepts.

Table 9
Responses of the user satisfaction survey.

Question	Neutral	Agree	Strongly agree
I think the training questions are easy to understand	25.00%	66.67%	8.33%
I think the degree of difficulty is appropriate	41.66%	50.01%	8.33%
I think the training questions are interesting	8.33%	58.34%	33.33%
After safety training, I learned useful knowledge	16.67%	66.67%	16.66%
I think this system improves the pertinence of training	33.34%	58.33%	8.33%
Overall, I am satisfied with this safety training	16.67%	33.33%	50.00%

not been measured in real construction sites. Moreover, this study has not compared the proposed training framework with traditional training methods with control experiments. Controlled experiments with participants from real sites with different job trades and different learning characteristics need to be implemented in future research.

Secondly, the knowledge tracing model used in this study is Bayesian-based. Meanwhile, the deep knowledge tracing models are developed that employ deep learning approaches such as Recurrent Neural Network (RNN) (Piech et al., 2015) Memory-Augmented Neural Networks (MANN) (Miller et al., 2016), and Dynamic Key-Value Memory Networks (DKVMN) (Zhang et al., 2017), to accurately describe more learning the statues with much higher volume of learning data in mass online courses. However, the deep learning models required a large quantity of learners' data to generate predictions through neural networks. Therefore, this research could be further improved with more participants from more job trades so that more accurate deep-learning models could be applied.

7. Conclusions

Our research proposed an adaptive learning-based safety training framework that is more situational, accessible, and understandable to heterogeneous people. The measurement survey of learning motivation was developed and embedded in this adaptive system. It also extracted critical safety knowledge from relevant regulations and photos for the behavioral safety knowledge database. In this way, this research formulated a training system with a personalized. Based on the cognitive diagnosis model, learners' answers are evaluated in the training system as input to the recommendation algorithm. We draw the main conclusion as follows:

- ➢ A novel adaptive safety training framework with the BKT model is proposed to improve safety training outcomes in construction. The proposed framework integrated a safety knowledge database with questions from more than 1000 photos and a learner model to differentiate heterogeneous people's learning characteristics from their job trades, learning motivations, work experience, and demographic information.
- ➢ The probability of learners' mastery of 74.3% of knowledge concepts was improved after ten rounds of safety training that included 139 test questions and 35 knowledge concepts, with the most significant improvement of 93%.
- ➢ 83.33% of the respondents felt gained after the training, and 66.67% of the respondents affirmed the effectiveness of the training system in improving the pertinence of training.

Enacting an efficient training system to mitigate unsafe behavior will require further research to automatically integrate computer vision approaches to automatically identify unsafe behavior from the photos. Moreover, in future development and research of this system, wearable devices and sensors should be used to examine learner attention allocation, memory, cognitive load, fatigue, and tension more precisely to enhance training performance.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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