Designing and Developing a Novel Hybrid Adaptive Learning Path Recommendation System (ALPRS) for Gamification Mathematics Geometry Course

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ABSTRACT
Since recommendation systems possess the advantage of adaptive recommendation, they have gradually been applied to e-learning systems to recommend subsequent learning content for learners. However, problems exist in current learning recommender systems available to students in that they are often general learning content and unable to offer personalized service. To overcome this, in the context of a learning style based on an Interpretive Structural Model (ISM), an adaptive learning path recommendation system is proposed comprising: (a) Fuzzy Delphi Method, (b) Fuzzy ISM and (c) Kelly Repertory Grid Technology. The results show that the learning outcome with ALPRS is better than those from general learning course guided recommendation mechanisms, and the scores of system satisfaction with ALPRS and personal service are higher than 90%. Results of recall (95%), precision (68%), F1 index (45%) and MAE (8%) prove that ALPRS outperforms other approaches. Finally, three contributions are offered in this study:(1) a novel hybrid ALPRS is proposed and its practicability is tested; (2) a prototype gamification geometry-teaching material module is developed for the promotion in MSTE (Mathematics, Science and Technology Education) areas; (3) the adaptive geometry-learning path diagram generated with ISM based on learning styles could offer a basis for further studies.
Keywords: Mathematics education, Intelligent Learning Recommender System, Gamifying, Learning Style, Kelly Repertory Grid

INTRODUCTION

Following the boom of digital media in recent years, much teaching material now incorporates the characteristics of entertainment multimedia, applying the design idea of gamification, and allowing e-learning to move towards gamification design in order to reinforce learning. Mathematics, as a logic and symbolic language with high complexity, presents functions that express the relationship of quantity, space, time, shape, distance and order (Brown, 1953). It is therefore very possible to assist learning with digital interactive multimedia teaching

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State of the literature

- To construct an adaptive learning path recommendation system (ALPRS) through expert knowledge to improve the shortcomings of traditional recommendation systems.
- The research has indicated that learning styles affect learners' preferences for specific teaching materials and the learning outcome, as well as the selection of a learning unit path.
- Learning styles therefore should be regarded as an important learning recommendation element.

Contribution of this paper to the literature

- The novel hybrid adaptive learning recommendation system (ALPRS) was proposed and its practicability tested.
- A prototype gamification geometry teaching material module was developed for the promotion in MSTE areas.
- The adaptive geometry learning path diagram generated with ISM-based on learning styles could serve as a reference for further studies.

materials. Mathematics learning in elementary schools contains five major topics: Number and Quantity, Geometry, Algebra, Statistics and Probability, and Cawley (1984) proposed the following factors in mathematics learning difficulties: (1) mathematics instruction, including unsuitable teaching materials and bad learning methods, (2) psychological function, containing difficulties in short-term and long-term memory obstacles, communication and discrimination, (3) physiological function, covering visual, auditory and movement obstacles and (4) environment, including inadequate resources and equipment. Donoghue (2003) also points out the importance of geometry education and regards geometric learning as brain training as geometric proofs could also train logical reasoning and demonstration abilities. In this case, integrating a geometry unit in mathematics into the learning recommendation system to assist in learning and solving mathematical learning difficulties has become a primary issue in mathematics education.

The "Recommendation system" (RS), first proposed by Resnick and Varian (1997), is based on user needs to make decisions among numerous and complex choices (Selin, 2002), allowing users to shorten thinking time and to quickly make choices. The current Internet recommendation system technology and approaches could be divided into (Schafer, 1999): (1) non-personalized recommendation, (2) attribute-based recommendation, (3) item-to-item correlation and (4) personal-to-personal correlation recommendation. The emergence of personal service has many companies preferring to use RS to directly attract customers concerned about certain products (Linden, Smith & York, 2003; Schafer, Konstan & Riedl, 1999). Customers would further acquire personal service information through RS and choose the information of interest in advance (Adomavicius & Tuzhilin, 2005). Such integrated adaptive service is therefore broadly applied to the recommendation mechanism of commercial products (Klašnja-Milićević et al., 2011; Hsu, Hwang & Chang, 2010).

As RS shows the advantages of adaptive recommendation, it has been gradually applied to e-learning systems to recommend subsequent learning content for learners (Kristofic, 2005). Many current learning recommendation systems do not consider the advantage of adaptation (Emurian, 2006; Holland, Mitrovic & Martin, 2009; Sykes & Franek, 2003); unsuitable course content results in poor learning intentions and inferior learning effects. For this reason, many researchers have seen the need to study the difference in learning outcomes with the Kolb (Kolb, 1984) and Dunn and Dunn (Dunn, Dunn & Freeley, 1984) learning style models in adaptive learning, and to apply various approaches to understand learners' learning styles, e.g. tracking a learner's learning process or learning content to infer the learning style (Kelly & Tangney, 2004). After acquiring learners' learning styles, the system could present adaptive teaching materials with the most suitable learning sequence, and track and analyze educational resources for different styles (Ivanovic, Pribela, Vesin & Budimac, 2008). When learners' styles are taken into the consideration via a recommendation mechanism and active participation and users' interactive learning of the learning recommendation system are reinforced, learning outcomes would be maximized, thus achieving the recommendation purpose. Therefore making a learning recommendation system more adaptive with better learning effect becomes an important issue.

Most adaptive recommendation systems are applied to business fields, so it is necessary to reinforce recommendation systems for education and learning. The adaptive learning recommendation system technology becomes successful with the establishment of personal learning styles and learning paths, and with the integration of the functions of gamification learning. Geometry for G5 and G6 is used as the recommendation learning content. Accordingly, addressing problems in relevant literature, this study aims to:

(1) integrate a novel hybrid approach to propose an adaptive learning recommendation system (ALPRS) and test its practicability.

(2) develop a prototype gamification geometry-teaching material module, which could be promoted in MSTE (Mathematics, Science and Technology Education) areas.

(3) output an adaptive geometry learning unit path diagram through ISM.

LITERATURE REVIEW

Gamification learning

Gamification refers to using game design items and features for non-game content (Deterding et al., 2011), whereby it can also be broadly applied to education, especially in lerning achievement (e.g. score, virtual currency, grade) to the interactive environment of community learning sharing. Past research indicates that gamification learning could effectively enhance learning intention and reinforce learning outcomes (Simões, Redondo & Vilas, 2013; Hamari & Koivisto, 2015); research also mentions that students consider gamification learning as being easier than other learning methods (DeVries and Edwards,

1972). Prensky (2001) argues that a competitive/cooperative spirit is induced in a game, and that learning may be achieved through playfulness, achievements and meeting challenges. Brophy and Good (1986) consider that embedding repeated practice in games helps memory and learning intention. Games could also provide continuing practice, following, which learners could acquire greater accuracy and improve their memories (Driskell, Willis and Cooper, 1992). Research has also pointed out several functions of games, such as instruction, entertainment, assisting in exploring new skills, promoting self-esteem, practicing skills and changing attitudes, thereby imparting great value to education (Dempsey, Lucassen, Haynes and Casey, 1996).

Fuzzy Delphi Method

The Delphi Method (DM), first proposed by Dalkey and Helmer (1963), mainly acquires reliable consensus through a group of experts (Mereditha, Raturia, Amoako-Gyampahb & Kaplana, 1989). However, traditional DM, requiring 3-4 rounds of opinion collection, results in low expert opinion convergence, high execution costs and easy loss of precious opinions (Kuo & Chen, 2008; WANG, YEO & NG, 2014; Kardaras, Karakostas & Mamakou, 2013). Accordingly, Klir and Folger introduced Fuzzy Theory into DM, as the Fuzzy Delphi Method (FDM), to improve handling problems in the traditional Delphi Method (Murry, Pipino & Gigch, 1985). The advantage of doing this is that it merely requires one round of expert opinions to achieve opinion convergence and consensus. In this case, all expert opinions are respected and taken into account. Common fuzzy membership functions contain Triangular Fuzzy Number (TFN), Trapezoidal Fuzzy Number and Gaussian Fuzzy Number (Hsu et al., 2010).

Learning style

Based on human psychological learning theories, Kolb (1984) developed four learning areas of readiness: thinking, feeling, listening and practicing. Such readiness can be seen in the contrast of continuing features of information processing methods and information receiving preference from four directions of concrete experience (CE) versus abstract conceptualization (AC) and active experimentation (AE) versus reflective observation (RO), as depicted in **Figure 1**. All learning behavior may be represented by knowledge transformation composed of two dimensions and four learning stages. Consequently, learning style contains four learner characteristics: divergers, assimilators, convergers and accommodators (Truong, 2016; Chang, 2015). A learner's learning method, thinking style and strategy were correlated with the learning outcome; especially in nursing, language, building design, mathematics education and programming (Cano-García & Hughes, 2000; Kvan & Jia, 2005; Baker, Pesut, McDaniel & Fisher, 2007; Gyeong & Myung, 2008; Hauer, Straub, & Wolf, 2005) the reinforcement effect on learning has been proved. Research has further indicated that accommodators and assimilators can easily accept new and different learning methods (Su, 2006), while divergers have difficulty in accepting them (Lin & Yang, 2010). Moreover, accommodators' achievements in learning outcomes are better than divergers' in e-learning and teaching
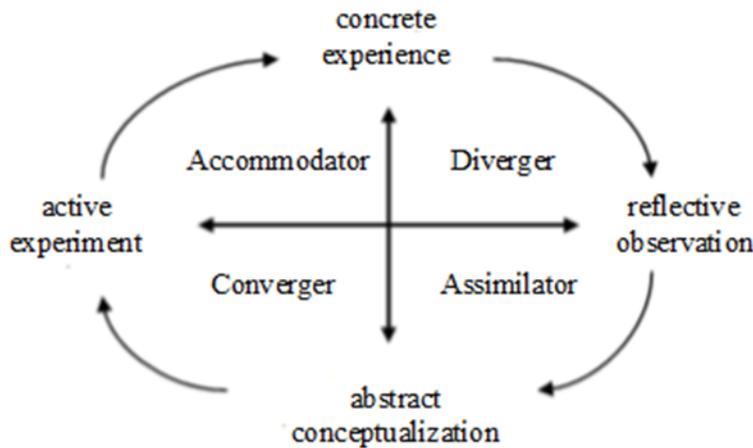
Figure 1. Learning style quadrant diagram

methods (Chang & Huang, 2008). Accordingly, learning style can be suitably applied to the adaptive recommendation system in this study.

Interpretive Structure Model (ISM)

ISM, as a structure modeling (Warfield, 1976), can turn complex elements into an orderly organization to effectively classify the mutual effect among elements. Graph theory and hierarchical diagrams are mainly utilized for describing the order of the logical relationship of target elements, and for presenting abstract element sequences with specific and comprehensive structurally hierarchical graphs (Jharkharia & Shankar, 2004). Computers can assist a group in constructing the collected knowledge for a dialogue among group members to effectively enhance the use and efficiency of knowledge when a group faces interactive learning and decisions for some complex systems and issues (Hwang & Lin, 1987). Hsiao (2013) discusses the problems in product design with ISM and MICMAC in construction of a hierarchical model. Based on such a model, the influence and dependence of all factors in the entire system can be clearly presented and the interaction among factors can be reflected, so that researchers can intuitively understand the changes of the entire system and the components. ISM has recently become an effective method to analyze system elements and solve complex and multi-relationship technology in design environments (Dubey et al., 2015; Beikkhakhian et al., 2015). As a result, the introduction of ISM to research could effectively solve the correlation path problem in the complex structure of course units.

Repertory Grid Technology

Repertory grid technology (RGT) is applied to explore teachers' teaching beliefs after organizing Kelly's (George Kelly, 1955) Personal Construct Theory. Such interviews can help teachers express and construct their teaching beliefs in their own words, and are more meaningful than paper tests. Applying such a method allows teachers to describe their teaching behavior and to write their responses on cards for classification and analyses, as well

as to construct experts' knowledge and characteristics through the experts' classification process. The repertory grid therefore is a kind of semi-structural interview, and the major contents of elements, constructs and linking mechanism are induced through dialogue and interaction between researchers and experts or knowledge workers in seeking similar attributes to distinguish data with different attributes (Keynan, Assaraf & Goldman, 2014; Yeh & Cheng, 2015). RGT used to be applied to psychology, as it could clearly and reliably describe a person's thinking methods, and was then broadly applied to other fields (Ben-Zvi Assaraf & Orion, 2010a,b; Bencze, Brown & Alsop, 2006), such as applied technology education, including earth science cognition (Bezzi, 1999); higher education (Nicholls, 2005); museum learning education (Canning & Holmes, 2006), and environmental literacy education for junior high school students (Goldman, Ben-Zvi Assaraf & Shaarbani, 2013).

ADAPTIVE LEARNING PATH RECOMMENDATION SYSTEM (ALPRS)

The adaptive learning path recommendation system (ALPRS) proposed in this study could present a course unit with distinct learning paths according to learners' learning styles, and solve the shortcomings of previous research which failed to give recommendations aimed at users' particular learning characteristics and styles. In this case, ALPRS would handle the inferences, aimed at learners' styles and characteristics, to find the most suitable learning unit path for satisfying their learning needs. The design principles and methods are described below. The ALPRS flow chart is shown in **Figure 2**, and is divided into three processing stages: (1) data processing, (2) modeling and (3) recommendation and evaluation, detailed in five major steps.

The required learning unit for the adaptive learning path recommendation system (ALPRS) is based on geometry learning indices for G5 and 6 as regulated by the Ministry of Education. The course unit is based on existing literature, advice from 13 mathematics education experts, and according to geometry learning indices. The experts complete the course unit list based on the FDM steps for successive recommendation and evaluation of unit attributes. Each expert was further charged with the responsibility of ensuring the provided course unit conforms to the learning indices. Furthermore, ALPRS would proceed with data preprocessing, aiming at the geometry learning unit; the learners' style category would be established based on Kolb's learning style scale, which also calculates the integral of concrete experience (CE), abstract conceptualization (AC), active experimentation (AE) and reflective observation (RO). The scores of the learners' information receiving preferences and information processing methods are then calculated for the coordinate quadrature of learning style to form four types of learning styles: divergers, assimilators, convergers and accommodators. After establishing these four learning styles, the category is combined with ISM to generate the adaptive learning path diagram. The ISM generates the adjacency matrix and relationship graph through the geometry unit established by the experts. The achievement matrix of the geometry unit is then generated, and the learning path diagram of learning styles is eventually completed. Repertory Grid Technology (RGT) is utilized for determining the adaptive learning recommendation rules, where the experts extract all learning style elements
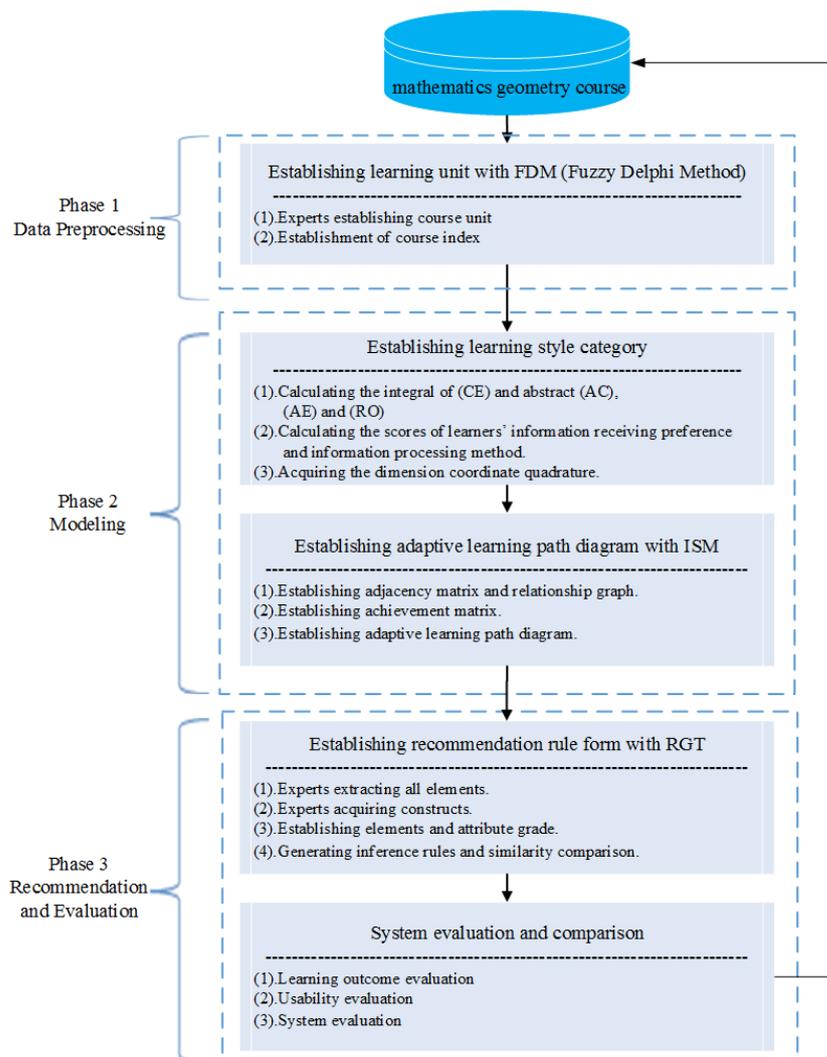
Figure 2. Adaptive learning path recommendation system

and adaptive learning path constructs to establish the learning style elements and adaptive learning path attribute grade for generating the RGT inference rules. The recommendation of the optimal rules are compared and analyzed through a similar algorithm. Finally, recall, precision, F1 index and Mean Absolute Error (MAE) are used as the measurement indices of ALPRS efficacy to evaluate the efficacy of the recommendation system. Learners' learner characteristics and path references are found by means of the ALPRS adaptive learning path inference. The geometry recommendation most suited for the learners is given in order to achieve the adaptive learning effect. The design and the algorithm steps of the adaptive learning path recommendation system (ALPRS) are described as follows.

Establishing a learning unit with Fuzzy Delphi Method (FDM)

(1). Experts establish course units by collecting literature data and extracting experts' decisions with FDM. Knowledge attributes are established for the recommendation evaluation value.

(2). Establishment of course index is achieved by requesting expert opinions via questionnaire survey for the common opinions, and applying Max-Min to the calculation (**Figure 3**), which is presented with statistics. The Max-Min calculating steps are shown below.

Step 1: Establishing the accumulative time function with maximum identity $F_1(x)$ and the accumulative time function with minimum identity $F_2(x)$.

Step 2: Calculating the first "quartile", the median and the third "quartile" (C_1, M_1, D_1) of $F_1(x)$, and the first "quartile", the median, and the third "quartile" of $(C_2, M_2, D_2)F_2(x)$ according to the Triangular Fuzzy Number.

Step 3: Individually linking (C_1, M_1, D_1) and (C_2, M_2, D_2) to acquire the predictive value X^*.

Figure 3. Max-Min Gray Zone

Establishing the learning style category

Kolb's learning style scale is scored by summing up the scores of A in all questions (**Table 2**) to acquire a concrete experience score (CE), summing up the scores of B in all questions to acquire a reflective observation score (RO), summing up the scores of C in all questions to acquire an abstract conceptualization (AC), and summing up the scores of D in all questions to acquire an active experimentation score (AE). The steps are explained below.

(1). Calculating the integral of concrete experience (CE), abstract conceptualization (AC), active experimentation (AE) and reflective observation (RO). See Eqs. (1-4).

(2). Calculating the scores of learners' information receiving preference and information processing methods. See Eqs. (5-6).

(3). Acquiring the dimension coordinate quadrature.

$$CE = \sum_{i=1}^{n} a_i = a_1 + a_2 + \cdots + a_n \tag{1}$$

$$RO = \sum_{i=1}^{n} b_i = b_1 + b_2 + \cdots + b_n \tag{2}$$

$$AC = \sum_{i=1}^{n} c_i = c_1 + c_2 + \cdots + c_n \tag{3}$$

$$AE = \sum_{i=1}^{n} d_i = d_1 + d_2 + \cdots + d_n \tag{4}$$

$$AE_{(d)} - RO_{(b)} = \sum_{i=1}^{n} (d_i - b_i) \Rightarrow \begin{cases} \geq 0, (+) \\ < 0, (-) \end{cases} \tag{5}$$

$$AC_{(c)} - CE_{(a)} = \sum_{i=1}^{n} (c_i - a_i) \Rightarrow \begin{cases} \geq 0, (+) \\ < 0, (-) \end{cases} \tag{6}$$

Establishing an adaptive learning path diagram with ISM

The Interpretive Structure Model (ISM) is utilized at this stage to establish a more scientific "learning path" to make the instruction more logical and rational.

(1). Establishing an adjacency matrix and relationship graph

(2). Establishing an achievement matrix

(3). Establishing an adaptive learning path diagram

Establishing a recommendation rule form with Repertory Grid Technique (RGT)

(1) Experts extract all elements. The learning style attributes are decided at an expert's conference.

(2) Experts acquire constructs. The learning style path elements are established through ISM to pair the learning style attributes.

(3) Elements and attribute grade are established. Each expert's diagnosis and evaluation are organized, and the evaluation consensus is acquired through FDM. Finally, the evaluation is tested by users to reduce the evaluation error of experts and have the expert diagnosis approach the desired actual practice.

(4) Inference rules and a similarity comparison are generated. FOCUS, proposed by Thomas and Shaw (1976), is used for the similarity matching. See Eqs. (7)~(8).

A renowned similarity analysis was adopted. This approach involves two methods: the common COSINE similarity method and a FOCUS analysis available in the repertory grid package (Chen, 2010). Salton and McGill (1983) proposed the COSINE similarity method to measure similarity between repertory grids for user preferences and learning style attributes, shown by Eq. (7). The FOCUS analysis method was proposed by Thomas, McKnight and Shaw (1976), and is detailed in Eq. (8).

$$\text{Sim}(TA_i, U_j) = \cos(\theta) = \frac{T_i \cdot U_j}{|T_i||U_j|} = \frac{\sum_{t=1}^{n} T_{i,t} * U_{j,t}}{\sqrt{\sum_{t=1}^{n} T_{i,t}^2} * \sqrt{\sum_{t=1}^{n} U_{j,t}^2}}. \tag{7}$$

$$\text{Sim}(T_i, U_j) = 1 - \text{distance}(T_i, U_j)$$
$$= 1 - \left(\frac{\sum_{t=1}^{n}|T_{i,t} - U_{j,t}|}{s-1}\right) / n \tag{8}$$

System evaluation and comparison

The measurement indicators of the system evaluation in this study, i.e. recall, precision, F_1 index and Mean Absolute Error (MAE) (Her-locker et a1., 2004; Sarwar et al., 2001), are applied to explain ALPRS efficacy. The equations are defined as (9) ~ (12).

(1) Recall: It is defined in this study as the ratio of the recommendation course unit as it conforms to learners, and conforms to the course unit at the first stage.

(2) Precision: It is defined in this study as the ratio of the recommendation course unit, as it conforms to user needs, in the recommended course unit in this system.

(3) F_1 index: The above two indicators (Recall and Precision) would appear contradictory in practical application in that the enhancement of precision would reduce recall. They are therefore integrated into the F_1 index.

(4) Mean Absolute Error: Mean Absolute Error (MAE) is an indicator to evaluate the error between the recommendation system predictive value and the users' actual score (Sarwar et al. 2001). N stands for the total scoring data of users' course recommendation within the recommendation system. Let q_i, i =1,..., N be the predictive value estimated by an algorithm, 1,..., j; q $_j$ = N is the actual given score of a learner. The smaller MAE reveals the higher correctness of the algorithm.

$$\text{Precision} = \frac{\sum_{i=1}^{P}|TS(U_i) \cap \text{Rec}(U_i)|}{\sum_{i=1}^{p}|\text{Rec}(U_i)|} \tag{9}$$

$$\text{Recall} = \frac{\sum_{i=1}^{P}|TS(U_i) \cap \text{Rec}(U_i)|}{\sum_{i=1}^{p}|TS(U_i)|} \tag{10}$$

$$F_1 = 2.\frac{\text{Precision.Recall}}{\text{Precision} + \text{Recal}} \qquad (11)$$

$$MAE = \frac{\sum_1^N |p_i - q_j|}{N} \qquad (12)$$

SYSTEM IMPLEMENTATION AND EVALUATION

A gamification geometry recommendation system is designed in this study in order to assist the geometry practice for G5 and 6. It is expected that the convenient mobility, simple operation and gamification entertainment will motivate student interest in learning and practicing the geometry unit on object shape, volume, circumference and volume, in any circumstances. The gamification content includes: (1) entertainment and playfulness, (2) rules and objectives, (3) interaction and feedback, (4) adaptation, (5) competition and challenge, and offering achievement systems, (6) problem solving and task challenges, (7) community interaction and (8) visual image and story plots (Ebner & Holzinger, 2007; Hsiao, 2007; Prensky, 2001). See **Figure 4**.

Figure 4. Gamification geometry recommendation system interface

Establishment of a learning unit list with Fuzzy Delphi Method (FDM)

The Delphi Method requests expert opinions through questionnaire surveys, acquires common opinions of experts and presents the result via statistics. The number of experts therefore cannot be too many; it is generally restricted to about 13 (Noorderhaben, 1995). To reduce the number of abundant surveys and communications, FDM is utilized in this study. The recommendation course unit is acquired with FDM. Thirteen mathematics education experts generated 13 units: (a) unit 1-polygon, (b) unit 2-cuboid and cube, (c) unit 3-parallelogram and triangle area, (d) unit 4-trapezoid area and application, (e) unit 5-line symmetric graph, (f) unit 6-sector, (g) unit 7-circular ratio and area, (h) unit 8-sector area, (i) unit 9-cylinder and cone, (j) unit 10-cylinder product, (k) unit 11-thumbnail and scale, (l) unit 12-angle, and (m) unit 13-triangle. All units are in accordance with the geometry learning indices for G5 and 6 as regulated by the Ministry of Education. Max-Min (Ishikawa et al., 1993) is further used for generating the threshold 0.65. (M) and (N) are deleted, as shown in **Table 1**.

Table 1. Criteria selected by experts using FDM

Unit	$F_i^1(x)$			$F_i^2(x)$			x_i^*	Threshold Values
	C_i^1	M_i^1	D_i^1	C_i^2	M_i^2	D_i^2		
(A)	7.57	8.46	9.34	5.33	8.17	7.11	7.62	
(B)	7.50	8.43	9.36	5.26	8.14	7.13	7.56	
(C)	6.58	7.58	8.57	4.34	7.00	6.34	6.58	
(D)	8.46	8.53	8.59	6.22	8.27	6.36	8.15	
(E)	8.45	8.51	8.57	6.21	8.25	6.34	8.14	
(F)	6.58	7.58	8.58	4.34	7.15	6.57	6.58	
(G)	6.54	8.06	9.58	4.30	7.73	7.47	6.90	6.50
(H)	7.91	8.48	9.04	5.67	8.20	6.81	7.82	
(I)	7.82	8.42	9.02	5.58	8.13	6.79	7.74	
(J)	6.46	7.62	8.77	4.22	7.05	6.54	6.53	
(K)	7.55	8.23	8.90	5.31	7.87	6.67	7.48	
(L)	6.22	7.38	8.53	3.98	6.81	6.30	6.29	
(M)	6.13	7.29	8.44	3.89	6.72	6.21	6.20	

The two extracted factors, shown in gray, were below the threshold values 6.50

Establishment of a learning style category table

Calculating the integral of concrete experience (CE), abstract conceptualization (AC), active experimentation (AE) and reflective observation (RO)

Kolb's learning style scale covers 12 multiple choice questions (**Table 2**). The scale is preceded by the subjects ordering of preferences according to the four options, which represent four learning styles, in each question. The scores are acquired by summing up all first options as the concrete experience (CE) score, all second options as a reflective observation (RO) score, all third options as an abstract conceptualization (AC) score and all fourth options as an active experimentation (AE) score.

Table 2. Kolb's learning style scale

Answer	Q1: When I learning geometry,
2	A. I stress on analysis.
4	B. I rely on my mood.
3	C. I like to ask myself questions.
1	D. I emphasize learning effectiveness.

Calculating the scores of learners' information receiving preferences and information processing methods

The concrete experience score is further deducted from the abstract conceptualization score to acquire the preferred "concrete experience or abstract conceptualization" score, and the active experimentation score is deducted from the reflective observation score to acquire the preferred "active experimentation or reflective observation" score.

Acquiring the dimension coordinate quadrature

Finally, the positive and negative values of such two dimensions are interwoven into four quadrants of divergers (+,+), assimilators (−,+), convergers (−,−), and accommodators (+,−); the subjects are divided into four learning styles, as depicted in **Table 3**. After testing the internal consistency, Cronbach's α appears as .88, .83, .85 and .90, respectively, and the overall reliability is .87.

Table 3. Kolb learning style scale scoring and correspondent learning style category

Learning style	Information processing method integral	Information receiving preference integral
(Divergers)	(AE)- (RO) = (+)	(AC) - CE)= (+)
(Assimilators)	(AE)- (RO) = (−)	(AC) - CE)= (+)
(Convergers)	(AE)- (RO) = (−)	(AC) - CE)= (−)
(Accommodators)	(AE)- (RO) = (+)	(AC) - CE)= (−)

Establishment of the adaptive learning path diagram with ISM

Establishing the adjacency matrix and relationship graph

Using ISM methodology we create an initial structural self-interaction matrix (SSIM) to show the interrelationships among the variables. Each indicates the relationship that is developed between the identified factors from the FDM by expert consultation. Barve et al. (2009) discussed the existence of any relation between any two variables (i and j), and the associated direction of their relation. With the help of four symbols, the direction of the relationship between variables (i and j) is denoted as follows:

A: Factor j will lead to the achievement of factor i

V: Factor i will lead to the achievement of factor j

O: Factor i and j are unrelated.

X: Factor i and j will lead to mutual achievement

The 11 variables (A~K) identified as learning content factors were selected by experts using FDM. Based on the contextual relationships, the SSIM is developed mindful of learning content, as shown in **Table 4**.

Table 4. Structural self-interaction matrix (SSIM)

	(K)	(J)	(J)	(H)	(G)	(F)	(E)	(D)	(C)	(B)	(A)
(A)	V	V	V	A	V	V	O	X	V	X	X
(B)	A	V	V	A	O	V	V	A	V	X	
(C)	A	A	V	O	V	O	A	V	X		
(D)	A	A	V	V	V	V	A	X			
(E)	O	A	O	V	V	V	X				
(F)	A	A	V	V	V	X					
(G)	O	X	V	X	X						
(H)	A	A	V	X							
(I)	A	A	X								
(J)	A	X									
(K)	X										

Establishing the reachability matrix

Before transforming the SSIM into a binary matrix, the matrix calculates all the factors from the fuzzy numbers; the initial reachability matrix is derived by substituting V, A, X and O with 1 and 0 as per the substitution rules mentioned below (Barve et al., 2009):

- if the (i,j) entry in the SSIM is V, then the (i,j) entry in the reachability matrix becomes 1 and the (j,i) entry becomes 0

- if the (i,j) entry in the SSIM is A, then the (i,j) entry in the reachability matrix becomes 0 and the (j,i) entry becomes 1

- if the (i,j) entry in the SSIM is X, then the (i,j) entry in the reachability matrix becomes 1 and the (j,i) entry becomes 1

- if the (i,j) entry in the SSIM is O, then the (i,j) entry in the reachability matrix becomes 0 and the (j,i) entry becomes 0.

Based on the SSIM, the final learning content relationship reachability matrix is built from the initial reachability matrix by following the mechanism of transitivity, as shown in **Table 5**. This table also shows the driving power and dependence of each variable for factor grouping, and calculates the influence and dependence. "Influence" means that the driving power of a particular factor refers to the total number of factors that are influenced by it, and "dependence" represents the total number of variables affecting it (Barve et al., 2009).

Table 5. Reachability matrix

	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)	Y
(A)	0	1	1	1	1	0	0	1	0	1	0	6
(B)	1	0	0	0	0	0	0	1	1	0	1	4
(C)	0	1	0	1	1	1	1	0	0	1	0	6
(D)	1	0	0	0	0	0	1	0	1	0	1	4
(E)	1	1	1	1	0	1	1	0	0	1	0	7
(F)	0	0	0	1	0	0	0	0	1	1	1	4
(G)	1	1	0	1	0	0	0	0	1	1	1	6
(H)	0	0	0	1	0	0	0	0	0	1	0	2
(I)	1	0	0	1	0	1	1	0	0	0	1	5
(J)	0	1	1	1	1	1	1	0	1	0	1	8
(K)	0	1	1	1	1	1	1	1	0	1	0	8
X	5	6	4	9	4	5	6	3	5	7	6	

Driving power =Y-axis; Dependence power =X-axis

Establishing the adaptive learning path diagram

After creating a reachability matrix, we utilized the Matriced Impacts Croises Multiplication Appliqueeaun Classement (MICMAC) analysis to identify the driving and dependence power of the learning content hierarchical structure for weighting and alternative solutions. In separating the reachability matrix into different levels, the reachability and antecedent set for each factor were found from the final reachability matrix (Barve et al., 2009). By using the MICMAC analysis, the reachability matrix was created, to depict a four style learning path, as shown in **Figure 5**.
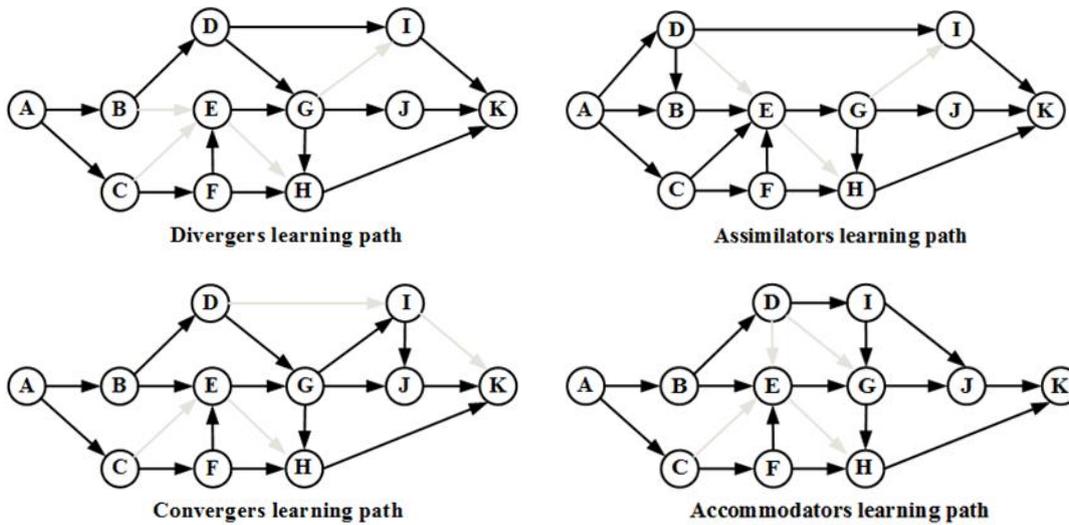
Figure 5. Four style learning path

RGT inference and calculation

Semi-structured expert interviews were conducted at this stage. Three major contents: elements, constructs and linking mechanisms are involved in the search for similar attributes to distinguish data with different attributes (Kelly, 1955). The experts first extract all learners' learning style path elements through ISM, and place all elements, i.e. Path A, Path B, Path C and Path D in **Figure 5**. On the upper row (**Table 6** herein). All experts then extract constructs, and 13 attributes are extracted for learning styles, including (A1) emotional ability, (A2) observation ability, (A3) imagination ability, (B1) creative ability, (B2) abstract conceptualization, (B3) inductive reasoning, (C1) integration and assimilation, (C2) decision making, (C3) active experimentation, (C4) concrete experience, (D1) crisis management, (D2) opportunity search, and (D3) adventure and trial. The learning path elements generated with ISM and learning style attributes are filled in the grade in the table (**Table 6** herein). The inference rules are finally generated from the repertory grid, and the recommendation rule similarity comparison is completed with Eq. (8).

System evaluation and comparison

The system is evaluated by examining the users' learning outcomes, perception of system use and objective value. The learning outcome is used for the quasi-experimental design; the perception of system use is evaluated via questionnaire after the user test; the objective value is evaluated with four measurement indicators of recommendation system efficacy, i.e. recall, precision, F1 index, and Mean Absolute Error (MAE) (Her-locker et a1., 2004; Sarwar et al., 2001), in order to determine the ALPRS efficacy.

Table 6. Adaptive learning path repertory grid recommendation form

	Path A	Path B	Path C	Path D
A1	5	4	2	1
A2	1	1	4	2
A3	3	1	3	5
B1	1	1	1	4
B2	5	3	2	4
B3	4	2	2	1
C1	3	4	1	1
C2	1	1	4	2
C3	5	3	2	4
C4	3	4	1	1
D1	5	4	2	1
D2	3	1	3	5
D2	3	1	3	5

Learning outcome evaluation

The pretest, posttest and tracking test design of the experimental group and the control group were applied to the quasi-experimental design in this study. The experimental group utilized ALPRS and the control group used a general learning course guided recommendation for the 16-week instructional experiment, in which the first 11 weeks were the experimental phase and the last 5 weeks, the tracking and observation phase. A total of 48 G6 students (male=25, female=23) in the experimental group received ALPRS to complete the gamification geometry unit, and the sequence of all learning units is classified according to the students' learning styles for the adaptive learning path recommendation. The students received system feedback and made modifications after completing the recommendation unit; ALPRS could make modifications and receive feedback based on the correctness and satisfaction of each course recommendation. The teacher merely guided the students in the gamification geometry-learning mechanism in the experiment. A total of 46 students (male=22, female=24) in the control group applied the general learning course guided recommendation, in which the teacher proceeds with the course unit sequence and with guidance. The students were not classified according to learning styles, and all students were guided in the same course unit. The teacher also instructed the students in unit practice, offered solutions and gave feedback to all questions. A unit test followed the course. The experimental results in **Table 7** show no significant differences in the pretest score between the experimental group and the control group, while the experimental group scored 84 and the control group 74 on the posttest, revealing remarkable differences in learning outcomes between the two groups (*F=15.35**). As a result, it proves that the ALPRS proposed in this study, giving distinct learning unit recommendation to students with different learning styles, followed by system modification and feedback according to course recommendation performance, could benefit geometry-learning outcomes.

Table 7. Analysis of differences in learning outcome with the quasi-experimental design

Group	Gender	Pretest (Week 1~3)		Posttest (Week 4~11)		Tracking test (Week 12~16)		F
		Mean	SD	Mean	SD	Mean	SD	
Experimental group(n=48)	M=25,F=23	74	11	86	9	88	11	15.35[*]
Control group(n=46)	M=22,F=24	76	12	74	14	78	15	0.27

Usability evaluation

The satisfaction scale in this study refers to the recommendation system satisfaction scale developed by Liang et al. (2006), including four dimensions of information: content, personal service, user interface and system satisfaction. Cronbanch's α of the dimensions is 0.86, higher than 0.7, revealing the favorable reliability of the dimensions in this satisfaction scale (Hair 1998). The students (n=48) in the experimental group received the recommendation system satisfaction questionnaire on the 11th week after completing the quasi-experimental design. The full score for the dimensions in the questionnaire is 100, **Figure 6**, and the overall system satisfaction reached 92, presenting good user satisfaction with ALPRS and personal service (91) offered by the system.
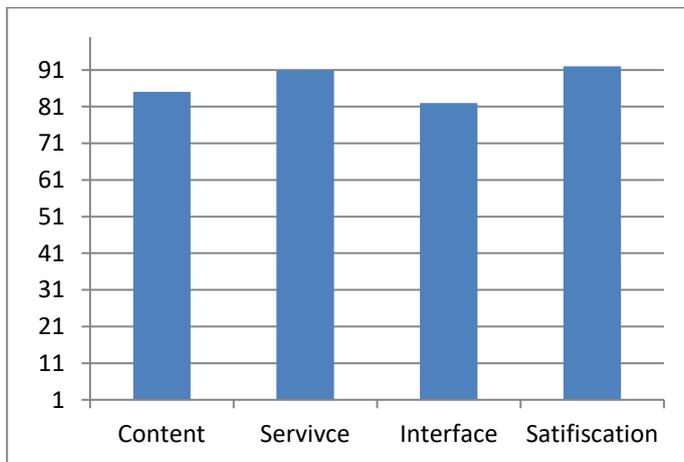

Figure 6. ALPRS usability evaluation diagram

System evaluation

Four recommendation system efficacy measuring indicators, recall, precision, F1 index and Mean Absolute Error (MAE) (Her-locker et a1., 2004; Sarwar et al. 2001) were used for evaluating the system efficacy, as shown by Eqs (9,10,11 and 12). A total of 11 weeks of instructional experiment data was processed for the system efficacy evaluation, with 650 records of recommendation, collected from 48 students in the experimental group. The recommendation results were further acquired through ALPRS, and three recommendation approaches were picked for the ALPRS recommendation system efficacy measurement

indicator experiment: (1) learning style +ISM+RGT recommendation mechanism proposed by ALPRS, (2) ISM+RGT and (3) general RGT recommendations. From the efficacy comparison in **Table 8**, it can be seen that approach 1 is a hybrid adaptive learning path recommendation mechanism, focusing on personal learning unit recommendation. Since it is a novel hybrid approach combining learning style, ISM and RGT, the experimental results show that the recall (95%), precision (68%) and F1 index (45%) acquired with ALPRS are better than those from the other two approaches, and MAE (8%) is lower than the other two approaches. It also shows that the correctness of ALPRS recommendation mechanism is also higher than the approaches 1 and 2, and the error is smaller than in the other two approaches. From the experiment, the recommendation geometry acquired from ALPRS could cover the recommendation of approaches 1 and 2 with greater effectiveness.

Table 8. Efficacy comparison of different recommendation evaluation indices

	(Approach 1) Learning Style +ISM+RGT	(Approach 2) ISM+RGT	(Approach 3) RGT
Recall	95%	88%	85%
Precision	68%	55%	51%
F_1 index	45%	38%	36%
MAE	8%	13%	19%

CONCLUSION AND DISCUSSION

Conclusion

This study aimed to construct an adaptive learning path recommendation system (ALPRS) through expert knowledge to improve the shortcomings of traditional recommendation systems, which do not consider learning styles, and to further provide recommendation course content conforming to learner needs. The research has indicated that learning styles affect learners' preferences for specific teaching materials and the learning outcome, as well as the selection of a learning unit path. Learning styles therefore should be regarded as an important learning recommendation element. Accordingly, this study combined FDM for geometry-learning evaluation, classified learners' styles with Kolb's learning style scale, and integrated learning styles with ISM to generate the course unit path with four learning styles, and discover personal learning units and reading sequences. Finally, the experts applied RGT to complete the recommendation rule inferences and practice a gamification adaptive geometry recommendation system, integrating the recommendations with different learning styles to verify the practicability of the structure and evaluate the system efficacy. The research findings show that the learning outcome with ALPRS is better than with a general learning course-guided recommendation mechanism, and the scores of system satisfaction with ALPRS and personal service are higher than 90: recall (95%), precision

(68%), F1 index (45%) and MAE (8%). ALPRS outperforms other approaches. Our research results are consistent with those of Felder and Silverman (1988), in which good learning recommendation effects are in evidence with a combination of learning styles with the learning recommendation system. Although only the geometry unit in mathematics education for G5 and 6 is applied in this study, there are five other major topics in mathematics for elementary schools: number and quantity, geometry, algebra, statistics and probability and link. The other four topics could be applied to the ALPRS mechanism proposed in this study, and the recommendation course could be promoted to MSTE (Mathematics, Science and Technology Education) areas. Finally, three contributions are offered in this study: (1) the novel hybrid adaptive learning recommendation system (ALPRS) was proposed and its practicability tested; (2) a prototype gamification geometry teaching material module was developed for the promotion in MSTE areas; (3) the adaptive geometry learning path diagram generated with ISM-based on learning styles could serve as a reference for further studies.

Future research

For further research, the AprioriAll algorithm could be added in the learning path recommendation mechanism to test the correlation between learners' learning styles and learning units, and the predictive capability of fuzzy time series could be used for big data analyses and for reinforcing the quality of intelligent learning recommendation system to ensure the analysis of time and correlation, as well as to create predictable learning units worthy of recommendation. In addition, the Item Response Theory (IRT) could be applied to the learning evaluation mechanism to reinforce the capability of learning tests and to discover well-suited learning paths so that the system is both intelligent and user-friendly.

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REFERENCES

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering, *17*(6), 734–749.

Selin, B., Bulut, M. M., & Volkan, A. (2002). Projection based method for segmentation of human face and its evaluation. *Pattern Recogn. Lett., 23*, 1623-1629.

Baker, C. M., Pesut, D. J., McDaniel, A. M., & Fisher, M. L. (2007). Evaluating the impact of problem-based learning on learning styles of master's students in nursing administration. *Journal of Professional Nursing, 23*, 214–219.

Barve, A., Kanda, A., & Shankar, R. (2009) The role of human factors in agile supply chains. *European Journal of Industrial Engineering, 3*(1), 2–20.

Beikkhakhian, Y., Javanmardi, M., Karbasian, M., & Khayambashi, B. (2015). The application of ISM model in evaluating agile suppliers selection criteria and ranking suppliers using fuzzy TOPSIS-AHP methods. *Expert Systems with Applications, 42*(15–16), 6224-6236.

Bencze, L., Brown, G. M., & Alsop, S. (2006). Teachers' tendencies to promote student-led science projects: Associations with their views about science. *Science Education, 90*, 400–419.

Ben-Zvi Assaraf, O., & Orion, N. (2010a). Systems thinking skills at the elementary school level. *Journal of Research in Science Teaching, 47*(5), 540–563.

Ben-Zvi Assaraf, O., & Orion, N. (2010b). Four case studies, six years later: Developing system thinking skills in junior high school and sustaining them over time. *Journal of Research in Science Teaching, 47*(10), 1253–1280.

Bezzi, A. (1999). What is this thing called geoscience? Epistemological dimensions elicited with the repertory grid and their implications for scientific literacy. *Science Education, 83*, 675–700.

Brophy, J., & Good, T. L. (1986). Teacher behaviors and student achievement. In M. C.Wittrock (Ed.), Third Handbook of Research on Teaching. 328-375, New York: Macmillan.

Brown, C. (1953). The teaching of secondary mathematics. New York: Harper & Bros.

Canning, C., & Holmes, K. (2006). Community consultation in developing museum projects: A case study using the repertory grid technique. *Culture Trends, 15*(4), 275–297.

Cano-García, F., & Hughes, E. H. (2000). Learning and thinking styles: An analysis of their interrelationship and influence on academic achievement. *Educational Psychology, 20*, 413–430.

Cawley, J. F. (Ed.) (1984). Developmental teaching of mathematics for the learning disabled. Rockville, MD: Aspen Systems.

Chang, J. C., & Huang, S. T. (2008). The effect of e-learning on vocational high school students' learning achievement with different learning styles. *Journal of Technological and Vocational Education, 2*, 37–57.

Chang, J.-H. (2015). The effects of adopting the innovative dynamic product design method on the performance of students of different learning styles. *Thinking Skills and Creativity, 17*, 88-101.

Chen, Q. L. (2010). An exploration of back-of-the-book indexing behavior with repertory grid technique. *Journal of Library and Information Science, 36*(2), 35-51.

Hsu, C. K., Hwang, G. J., & Chang, C. K. (2010). Development of a reading material recommendation system based on a knowledge engineering approach. *Computers & Education, 55*, 76–83.

Dalkey, N. C., & Helmer, O. (1963). An experimental application method to the use of experts. *Management Science, 9*(3), 458–467.

Dempsey, J. V., Lucassen, B., Haynes, L., & Casey M. (1996). Instructional applications of computer games. (ERIC Document Reproduction Service No. ED394500).

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness: Defining ''Gamification''. In Proceedings of MindTrek.

Donoghue, E. F. (2003). Algebra and geometry textbooks in twentieth-century America. In G. M. A. Stanic & J. Kilpatrick (Eds.), A history of school mathematics (pp. 329-398). Reston, VA: National Council of Teachers of Mathematics.

Driskell, J. E., Willis, R. P., & Cooper, C. (1992). Effect of overlearning on retention. *Journal of Applied Psychology, 77*, 615-622.

Dubey, R., Gunasekaran, A., Wamba, S. F., & Bag, S. (2015). Building Theory of Green Supply Chain Management using Total Interpretive Structural Modeling (TISM). *IFAC-PapersOnLine, 48*(3), 1688-1694.

Dunn, R., Dunn, K., & Freeley, M. E. (1984). Practical applications of the research: responding to students' learning styles-step one. *Illinois State Research and Development Journal, 21*(1), 1–21.

Ebner, M., & Holzinger, A. (2007). Successful implementation of user-centeredgame based learning in higher education: An example from civil engineering. *Computers & Education, 49*(3), 873–890.

Emurian, H. (2006). A web-based tutor for java: evidence of meaningful learning. *International Journal of Distance Education Technologies, 4*(2), 10–30.

Goldman, D., Ben-Zvi Assaraf, O., & Shaarbani, D. (2013). Influence of a non-formal Environmental Education program on junior high school students' environmental literacy. *International Journal of Science Education, 35*(3–4), 515–545.

Gyeong, J. A., & Myung, S. Y. (2008). Critical thinking and learning styles of nursing students at the baccalaure ate nursing program in Korea. *Contemporary Nurse, 29*, 100–109.

Hamari, J., & Koivisto, J. (2015). "Working out for likes": An empirical study on social influence in exercise gamification. *Computers in Human Behavior, 50*, 333-347.

Hauer, P., Straub, C., & Wolf, S. (2005). Learning styles of allied health students using Kolb's LSI-IIa. *Journal of Allied Health, 34*, 177–182.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems, 22*(1), 5e53.

Holland, J., Mitrovic, A., & Martin B. (2009). J-Latte: a constraint-based tutor for java. In 17th International Conference on Computers in Education, Hong Kong, 142–146.

Hsiao, H. C. (2007, March). A brief review of digital games and learning. In Digital Game and Intelligent Toy Enhanced Learning, 2007. DIGITEL'07. The First IEEE International Workshop on (pp. 124-129). IEEE.

Hsu, Y., Lee, C., & Kreng, V. (2010). The application of fuzzy Delphi method and fuzzy AHP in lubricant regenerative technology selection. *Expert Systems with Applications, 37*, 419–425.

Hwang, C. L., & Lin, M. J. (1987). *Group Decision Making under Multiple Criteria*. Berlin Heidelberg: Springer-Verlag.

Ishikawa, A., Amagasa, M., Shiga, T., Tomizawa, G., Tatsuta, R., & Mieno, H. (1993). The max–min Delphi method and fuzzy Delphi method via fuzzy integration. *Fuzzy Sets and Systems, 55*, 241–253.

Ivanovic, M., Pribela, I., Vesin, B., & Budimac, Z. (2008). Multifunctional environment for E-learning purposes. *Novi Sad Journal of Mathematics, NSJOM, 38*(2), 153–170.

Schafer, J. B. (1999). Recommender Systems in E-Commerce, E-Commerce of the ACM.

Jharkharia, S., & Shankar, R. (2004). IT enablement of supply chains: modeling the enablers. *International Journal of Productivity and Performance Management, 53*(8), 700–712.

Kardaras, D. K., Karakostas, B., & Mamakou, X. J. (2013). Content presentation personalization and media adaptation in tourism web sites using Fuzzy Delphi Method and Fuzzy Cognitive Maps. *Expert Systems with Applications, 40*(6), 2331-2342.

Kelly G. A. (1955). *The psychology of personal construct*. New York: Norton.

Kelly, D., & Tangney, B. (2004). *Predicting learning characteristics in a multiple intelligence based tutoring system*. Berlin: Springer-Verlag, 9–30.

Klašnja-Milićević, A., Vesin, B., Ivanović, M., & Budimac, Z. (2011). E-Learning personalization based on hybrid recommendation strategy and learning style identification. *Computers & Education, 56*(3), 885-899.

Kolb, D. (1984a). *Experiential learning: Experience as the source of learning and development*. New Jersey: Prentice-Hall.

Kolb, D. (1984b). Individuality in learning and the concept of learning styles. In Experiential learning (pp. 61–98). Englewood Cliffs, New Jersey: Prentice-Hall.

Kristofic, A. (2005). Recommender system for adaptive hypermedia Applications. In Proceeding of Informatics and Information Technology Student Research Conference, Bratislava, 229–234.

Fan, K. K., Xiao, P. W., & Su, C. H. (2015). The effects of learning styles and meaningful learning on the learning achievement of gamification health education curriculum. *Eurasia Journal of Mathematics, Science & Technology Education*, *11*(5), 1211-1229.

Kvan, T., & Jia, Y. (2005). Students' learning styles and their correlation with performance in architectural design studio. *Design Studies, 26*, 19–34.

Liang, T. P., Lai, H. J., & Ku, Y. C. (2006). Personalized content recommendation and user satisfaction: Theoretical synthesis and empirical findings. *Journal of Management Information Systems, 23*(3), 45-70.

Lin, L., Yang, M. O., Li, J., & Wang, Y. (2012). A systematic approach for deducing multi-dimensional modeling features design rules based on user-oriented experiments. *International Journal of Industrial Ergonomics, 42*, 347–358.

Manoliadis, O., Tsolas, I., & Nakou, A. (2006). Sustainable Construction and Drivers of Change in Greece: A Delphi Study. *Construction Management & Economics, 4*, 113-120.

Mereditha, J. R., Raturia, A., Amoako-Gyampahb, K., & Kaplana, B. (1989). Alternative research paradigms in operations. *Journal of Operations Management, 8*(4), 297–326.

Murry, T. J., Pipino, L. L., & Gigch, J. P. (1985). A pilot study of fuzzy set modification of Delphi. *Human Systems Management, 5*(1), 76–80.

Noorderhaben, N. (1995). *Strategic decision making*. UK: Addison-Wesley.

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of ACM, 40*, 56-58.

Prensky, M. (2001). *Digital game-based learning*. McGraw-Hill, New York.

Felder, R. M., & Silverman, L. K. (1988). Learning and Teaching Styles in Engineering Education. *Engineering Education, 78*(7), 674-681.

Salton, G., & McGill, M. J. (1983). *Introduction to modern information retrieval*. Auckland: McGraw-Hill.

Sarwar, B., Karypis, G., Konstan, J., & Reidl, J. (2001). Item-based collaborative filtering recommendation algorithms, Proceedings of the Tenth international conference on World Wide Web (WWW10), Hong Kong, China, May 1-5.

Hsiao, S. W., Ko, Y. C., Lo, C. H., & Chen, S. H. (2013). An ISM, DEI, and ANP based approach for product family development. *Advanced Engineering Informatics, 27*(1), 131–148.

Simões, J., Redondo, R. D., & Vilas, A. F. (2013). A social gamification framework for a K-6 learning platform. *Computers in Human Behavior, 29*(2), 345-353.

Sykes, E. R., & Franek, F. (2003). An intelligent tutoring system prototype for learning to program java. In: The third IEEE International Conference on Advanced Learning Technologies (ICALT'03) Athens, Greece, 485–492.

Thomas, L. F., McKnight, C., & Shaw, M. L. G. (1976). *Grids and group structure*. Uxbridge, Middlesex: Centre for the Study of Human Learning, Brunel University.

Truong, H. M. (2016). Integrating learning styles and adaptive e-learning system: Current developments, problems and opportunities. *Computers in Human Behavior, 55*, Part B, 1185-1193.

Wang, Y., Yeo, G.-T., & Ng, A. K. Y. (2014). Choosing optimal bunkering ports for liner shipping companies: A hybrid Fuzzy-Delphi–TOPSIS approach. *Transport Policy, 35*, 358-365.

Warfield, J. (1976). *Societal Systems: Planning, Policy and Complexity*. John Wiley & Sons, Inc., New York, NY.

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