Computers & Education 68 (2013) 199–210

Contents lists available at SciVerse ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

Data mining for providing a personalized learning path in creativity: An application of decision trees

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ARTICLE INFO

Article history:
Received 17 November 2012
Received in revised form
5 May 2013
Accepted 7 May 2013

Keywords:
Intelligent tutoring systems
Architectures for educational technology systems
Teaching/learning strategies

ABSTRACT

Customizing a learning environment to optimize personal learning has recently become a popular trend in e-learning. Because creativity has become an essential skill in the current e-learning epoch, this study aims to develop a personalized creativity learning system (PCLS) that is based on the data mining technique of decision trees to provide personalized learning paths for optimizing the performance of creativity. The PCLS includes a series of creativity tasks as well as a questionnaire regarding several key variables. Ninety-two college students were included in this study to examine the effectiveness of the PCLS. The experimental results show that, when the learning path suggested by a hybrid decision tree is employed, the learners have a 90% probability of obtaining an above-average creativity score, which suggests that the employed data mining technique can be a good vehicle for providing adaptive learning that is related to creativity. Moreover, the findings in this study shed light on what components should be accounted for when designing a personalized creativity learning system as well as how to integrate personalized learning and game-based learning into a creative learning program to maximize learner motivation and learning effects.

1. Introduction

In recent decades, rapidly developing WWW (World Wide Web) and multimedia technology (Multimedia) has been applied widely to teaching and learning (e.g., Lee, 2012; Wang, Jia, Sugumaran, Ran, & Liao, 2011). Web-based learning portfolios can be retrieved and maintained automatically based on the framework of information and communication technology (ICT) when learners interact with an e-learning platform (Chen & Chen, 2009). As a result, learning programs have become more interesting than ever, and learners can learn anywhere on Web-based learning systems. Recently, it has been suggested that a learning system should provide personalized and adaptive learning programs to improve learning via artificial intelligence (AI) or data mining techniques (Chen, 2008). The recommendation that personalized learning systems have adaptive learning mechanisms is based on two rationales (Brusilovsky, 1999): (1) A learning system should provide different learning strategies and an optimal learning path for learners from divergent knowledge backgrounds and with different learning abilities; routine learning materials and paths might not meet the learners' needs. (2) Traditional Web-based learning systems neglect the customization of learning materials to the learners' needs; an adaptive function should be integrated into the learning system to enhance learning.

Creativity is the ability to produce ideas or solutions that are original and appropriate (Cropley, 2000; Mayer, 1999; Zeng, Proctor, & Salvendy, 2011). For people to succeed in this e-learning and information technology-driven society, creativity is required. The cultivation of creativity has, therefore, received a considerable amount of attention in higher education. Although past studies have suggested that both environmental factors (e.g., family environment, school education, and social milieu) (e.g., Csikszentmihalyi, 1996; Simonton, 2000; Tan, 2001) and personal factors (King & Gurland, 2007) influence the development of creativity, personal factors remain the most critical (Yeh, 2011). To date, only a few studies have incorporated personal factors into a learning system that improves the learning of creativity (Jennifer & Jeff, 2012); most of the existing creativity learning systems force learners to follow the same learning path or content (Jeong,

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http://dx.doi.org/10.1016/j.compedu.2013.05.009

Choi, & Song, 2012). To optimize the learning of creativity, a Web-based education system should provide an intelligent learning environment that is tailored to meet the learners' needs (Peredo, Canales, Menchaca, & Peredo, 2011). Data mining, especially with decision tree techniques, has been suggested to be an effective vehicle for meeting individual requirements and enhancing learning efficiency in a Web-based learning environment (Chen, 2008). Therefore, this study aims at developing a personalized creativity learning system (PCLS) in which the decision tree technique is employed to provide adaptive learning paths for college students with varied backgrounds and personal traits.

2. Personalized learning models and techniques

Personalized education aims to provide learners with customized recommendations through interactions and, furthermore, to fulfill the requirements of various learners (Cristobal, Sebastian, Amelia, & Paul, 2009). With the rapid development of e-learning techniques, developing personalized e-learning programs has received a considerable amount of attention. Personalized learning programs empower learners to adjust or create learning paths by themselves (Toh, Chen, Zhang, Norris, & Soloway, 2009). Accordingly, the central advantage of personalized e-learning lies in its ability to meet the needs of diverse students in the current e-learning epoch.

Over the past decade, models have been proposed for personalized learning. For example, Ozpolat and Akar (2009) proposed an automatic student modeling method that is based on a keyword mapping and clustering method. Along the same line, Lee (2012) presented a learning preference forecasting model that classifies learning preferences by preference degrees (Lee, 2012).

In addition, some machine learning technologies have been applied in the development of personalized e-learning. Through machine learning techniques, intelligent agent systems can assist in predicting learners' preferences or needs (Rosa & Alessandro, 2012). For example, clustering and association rule algorithms have been applied in the personalized English Learning Recommendation System (Hsu, 2008). Feature selection can be employed to increase individual learning performance and to release the effects of unnecessary information on decision making (Méndez, Fdez-Riverola, Iglesias, & Díaz, 2006). In the same vein, a fuzzy technique has been employed to determine the difficulty parameters of courseware and to construct the content of courseware for personalized recommendation services (Chen & Duh, 2008).

3. Personalized learning of creativity

3.1. Definitions of creativity

The study of creativity has occurred over the past six decades since it was first advocated by Guilford at the American Psychological Association in 1950 (Guilford, 1987). Definitions of creativity have been proposed by a large number of researchers. Some researchers have defined creativity from a more personal perspective. For example, Franken (1994) declared that creativity is a tendency toward idea recognition, which could be useful in communicating, solving problems, and entertaining ourselves and others. Zeng et al. (2011) noted that creativity is a goal-oriented cognitive process that has various types of expression, such as ideas, solutions, and services. Piffer (2012) claimed that creativity is related to an individual's intention to adopt, use, and appreciate things. Amabile (1996) defined creativity as the production of responses or works that are reliably assessed by appropriate judges as being original.

In contrast, some researchers have defined creativity from a more person–environment interaction perspective (e.g., Mayer, 1999; Yeh, 2004, 2011). For example, Plucker, Beghetto, and Dow (2004) regarded creativity as a perceptible interaction among aptitude, process, and environment. Csikszentmihalyi (1990) proposed the *Systems Model of Creativity* and suggested that three systems highlight creativity, namely the interactions of the field, the domain, and the person. Sternberg and Lubert (1996) proposed the *Investment Theory of Creativity* and claimed that a confluence of six distinct but interrelated resources is required for creativity. These resources are intellectual ability, knowledge, a specific style of thinking, personality, motivation and the environment. Moreover, Yeh (2011) integrated the well-known theories of creativity and concluded that creativity is a process of producing original and valuable products via the interaction of a creative person and the environment, within a specific cultural context. In recent years, it appears that most creativity researchers have focused on discussing the individual talents and traits of creativity (Amabile, Teresa, & Julianna, 2012).

3.2. Personal factors that influence creativity

In this study, we employ Yeh's (2011) theory of creativity and evaluate creativity through participants' abilities to produce original and appropriate solutions while solving problems. Determining what personal traits and educational experience might influence creativity has attracted a considerable amount of attention from researchers (Hwang, Hong, Yang, Chang, & Lian, 2007). Some empirical findings have suggested that college students from different colleges might perform differently in creativity. For example, Haller and Courvoisier (2010) found that differences in creativity exist for science and arts students because of the different thinking styles that are predominant in their professional fields. Complexity domain knowledge generates a variety of types of thinking styles to adapt to situational demands; accordingly, individuals' creativity could vary across domains. Along the same line, Furnham, Batey, Booth, Patel, and Lozinskaya (2011) conducted an in-depth investigation with regard to creativity variables; they concluded that natural science, social science, and arts students have a unique learning style with respect to creativity. Accordingly, the college major can be an important predictor of college students' creativity.

Learning styles are increasingly being incorporated into technology-enhanced learning (Graf, Viola, Leo, & Kinshuk, 2007). It has been suggested that learning styles applied in a creativity training system can enhance the ability of problem solving (Ogot & Okudan, 2007). Learning style is an individual's habitual pattern of acquiring and processing information in learning situations (James & Gardner, 1995). Felder and Silverman (1988) classified learning styles as active or reflective, sensing or intuitive, visual or verbal, and sequential or global. These learning styles could influence creativity in different ways. For example, the sensing/intuitive dimension of a learning style could impact innovation (Graf et al., 2007), and a visual learning style is related to creativity (Annetta et al., 2013). We employed Felder and Silverman's (1988) types of learning styles in this study.

In addition to college majors and learning styles, self-perception of creativity can also be an important predictor of creativity (Cropley & Kaufman, 2012). Self-assessments of our abilities, which often serve as self-fulfilling prophesies, influence what we attempt to do and how much effort we expend (Haimovitz, Wormington, & Corpus, 2011; Hughes, Furnham, Batey, 2012). Moreover, it has been found that self-estimates of our abilities are important not only for self-perception but also for performance (e.g., Ackerman, Chamorro-Premuzic, & Furnham, 2011; Putwain, Kearsley, & Symes, 2012). Therefore, self-perception of creativity could influence an individual's creativity.

3.3. Game-based learning, personalized learning and creativity

Game-based learning is the teaching–learning activities that aim at improving learners' abilities of problem solving by adopting games in educational settings (Kirriemuir & McFarlane, 2004). It usually takes the advantages of computer games technology to create a fun, motivation, and interactive environment (Tang & Hanneghan, 2011). Developing learning programs based on game techniques has been recently regarded as an innovative development in education. A review of related literature shows that games can be a stimulating motivator for students of all ages (Amory, 2011). Prensky (2001) also pointed out that computer and video games are a combination of fun, play, rules, goals, and challenges, which gives learners enjoyment, passionate involvement, and motivation; moreover, the interactive characteristics of games facilitate learning. Therefore, game techniques are included frequently as a positive component of personalized learning. For example, Jung and Graf (2008) proposed an approach to Web-based vocabulary learning via personalized word association games to make vocabulary learning more attractive to learners. Kalloo, Kinshuk, and Mohan (2010) employed personalized game-based mobile learning to help secondary school students improve their mathematical skills. Moreover, it has been found that game scenarios can provide learners with immediate rewards (Burguillo, 2010).

Some researchers have advocated that the school of future should be developed based on the integration of innovation, interactive creativity, and new technology (e.g., Craft, 2005; Natriello, 2007; Sawyer, 2006). Games include problem solving and adaptive learning (Prensky, 2005); via proving challenging tasks and feedback, learners construct their knowledge, develop their innovative solutions of problems, and further spark their flow and creativity (Kiili, 2005; Prensky, 2001). Accordingly, game-based learning should be an ideal tool for creativity learning. However, to date, only a few game-based learning systems for creativity have been developed. For example, Yeh (2012) developed a game-based learning system to provide an interface for evaluating learners' creativity. Chang, Wu, Weng, & Sung (2011) found that game-based learning enhanced motivation and cognitive performance that are essential for creativity. In the same vein, Kangas (2010) employed an innovative playground enriched by technological tools to develop a curriculum-based learning, in which game co-creation, play, and computer games were intertwined. The results showed that integrating a playful learning environment in teaching and learning is an effective way to foster creativity and imagination.

Personalized learning programs empower learners to adjust or create learning paths by themselves (Toh et al., 2009). The aforementioned literature of personalized learning and models indicates that developing personalized learning models has become a new trend in educational training. Moreover, personalized learning has been suggested an effective tool for creativity learning by adapting the individual needs and strengthen learning ability (Aroyo et al., 2006; Lucas, 2001). Accordingly, while personalized learning has a high potential for making learning activities more effective by suiting the learning process to learners' needs and enhancing learner motivation (Amory, 2011; Jeong et al., 2012; Jung, & Graf, 2008; Macro, Agnes, Inmaculada, & Gábor, 2012), game-based learning provides an innovation method for integrating creativity into learning system (Kangas, 2010) as well as makes learning enjoyable and motivates learners to learn (Amory, 2011; Jung & Graf, 2008; Kalloo et al., 2010). Accordingly, integrating these two concepts into a creativity learning system should enhance college students' learning motivation and the effects of their learning on creativity. We therefore incorporate these concepts into the *personalized creativity learning system* (PCLS) (see Fig. 1). Moreover, because personal characteristics, such as the college major, the self-perception of creativity, and the learning style, could influence college students' creativity, this study attempts to integrate these personal characteristics as well as the concepts of personalized learning (personal learning path) and game-based learning into the PCLS to predict an optimal learning path of creativity for college students with varied characteristics.

4. Application of data mining in the PCLS

4.1. Data mining, decision tree techniques, and the PCLS

Employing artificial intelligence (AI) in intelligent learning systems has become a trend in developing learning systems, and there is an increasing interest in employing data mining in educational systems, which makes educational data mining the focus of a new and growing research community (Romero & Ventura, 2007). Recently, data mining techniques, especially the decision tree technique, have been

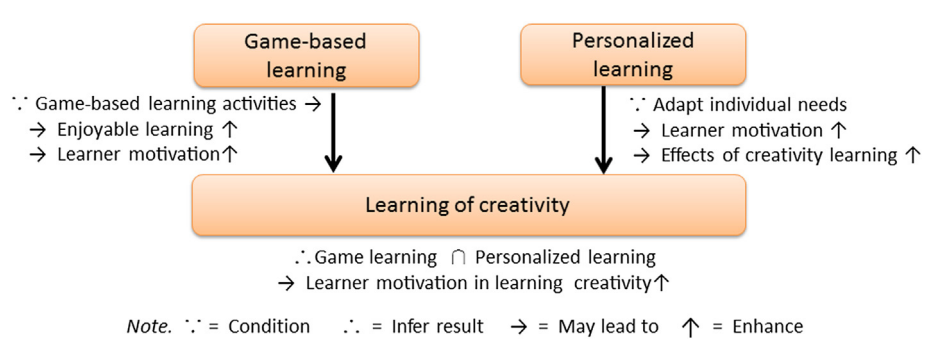

Fig. 1. The relationship between personalized learning, game-based learning, and creativity learning.

regarded as popular personalized learning techniques that are useful for optimizing personal learning (Chen, 2008; Jung & Graf, 2008; Witten & Frank, 2005). Data mining techniques are classified into four main types: classification, association, clustering, and sequential pattern mining. Sequential pattern mining results can provide decision makers with administration references by discovering new patterns from different perspectives and providing integrated information. More specifically, training data can be summarized into information that is based on a tree framework, in which related decision tree algorithms, such as the Iterative Dichotomiser 3 (ID3) (Quinlan, 1986), the CHi-squared Automatic Interaction Detector (CHAID) (Kass, 1980) algorithm, Classification and Regression Trees (CART), and C4.5 (Quinlan, 1996), are used for classification.

Currently, the decision tree technique has been widely applied in learning programs in various domains, such as commerce, marketing, and medicine (Cho, Kim & Kim, 2002; Khaing, 2010). Such a technique has the following strengths (Chien, Wang, & Cheng, 2007; Quinlan, 1996): (1) it reduces the constraints on the scale of the database quality and the variable types; (2) it can analyze both a continuous variable and discontinuous variables efficiently; and (3) its results with graphical or rule expressions can be understood easily and can be explained. Chen (2008) suggested that learning materials based on the tree mechanism can meet individual requirements and can enhance learning efficiency in a learning environment.

Although a few personalized programs have been developed to enhance creativity, some limitations must be addressed. These limitations are related to defined projects, on-demand alternatives, identification of personal needs, and personalized testing. Data mining, especially decision tree techniques, can provide solutions to these problems. Table 1 illustrates how a PCLS with decision trees can improve current limitations in personalized or creativity learning.

4.2. The aims of PCLS

The goal of personalization is to enhance the learning effectiveness and learning efficiency (Chen, 2008). For Web-based learning systems, personalizing curriculum sequencing is an important research issue because the same learning paths cannot meet every individual's needs. Therefore, many researchers have focused on developing e-learning systems with personalized learning mechanisms to assist Web-based learning and to provide adaptive learning paths for different learners. As mentioned previously, the decision tree is a widely applied data mining technique because of its strength in data analysis and its expression (Cho et al., 2002; Khaing, 2010). Therefore, this study attempts to employ the decision tree technique in the development of the PCLS.

In the PCLS, we include important personal factors that could influence creativity and different learning paths. The aim of the PCLS is to provide the learner with an adaptive learning path, based on the college major, self-perception of creativity, learning styles, learning paths, and data on creativity, by which we use the decision tree method to accomplish learner classifications; then, we recommend the most effective learning path for the learner.

4.3. The framework and the characteristics of the PCLS

The architecture of the PCLS is based on a Multi-Agent System (MAS). The developing framework of the PCLS is illustrated in Fig. 2. The PCLS is composed of two parts: personalized learning mechanisms and creativity training. The former is achieved via the construction of a user interface and the application of newly developed techniques for optimizing individual learning, whereas the latter is achieved via knowledge management in creativity-related theories and database administration during the learning process.

Specifically, the characteristics of the PCLS are as follows:

- Application of Web technology: Web technology is not constrained by the location and is suitable for mobile devices; it enhances the convenience of learning.
- Application of Data mining (decision trees) and AI techniques: These techniques are employed to maximize personalized learning and adaptive learning. Based on decision trees, the PCLS can evaluate learning performance and can personalize the learning path to enhance the learner's creativity. Moreover, mining data in a way that is based on statistical theories and algorithms can integrate learning information to form potential educational knowledge, which provides critical information to the teacher and the system developer to establish the learning process and the cognitive load of the learners.
- Application of multi-agents: In the PCLS, real-time learning performance can be efficiently evaluated with multi-agents based on the Web framework. Modulating the learning environment with different types of agents enhances the possibility of future updates and expansion. The Web-based framework in the PCLS is developed via PHP, Net, and JavaScript to enhance user convenience and portability; thus, the PCLS can be adapted to mobile devices such as smart phones and electronic pads.
- Integration of cross-domain knowledge: Creativity training in the PCLS is based on the integration of domain knowledge in psychology (the theory of creativity) and the educational theory of e-learning (game-based learning). Through the design of various types of game

Table 1
The current limitations in personalized learning of creativity and the proposed solutions in PCLS.

Current limitations in the personalized learning of creativity	Proposed solutions in PCLS via a decision tree
• Personalized learning is limited to the scope of the training data set. However, a large amount of data leads to complex projects that are poorly defined.	• Using tree induction techniques can classify and generate rules of a learning path that match the learner's learning traits
• Limited in providing on-demand alternatives.	• To adapt to practical solutions, the decision path could be verified by comparing the training part and the actual result.
• Weak in independently distinguishing each of the learner's needs.	• Specific feature selection for discovery of the potential parameters with gain ratio calculations.
• Lacks sufficient advances in the testing and consideration of user needs after implementation.	• One part of the data is defined as a decision node and is employed for training.

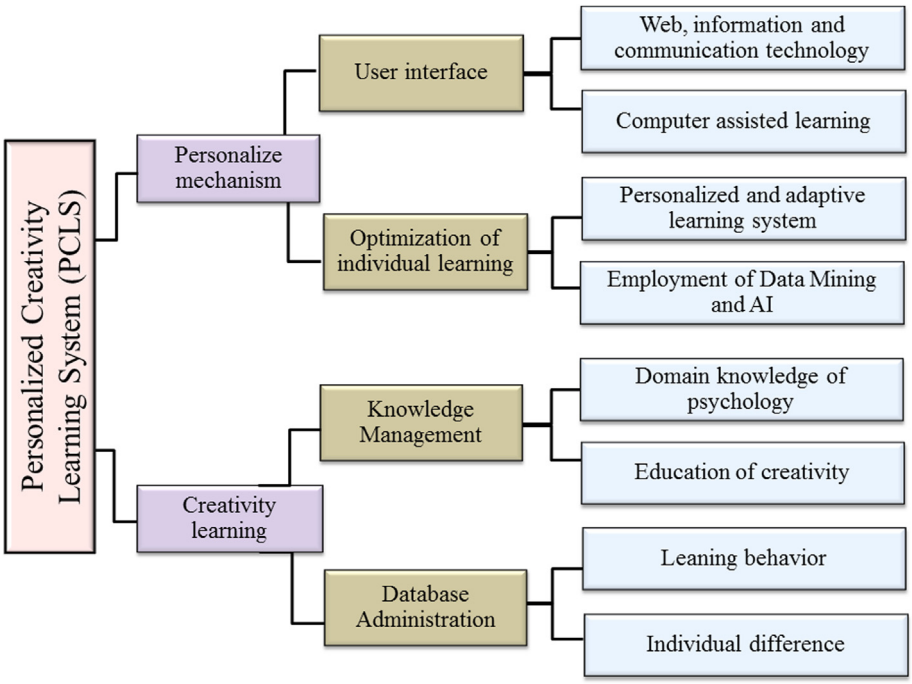

Fig. 2. The development framework of the PCLS.

scenarios and interactive mechanisms in real-time responses, the PCLS can provide the learner with real-time information and can adjust the learning path immediately via an agent system to maintain the learning quality and to increase the learner's motivation.

5. Methodology

5.1. Experimental design and participants

In this study, we developed the PCLS, and we used real data to illustrate how the proposed decision tree algorithm can be employed to personalize an individual's learning path for creativity. The data were obtained from 92 college students whose ages were between 18 and 26 years. The participants completed the experiment in approximately half an hour. They were paid US $5 dollars to participate. Moreover, we employed a rule-based agent to collect information on the participants' learning processes as well as their demographic variables and their ability to be creative. The collected information is displayed in Table 2.

5.2. Instrument: the PCLS

The PCLS, a Rule-based agent system, was intended to customize the creativity learning system by mining learning information. The system was primarily composed of four agents, namely, the User Interface Agent, the Creativity Game Agent, the Path Agent, and the Questionnaire Agent. Moreover, the techniques employed by the PCLS included knowledge retrieval, decision tree algorithms, and feature selection (see Fig. 3).

Table 2
Variables included in the PCLS.

Variables	Description	Type
Student ID	Identify sample	Numerical
Age	18–26 years old (mean = 21)	Numerical
Gender	Male (52%); female (48%)	Categorical
College Major	Science (type = 1): 22%; engineering (type = 2): 16%; liberal arts (type = 3): 25%; social science (type = 4): 25%; business (type = 5): 12%	Categorical
Creativity	Three creativity scenarios were included; the highest total score was 30 points (10 points in each scenario). 1 = correct answer; 2 = incorrect answer.	Numerical
Creativity learning path	Six types of learning paths were included (3! = 6)	Categorical
Learning style	Four types of learning styles were included: 1 = active or reflective; 2 = sensing or intuitive; 3 = visual or verbal; 4 = sequential or global.	Categorical
Self-perception of creativity	Likert's five point: 1 = strongly agree; 2 = agree; 3 = neural; 4 = disagree; 5 = strongly disagree	Categorical

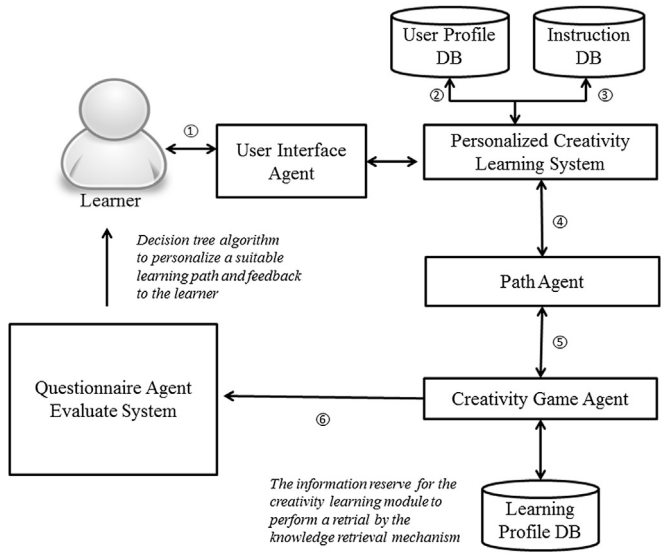

Fig. 3. Agent structures of the PCLS.

5.2.1. User Interface Agent

Through the User Interface Agent, the learner provided personal information that was required to register for an account. The personal information included the student's ID, age, gender, and college major. After a learner logs into the system, the User Interface Agent checks the validity of the user account by using the profile database.

5.2.2. Creativity Game Agent

In this study, the Situation-based Creativity Task (SCT) was employed to evaluate the participants' creativity (Yeh, 2012). The SCT, which was developed by Flash, was composed of situation- and game-based creativity tasks. The Creativity Game Agent built in the PCLS included three game scenarios from the SCT: the living room, the kitchen, and the bathroom. These game scenarios were designed to measure the participants' creativity, which is defined as the ability to produce original and appropriate solutions while solving problems (Yeh, 2011). In each game scenario, the learner was prompted to solve 10 problems by combining 2 items (e.g., balloon + vacuum cleaner) so that he/she could escape from the situation and win the game (see Fig. 4). The Creativity Game Agent was employed to administer the game scenarios. In each scenario, the primes of correct answers were provided; while a correct answer was scored as 1 point, an incorrect answer was scored as 0 point. The highest total score was 30 points (10 points in each scenario). All of the information from the learning processes that were obtained from each game scenario was saved in the Learning Profile Database.

5.2.3. Path Agent

The PCLS included three creativity game scenarios, and the order of the scenarios was a controlled variable in this study. The creativity game scenarios were presented in a random order. Accordingly, the game expression types included six ($3! = 6$) combinations, and the Path Agent automatically assigned a learning path to each learner.

5.2.4. Questionnaire Agent

The aim of the Questionnaire Agent was to analyze the learning information through feature selection and decision tree algorithms. Then, the PCLS identified potential features for decision variables and provided optimized results for learning with regard to the creativity of the learner.

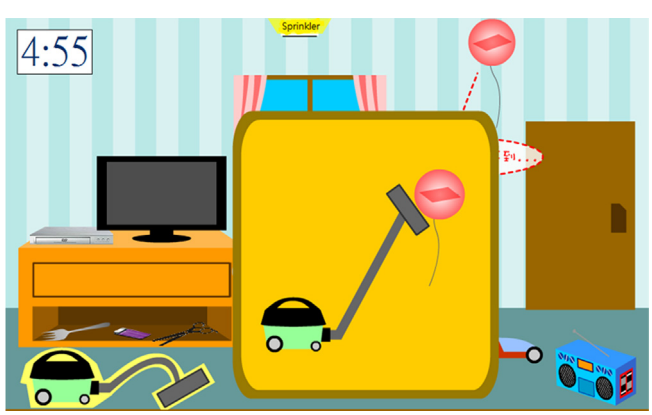

Fig. 4. The living room scenario in the PCLS.

5.2.5. Knowledge retrieval technique

In the PCLS, the creativity learning module saved rules into the knowledge database, and learning information was analyzed by the questionnaire agent. The rule-based agent system was a set of agents and creativity learning modules. The repeated decision algorithm training improved the intelligence of the rule-based agent, enhancing the learning of creativity. Accordingly, the PCLS could personalize student learning procedures as well as provide suggestions based on input information. In the PCLS, we expected that the knowledge retrieval and rule suggestions provided by the rule-based agent system could give learners an optimal learning path and, therefore, enhance their creativity.

5.2.6. Decision tree algorithm

Compared to other algorithms, decision tree algorithms are more powerful for analyzing the relationship between independent variables and dependent variables because of the tree searching schema (Barros, Basgalupp, Carvalho, & Freitas, 2012). In this study, we used the C4.5 decision tree algorithm and the central trend theory to classify the data. To ensure the consistency of the experiments, at least one node was set in each tree to avoid errors from a dramatic change in the variance. When the value of one node was less than the values of the other nodes, the calculation mechanism deleted the node during optimization of the tree path with entropy. Next, the second highest ratio variable was employed in the first procession result. In this study, we used the learning path as a branch guideline when creating the nodes.

5.2.7. Feature selection

The aim of feature selection was to choose the most significant features and to analyze the correlations between the significant features and the forecast variable. Feature selection not only enhanced the accuracy but also increased the performance of the personalized learning path. In the feature selection module, the parameters included the college major, and the forecast variable was the creativity ability. To normalize the features, the formula for the Gain Ratio (equation (1)) was used to calculate the ratio between each feature and the forecast variable.

$$Gain\ ratio = \frac{\left(Entropy_{before} - Entropy_{after}\right)}{Split\ \ gains} \tag{1}$$

5.3. Procedures for collecting data

All of the participants participated in the experiment in a computer lab. The experimental procedures were completed on a desktop computer with a 19-inch screen. Fig. 5 illustrates the procedure of the experiment in this study. First, game instruction was conducted to allow participants to learn the procedure of the experiment. Then, we collected real data for this study via the PCLS. The working procedures were as follows:

- Step 1: The learner registered personal information with the User Interface Agent.
- Step 2: After the learner logged in to obtain permission, the system verified the identity of the user.
- Step 3: An instruction screen was displayed. To ensure that the learner completely understood the procedures for how to complete the tasks in the PCLS as well as how to increase the reliability and validity of the collected data, the instruction subsystem was designed in the PCLS.
- Step 4: The Path Agents generated a learning procedure at random as a learning pathway for the learner.
- Step 5: The Creativity Game Agent prompted the learner to solve problems in the games. Upon completion of the games, the Creativity Game Agent integrated all of the information into the Learning Profile Database. To administer the knowledge in the creativity learning

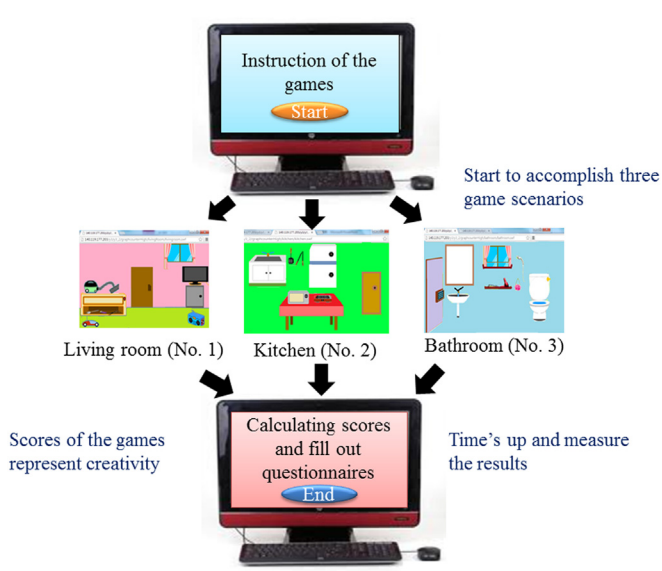

Fig. 5. The procedure of the experiment and the game scenarios.

Table 3
Gain ratio results.

Variable	Gain ratio	Priority
College major	0.087	1
Learning path	0.064	2
Self-perception of creativity	0.031	3
Learning style	0.013	4
Gender	0.006	5

activities, the knowledge retrieval mechanism, which organizes rules based on decision variables (the college major) in the knowledge database, was employed to acquire useful information.

- Step 6: The Questionnaire Agent used the decision tree algorithm to analyze learning information. Feature selection was also employed in the algorithm to determine the potential features of the decision variables. Then, the PCLS provided the optimized learning results to the learner based on the student's college major and creativity.

6. Experiment result

6.1. The preprocessing of the data

Preliminary analysis revealed that the decision tree is efficient when analyzing nominal variables. Therefore, we classified the creativity ability into 2 groups (High vs. Low) by the cut-point of the median.

The main contributions of the PCLS are evaluating the features that are related to creativity learning and personalizing the learning path with the decision tree algorithm. These two contributions are analyzed separately in this study.

6.2. Feature selection

To find effective predictors of creativity, the PCLS included five features. In this process, creativity was determined by the scores that were obtained from the game scenarios; while the scores in the top 50% were defined as "high creativity", the scores in the bottom 50% were defined as "low creativity". The results of the feature selection reveal that only two features that were employed in this study have a gain ratio that is greater than 0.05, namely, the college major and the learning path. The order of the five features is as follows: college major, learning path, self-perception of creativity, learning style, and gender (See Table 3). In other words, the college major and the learning path are important predictors of creativity. Therefore, we chose these variables as features and included them in the decision tree algorithm to examine their relationship to creativity.

6.3. Learning path analysis

The college major has the highest gain ratio; therefore, it has priority when entering the decision-making module. Fig. 6a illustrates the decision results for the creativity and the college major. These findings reveal that participants from the college of Science (type 1) have a high level of creativity.

Next, we apply the second highest ratio variable—the learning path—to the first procession result. In this study, we use the learning path as a branch guideline for creating the nodes. Consider the science college, for example, because approximately 71% of the participants have high creativity scores at the first stage. We take the learning path into account in the second stage. The result shows that 100% of the participants obtain higher creativity scores in the learning path "123" than in the other paths (see Fig. 6b). Accordingly, the logic editor retrieves this information and transfers the information into a rule, as in equation (2).

$$College_{science} \cap Path_{123} \rightarrow Higher\ \ Score_{Creativity} \tag{2}$$

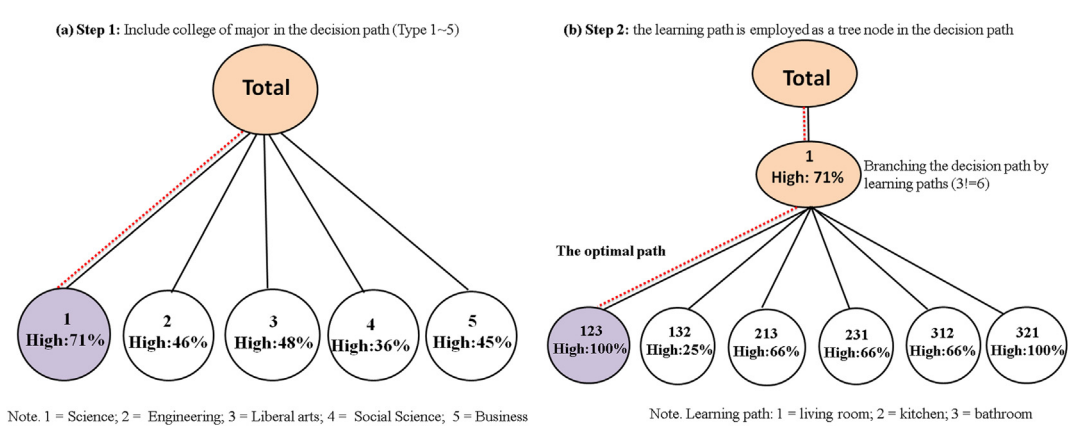

Fig. 6. Analyzing the decision tree model based on college majors and learning paths.

Table 4
The learning paths and the perceived difficulty of the game scenarios for the different college majors.

College major	Possibility of enhancing creativity		Suggested path	Difficulty order of game scenarios
	With random path	With suggested path		
Science (1)	71%	100%	123	3 > 2 > 1
Engineering (2)	46%	75%	312	3 > 2 > 1
Liberal arts (3)	48%	100%	132	2 > 1 > 3
Social science (4)	36%	100%	321	2 > 1 > 3
Business (5)	45%	100%	231	2 > 3 > 1

Moreover, when the participants employ the suggested optimal learning path, they have a 90% chance of obtaining an above-average score for creativity, and they have only a 10% chance of obtaining a below-average score for creativity (see Table 4). In contrast, when the participants employ a randomly assigned path, they have a 52% chance of obtaining an above-mean score for creativity and a 48% chance of obtaining a below-mean score for the creativity. The results also show that participants from different colleges have distinct learning paths for creativity.

To provide a supplementary explanation of the suggested path, we analyzed the questions that pertained to the participants' self-perception toward the games. The questions were as follows: (1) Question 1 (living room): I thought that the game was difficult in the living room scenarios. (2) Question 2 (kitchen): I thought that the game was difficult in the kitchen scenarios. (3) Question 3 (bathroom): I thought that the game was difficult in the bathroom scenarios. The results indicate that participants with different majors have different perceptions toward the difficulty of the game scenarios (see Fig. 7). For example, participants from the colleges of Science and Engineering feel that the bathroom scenario (No. 3) is the easiest, the kitchen scenario follows (No. 2), and the living room scenario is the most difficult (No. 1).

Moreover, participants from the colleges of Science, Liberal arts, and Social Science appeared to benefit more when they started with the most difficult game scenario, whereas participants from the colleges of Engineering and Business appeared to benefit more when they started with the easiest scenario. These results show how perceptions toward the difficulties of the game scenarios employed are related to the suggested paths.

7. Discussion

Providing a personalized or adaptive learning path has become a trend in education because a single learning path cannot meet every learner's requirements (Kalloo et al., 2010; Peter, Andreas & Tobias, 2010). Moreover, to succeed in this rapidly changing and information technology-driven society, creativity has become even more important than ever. The uniqueness of learning styles exists because individuals are engaged in learning based on personal learning interests (Lau & Yuen, 2010). Learning types, learning scenarios, and the order of learning are usually fixed in e-learning systems; as a result, little chance for adaptive learning is provided with regard to personal learning styles. Personalized learning has a high potential for making learning activities more effective (Amory, 2011; Kalloo et al., 2010; Macro et al., 2012; Peter et al., 2010). The development of data mining techniques, especially the decision tree technique, has provided a possible vehicle for customizing the learning environment to optimize personalized learning in creativity. Accordingly, this study aimed to develop a personalized learning system, the PCLS, to improve college students' learning of creativity via the data mining decision tree algorithm. The experimental results reported here suggest that our goal was successfully achieved. The findings of this study also lend support to the beliefs that personalized learning can make learning activities more effective by tailoring the learning process to learners' needs (Amory, 2011; Macro et al., 2012) and that game-based learning can enhance learning motivation (Amory, 2011; Kalloo et al., 2010). These two concepts can be integrated into a creative learning program to maximize learning motivation and the learning effect of creativity.

Internet applications have flourished, and Web-based techniques have been widely applied in teaching materials (Liu, Li, Pan, & Li, 2011). To make the PCLS more interesting and efficient, we employed a substantial amount of Web-based and information technology as well as computer-assisted learning techniques. Moreover, to optimize and customize personal learning paths for learners, we developed a training algorithm for the framework of the decision tree that incorporates the statistical central trend theory into the weight setting of each node. The experimental results reveal that the proposed training algorithm contributes to enhancing creativity performance. In the PCLS, we include the college major, gender, and learning path of participants as predictors of creativity. The gain ratio analysis shows that the college major and the learning path are important predictors, whereas gender is not, which demonstrates that educational training (or college major) (Furnham et al., 2011; Haller & Courvoisier, 2010; Hwang et al., 2007) and personalized learning are important factors in the learning

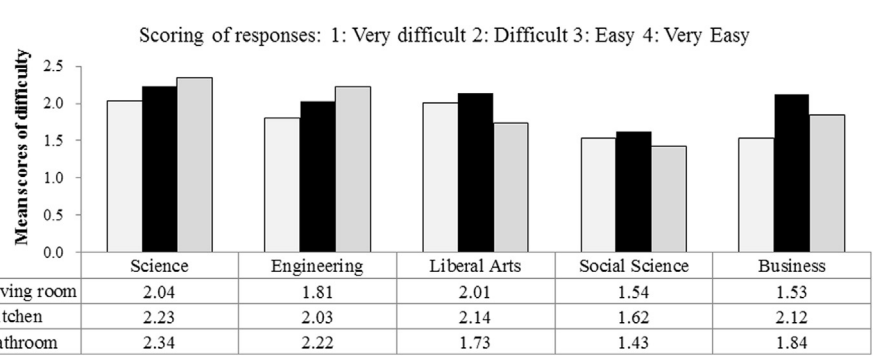

Fig. 7. Perceived difficulty toward the game scenarios.

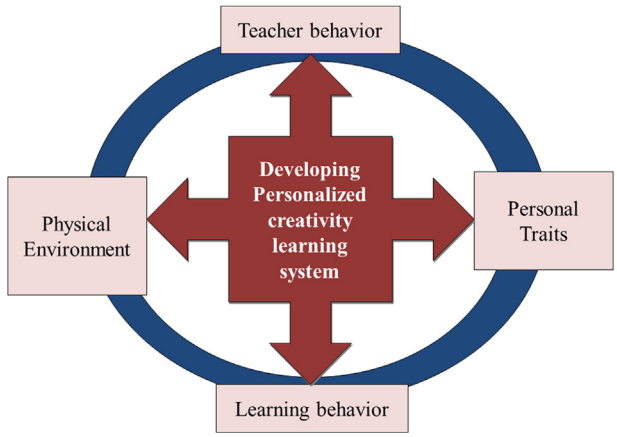

Fig. 8. The critical value of the PCLS.

of creativity. Notably, when using the college major as the first variable in the decision tree algorithm, the participants had a 90% chance of obtaining an above-average score for creativity, a result that is much higher than that (52%) obtained when a fixed path is employed. Strong evidence suggests that creativity is correlated with the domain of specialization. Accordingly, the proposed decision tree algorithm is highly accurate in predicting the optimal learning path for creativity, which supports the claim that learning materials based on the tree mechanism can meet individual requirements and can enhance learning efficiency (Chen, 2008).

In interpreting the influence of the learning path, we also analyzed the participants' perception toward game scenarios. The findings suggest that a degree of difficulty exists between the game scenarios, and the order of difficulty is different when examining the scenario as a whole and when examining the scenarios separately, for each college. Overall, the difficulty order of the game scenarios was as follows: bathroom, living room, and kitchen. These findings suggest that the perceived difficulty of the tasks is a mediator that can be used to improve the learning effects of creativity.

The PCLS provides valuable implications for designing a personalized learning system for higher-level thinking such as creativity. A successful personalized learning system should consider four aspects: the learning behavior, the physical environment, the personal traits, and the teacher behavior (see Fig. 8). In the PCLS, learning behaviors and information are recorded in the knowledge database; such information can be retrieved or maintained through a knowledge management approach. The learner can also administer the environment via knowledge management. When the learner receives feedback, the teacher can also receive training knowledge, which will help the teacher to determine the learner's cognitive loading status in the system. Moreover, in the PCLS, the decision tree method can recommend the best learning path for learners who have different personal traits based on learner classification. Accordingly, the PCLS can help teachers to understand the cognitive process of learners, to allow them to adapt their teaching behavior efficiently.

8. Conclusions and suggestions

Customizing the learning environment to optimize personal learning has become a popular developing trend in e-learning. In this study, we select an essential ability for college students, creativity, as an example to demonstrate how to develop an effective personalized learning system. To improve the limitations of creativity learning systems as well as to enhance learning motivation and outcomes, we develop the PCLS by integrating personalized learning theories, hybrid decision trees (which are a data mining technique), and game-based learning. More specifically, the PCLS that is developed here is characterized by the application of information and Web-based technologies, the application of data mining (decision trees) and AI techniques, the application of multi-agents, the integration of cross-domain knowledge, and the use of an on-line learning environment. The findings in this study suggest not only that the personalization aspect of the system helps learners to choose their optimal learning path but also that the game aspect of the system can make learning enjoyable. Moreover, the findings shed light on the components that should be accounted for when providing immediate feedback to the learner and the teacher to help them tailor their learning behavior or teaching behavior and to optimize the training effects.

In this study, because of the limited sample size, we could not include additional personal traits in the decision tree process. Future studies should increase the sample size and include more important personal traits to enhance the effect of personalized learning. Notably, the PCLS can be used as both the evaluation tool of personalized creativity learning as well as the personalized training system of creativity. This study mainly applies the PCLS as an evaluation tool to predict the personalized learning path for creativity. Follow-up studies can further use the PCLS as a training system to enhance college students' creativity. Moreover, we found that the perception of task difficulty could be a mediator in a personalized learning system. Whether there are other important mediators is a question that is worthy of exploration. Finally, because multi-agents are employed in the PCLS, future studies should adapt the PCLS to widely used mobile devices such as smart phones and electronic pads, which will address the need for ubiquitous learning.

Acknowledgment

The authors would like to thank the National Science Council of the Republic of China in Taiwan (Contract No. NSC 100-2511-S-004-002-MY3 and NSC101-2420-H-004-014-MY2) for financially supporting this research.

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