Computers & Education 54 (2010) 404–415

Contents lists available at ScienceDirect

Computers & Education

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

A Heuristic Algorithm for planning personalized learning paths for context-aware ubiquitous learning

Gwo-Jen Hwang [a,*], Fan-Ray Kuo [a], Peng-Yeng Yin [b], Kuo-Hsien Chuang [b]

[a] Department of Information and Learning Technology, National University of Tainan, 33, Sec. 2, Shulin St., Tainan City 70005, Taiwan
[b] Department of Information Management, National Chi Nan University, Pu-Li, Nan-Tou County 545, Taiwan

A R T I C L E I N F O

Article history:
Received 13 December 2008
Received in revised form 22 August 2009
Accepted 24 August 2009

Keywords:
Interactive learning environments
Mobile learning
Context-awareness
Ubiquitous learning
Heuristic Algorithms

A B S T R A C T

In a context-aware ubiquitous learning environment, learning systems can detect students' learning behaviors in the real-world with the help of context-aware (sensor) technology; that is, students can be guided to observe or operate real-world objects with personalized support from the digital world. In this study, an optimization problem that models the objectives and criteria for determining personalized context-aware ubiquitous learning paths to maximize the learning efficacy for individual students is formulated by taking the meaningfulness of the learning paths and the number of simultaneous visitors to each learning object into account. Moreover, a Heuristic Algorithm is proposed to find a quality solution. Experimental results from the learning activities conducted in a natural science butterfly-ecology course of an elementary school are also given to depict the benefits of the innovative approach.

© 2009 Elsevier Ltd. All rights reserved.

1. Background and motivation

With the rapid development of mobile, wireless communication and sensor technologies, opportunities for conducting new learning strategies by integrating authentic learning environments and the resources of the digital world have attracted much attention from researchers from both the fields of education and computer science (Chen, Kao, & Sheu, 2003; Hwang, 2003). A context-aware ubiquitous learning (u-learning) environment provides such a learning scenario that individual students are guided to learn in a real-world situation with supports or instructions from a computer system, using a mobile device to access the digital content via wireless communications; in the meantime, the learning system is able to detect and record the learning behaviors of the students in both the real-world and the virtual world with the help of the sensor technology (Ogata & Yano, 2004; Hwang, Tsai, & Yang, 2008). Such a new technology-enhanced learning model not only supports learners with an alternative way to deal with problems in the real-world, but also enables the learning system to more actively interact with the learners (Hwang, 2006; Murakami, 2003).

Although such technology-enhanced learning approaches have been proven to be effective, past experiences have also revealed the difficulties of applying them. In terms of technique, these difficulties are easy to overcome; however, in terms of education, it is difficult to arrange the learning activities so that the students will be guided to learn the right thing in the right place at the right time. Especially, in a u-learning environment which includes diverse context parameters, cognitive overloading and disorientation might become a problem while the students are being guided to learn content from both the real-world and the digital world (Hwang, Wu, & Chen, 2007). Therefore, it has become an important challenge to plan personalized u-learning paths for individual students to learn in a context-aware u-learning environment.

Most of the previous studies on personalized learning path generation schemes have mainly focused on guiding the students to learn in the digital world; that is, each learning path represents a set of digitalized learning objects that are linked together based on some rules or constraints (Liu, Wu, Chang, & Heh, 2008). While determining such digitalized learning paths, the learning achievements, online behaviors or personalized features (such as learning styles) of individual students are usually taken into consideration (Chen, 2008a, 2008b, 2009; Chen, Lee, & Chen, 2004; Schiaffino, Garcia, & Amandi, 2008).

* Corresponding author. Tel.: +886 915396558; fax: +886 6 3017001.
E-mail addresses: gjhwang@mail.nutn.edu.tw (G.-J. Hwang), revonkuo@mail.nutn.edu.tw (F.-R. Kuo), pyyin@ncnu.edu.tw (P.-Y. Yin), s97213532@ncnu.edu.tw (K.-H. Chuang).

0360-1315/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.compedu.2009.08.024

While conducting learning activities in a real-world situation, the factors to be taken into account are quite different. For example, several studies have found that the number of students is an important factor that significantly affects the learning achievements of students due to the physical constraints of real-world positions (Westerlund, 2008; Zahorik, 1999). Din (2009) also indicated that, in the real-world learning environment, better learning performance will be achieved if the number of students is well controlled.

Thus, this study proposes a learning guidance strategy for a personalized context-aware u-learning system by taking the relevance of the real-world objects to be learned and the number of students who visit the same objects into consideration. The learning system incorporates RFID (Radio Frequency Identification) technology, an automatic identification method which stores and remotely retrieves data using devices called RFID tags, to detect the learning behaviors of students in the real-world so that it is able to guide them to interact with real-world learning objects. In this innovative approach, the repertory grid-oriented technique (Chu & Hwang, 2008) is applied to help the teachers describe the relevance between learning objects; accordingly, a Heuristic Algorithm is proposed to plan u-learning paths for individual students based on the relevance between each pair of learning objects and some practical considerations for conducting learning activities in the real-world. In addition, the experimental results from the learning activities conducted in an elementary school are presented to show the effectiveness of the innovative approach.

2. Objectives and problem definition

In a conventional authentic learning activity, the students are guided by a learning-mission sheet prepared by the teacher, and write down their findings on the sheet after visiting each of the learning objects. Such a learning activity allows the students to observe the real-world objects without personalized guidance or support; consequently, some students might fail to pay attention to the key features to be observed, or fail to complete the mission owing to a lack of sufficient information or guidance.

Consequently, in this study, a context-aware u-learning activity is considered, in which students are guided to observe several learning objects and complete their mission with support from the learning system via mobile devices (i.e. PDAs), wireless communication and sensor technology. That is, personalized support can be given to individual students to assist them in completing their learning-mission in an authentic learning environment. It should be noted that wherever in the conventional authentic learning environment or the context-aware u-learning environment the learner may be, to more effectively control the time of the learning activity, the learning procedure is usually divided into several stages with identical expected learning times; that is, the teachers will carefully design the missions in each stage, so that most of the students can complete their missions in the specified time. When the expected learning time is approached, all of the students are guided to start the next stage of their new mission. Such an arrangement aims to prevent the students from fooling around in one stage; moreover, it enables the teachers to more clearly observe the learning behaviors of students.

Although context-aware u-learning has been reported to be effective in several studies (Chu, Hwang, Huang, & Wu, 2008; Hwang et al., 2008; Hwang, Yang, Tsai, & Yang, 2009; Liu, Chu, Tan, & Chang, 2007; Ogata & Yano, 2004; Rogers et al., 2005; Wu, Yang, Hwang, & Chu, 2008), there are some problems to be coped with as follows:

(1) In the u-learning environment, there are many target objects for students to observe and learn about. As each target object represents different concepts or features to be learned, it is difficult for the students to determine the learning path for visiting the target objects without any guidance. If the learning path is not well arranged, they might fail to understand the relationships among those target objects. That is, they are likely to be disorientated in the learning process. Novak (1998) indicated that learning is a continuous process which adds new information to the existing information repository. If a learner can be guided to connect new information with their existing knowledge, the learning process is called meaningful learning. In the past decades, researchers have addressed the importance of guiding students to learn in a meaningful way; that is, to assist the students to learn new concepts based on the relevant concepts they already know (Araujo, Veit, & Moreira, 2008; Cardellini, 2004; Grabe & Grabe, 2007; Mass & Leauby, 2005).
(2) In conducting learning activities in real-world environments such as museums, ecology gardens or classrooms, researchers have found that the learning quality might be significantly affected if too many people attempt to visit or learn about the same target object simultaneously (Chang, Chang & Heh, 2007; Din, 2009; Jonassen, 1995; Limongelli, Sciarrone, Vaste, & Temperini, 2008). Thus, it is necessary to adequately guide them to visit a target object at the proper time, such that the learning quality for each target object can be better.

Assume that the degrees of relevance among these target objects are known. In a learning path, it is more meaningful to arrange the students to successively visit two greatly relevant learning objects. Moreover, in designing the learning activities conducted in an authentic environment, the time for visiting the learning object is usually the same, so that the students who are observing different learning objects can start to learn about the next learning object at the same time. Under these assumptions and criteria, we propose the following equation to evaluate the fitness for designing personalized learning paths in a context-aware ubiquitous learning environment:

$$\text{Minimize } \alpha\left(\sum_{t=1}^{m}\sum_{i\neq j}\frac{|Num(A_i,t)-Num(A_j,t)|}{m^2(m-1)n/2}\right)+\beta\left(\sum_{k=1}^{n}\sum_{t=1}^{m-1}\frac{[1-\text{Relevance }(\text{Location}(S_k,t+1),\text{Location }(S_k,t))]}{(m-1)n}\right) \quad (1)$$

The meanings of the symbols in Eq. (1) are described as follows:

n indicates the number of students attending this context aware u-learning course
m denotes the number of learning objects. Identical learning time is reserved for each student to observe each learning object
t denotes the phase number in the learning activity, $1 \leqslant t \leqslant m$
S_k represents the k th student, $1 \leqslant k \leqslant n$
A_i means the i th learning object, $1 \leqslant i \leqslant m$
$Num(A_i, t)$ means the number of students located at the i th learning object in the t th phase
Relevance (Ai, Aj) indicates the degree of relevance between object i and object j, $0 \leqslant$ Relevance (A_i, A_j) $\leqslant 1.0$
Location (S_k, t) denotes that the location of the learning object for the k th student in the t th phase, Location (S_k, t) = A_i and $1 \leqslant i \leqslant m$

In the objective function, the term $\sum_{t=1}^{m}\sum_{i\neq j}\frac{|Num(A_i,t)-Num(A_j,t)|}{m^2(m-1)n/2}$ calculates the total difference of the number of students among the learning objects in the t th phase simultaneously, where the denominator is used to normalize the value of the term to a unit range [0, 1]; The term $\frac{[1-\text{Relevance}(\text{Location }(S_k,t+1),\ \text{Location }(S_k,t))]}{(m-1)n}$ computes the total amount of irrelevance between two successive learning objects observed by any students in the learning activity, and the denominator also plays the role of normalization to convert the value into [0, 1]. Moreover, α and β are two parameters, with $\alpha + \beta = 1.0$ representing the relative importance distributed to the two terms. Thus, the purpose of the study is to minimize the difference of the number of students among learning objects to ensure the learning quality and to design a more meaningful learning path for individual students by arranging them to visit greatly relevant learning objects successively.

3. A Heuristic Algorithm for determining personalized learning paths

The optimization algorithm consists of two stages: determining the relevance between each pair of learning objects, and finding the quality learning paths for individual students based on the relevant information.

3.1. Determining the relevance between learning objects

A repertory grid-oriented approach is employed to assist the teachers and domain experts in determining the relevance between each pair of learning objects. The repertory grid method originated from Kelly's personal construct theory (Kelly, 1955), which aims to elicit and analyze knowledge by identifying different concepts in a domain and distinguishing among them. In a repertory grid, the objects to be classified or identified are called "elements" and are placed in the columns on top of the grid. Experts compare the elements and identify traits between them; the positive traits are placed to the left, and the opposite traits to the right. Each pair of positive and opposite traits becomes a "construct" and is used to describe the characteristics of the elements. In each cell in the grid, users fill in the degrees or tendency of each element for the construct from 1 to 5, where 1 refers to a positive trait, 2 signifies a partially positive trait, 3 represents no tendency to either side, 4 is a partially opposite trait, and 5 means an opposite trait. Table 1 shows an illustrative example of a repertory grid with six elements (E_1, E_2, E_3, E_4, E_5 and E_6) that are classified based on five constructs. In this study, each element represents a butterfly host plant.

Once the repertory grid is obtained, a relevance analysis formula is invoked to analyze the relevance among elements (Kevill, Shaw, & Goodacre, 1982):

$$\text{Relevance }(EA,EB) = 1-\frac{\sum_{i=1}^{N}|RG(E_A,C_i)-RG(E_B,C_i)|}{K-1}\times\frac{1}{N}\times 100\% \tag{2}$$

where N is the number of learning objects and K is the maximum rating scale (in this case, $K = 5$), and RG (E_A, C_i) represents the rating for learning object E_A and construct C_i. Table 2 shows the degree of relevance among the elements in Table 1 by applying the formula.

3.2. Determining the optimal learning paths

The problem for finding the optimal learning path for each participating student can be described as a compound traveling salesman problem with multiple agents, where each agent seeks to minimize the path-dependent cost of his/her own traveling course while respecting the location-dependent cost between different agents at each time step. Analogously, in the context-aware U-learning problem, each student seeks a respective optimal learning path by minimizing the relevance loss between consecutive learning objects along this path, while simultaneously minimizing the difference in the numbers of students attending learning objects at distinct locations in each time phase.

For decades, swap, shift, and inversion have been the primitive operations embedded in various heuristics for solving the traveling salesman problem (Reinelt, 1994). To illustrate, consider a TSP involving six cities. So each candidate solution can be represented as a 6-permutation (see Fig. 1a), the swap procedure exchanges the order of two arbitrary cities in the current permutation as seen in Fig. 1b. While the

Table 1
Illustrative example of a repertory grid.

	E_1	E_2	E_3	E_4	E_5	E_6	
C_1	5	1	5	5	5	1	C_1'
C_2	5	1	1	5	5	5	C_2'
C_3	5	5	5	1	5	5	C_3'
C_4	1	1	1	5	5	1	C_4'
C_5	5	1	5	5	3	1	C_5'

Table 2
Relevance analysis results.

	E_1 (%)	E_2 (%)	E_3 (%)	E_4 (%)	E_5 (%)	E_6 (%)
E_1	100	40	80	60	70	60
E_2	40	100	60	0	30	80
E_3	80	60	100	40	50	40
E_4	60	0	40	100	70	20
E_5	70	30	50	70	100	50
E_6	60	80	40	20	50	100

3	6	2	4	1	5

(a)

3	1	2	4	6	5

(b)

3	1	6	2	4	5

(c)

3	6	4	2	1	5

(d)

Fig. 1. Illustration of primitive operations used in TSP heuristics.

shift operation chooses a sub-permutation p and shifts p one position to the right by moving the end-city of p to the position for the begin-city of p (see Fig. 1c). As shown in Fig. 1d, the inversion operation reverses the order of a selected sub-sequence. In an improvement-based heuristic, the current permutation is replaced by the new permutation after applying the primitive operation if the latter permutation gives a smaller cost than that of the former, and remains unchanged otherwise. The primitive operation is iteratively applied to improve the quality of the candidate permutation until a specified stopping criterion is met. In the following we propose a heuristic with variants embodying different selections of the primitive operations for coping with the personalized learning path planning in the context-aware U-learning problem.

We first describe the solution representation scheme for the underlying problem as follows. Each solution $X = (x_{11}, x_{12}, \ldots, x_{nm})$ is an $(n \times m)$-dimensional vector representing the learning paths of the n students, where x_{ij} indicates the index of the learning object that the i th student is attending in the j th time phase. To ensure that each student visits every learning object exactly once, we should stipulate that $x_{ij} \neq x_{ik}$ for $j \neq k$. In other words, the solution X consists of n m-permutations. It is worth noting that if a given sequence satisfies the m-permutation constraint, the new sequence obtained by applying the noted swap, shift, or inversion operation to the original sequence is still an m-permutation.

We denote $f(X)$ the fitness value obtained by computing Eq. (1) using X as the learning path for all students. Our proposed Heuristic Algorithm first generates an initial feasible solution X_0 at random. Each student's learning path is subject to a selection to be perturbed according to a perturbation rate. The perturbation is performed by executing a selected primitive operation. We define seven types of perturbation as follows. Perturbation A always executes the swap operation, perturbation B always executes the shift operation, and Perturbation C always executes the inversion operation. Perturbation AB executes either swap or shift operations with equal probability, perturbation AC executes either swap or inversion operations with equal probability, and perturbation BC executes either shift or inversion operations with equal probability. Finally, perturbation ABC executes any of the swap, shift or inversion operations with equal probability.

Let the learning path of student i be selected to be perturbed and τ is the assumed perturbation type with two arbitrary perturbation points j and k. We can formally define the perturbation as $Y_{h+1} = X_h \oplus \tau\ (x_{ij}, x_{ik})$, where X_h is the current solution and Y_{h+1} is the tentative solution obtained by applying perturbation τ to X_h. The new solution X_{h+1} is subject to the result by competing X_h against Y_{h+1}, that is X_{h+1} is set to Y_{h+1} if $f(Y_{h+1}) < f(X_h)$, and X_{h+1} is equal to X_h otherwise. The Heuristic Algorithm is executed until a specified maximal number, L_{max}, of iterations has been conducted. The precise steps of the Heuristic Algorithm with perturbation type τ are described in Fig. 2. It is noteworthy that the perturbation rate defines the neighborhood size of the local search conducted in the Heuristic Algorithm (τ). A solution move with a higher perturbation rate can augment the neighborhood size and increase the likelihood to escape from local optima; however, it induces more trials to fully exploit the neighborhood. On the other hand, a solution move with a lower perturbation rate may easily get trapped by the local barrier, but the operation needed to generate a trial solution is more computationally economic. Mladenovic and Hansen (1997) proposed the notion of the variable neighborhood search (VNS) method which involves multiple sizes of neighborhoods, and alleviates the

Heuristic Algorithm (τ)

Step 1. Generate an initial feasible solution X_0 at random.

Step 2. Set $h = 0$.

Step 3. Repeat until $h = L_{max}$

Step 3.1: The learning path of student i, $1 \le i \le n$, is subject to being selected with a permutation rate to perform the following permutation procedure

Step 3.1.1: Randomly select j, k such that $1 \le j < k \le m$

Step 3.1.2: $Y_{h+1} = X_h \oplus \tau(x_{ij}, x_{ik})$

Step 3.1.3: $X_{h+1} = Y_{h+1}$ if $f(Y_{h+1}) < f(X_h)$, and $X_{h+1} = X_h$ otherwise.

Step 3.2: $h = h + 1$

Step 4. Output X_h as the best learning path for all participating students.

Fig. 2. Precise steps of the Heuristic Algorithm.

	t=1	2	3	4	5	6
S_1	1	3	2	6	5	4
S_2	5	4	2	6	1	3
S_3	4	5	6	2	3	1
S_4	4	5	1	3	2	6
S_5	5	4	1	3	2	6
S_6	2	6	5	4	1	3
S_7	3	1	4	5	6	2
S_8	6	2	3	1	4	5
S_9	6	2	3	1	5	4
S_{10}	3	1	4	5	6	2

(a)

	t=1	2	3	4	5	6
S_1	1	3	2	6	5	4
S_2	5	**3**	2	6	1	**4**
S_3	4	5	6	2	3	1
S_4	4	5	1	3	2	6
S_5	5	4	1	3	2	6
S_6	2	6	5	4	1	3
S_7	3	1	4	5	6	2
S_8	6	2	3	1	4	5
S_9	6	2	3	1	**4**	**5**
S_{10}	3	1	4	5	6	2

(b)

Fig. 3. Illustration of swapping operations conducted in the Heuristic Algorithm.

problem of finding the optimal one. It is intriguing to further study the advantages of applying the Heuristic Algorithm with variable perturbation rates.

Next, we provide an illustrative example of how the Heuristic Algorithm proceeds. For simplicity of illustration, we define the neighborhood of the solution move as consisting of those that can be obtained by conducting two instances of swap-perturbation from the current solution. Provided that there are six learning objects and ten participating students, the relevance degrees among the learning objects are given in Table 2. Let Fig. 3a show the current solution X_h where the learning path for each student is indicated. For example, the learning path for student S_2 is E_5, E_4, E_2, E_6, E_1, and E_3. The fitness value for the current solution is 0.3713 by calculating Eq. (1) with $\alpha = \beta = 0.5$. Assume that students S_2 and S_9 are selected for performing the swap operation and the altered characters are typed in bold to indicate the changes, as shown in Fig. 3b. The first swap operation applied to S_2 swaps the order of E_3 and E_4 in the respective learning path, while the second swap operation applied to S_9 swaps the order of E_4 and E_5 in another learning path. The two swap operations result in a trial solution Y_{h+1} whose fitness value is derived as 0.3693. Because in this case $f(Y_{h+1}) < f(X_h)$, X_{h+1} is set to Y_{h+1}. The Heuristic Algorithm with the swap operation is iteratively executed until a specified maximal number, L_{max}, of iterations has been conducted. As such, continuous improvement of the solution quality is achieved.

4. A practical application

A butterfly-ecology course in an elementary school was conducted to test the effectiveness of the innovative approach. Twenty four kinds of butterflies and eighteen species of plants (i.e. eighteen learning objects) are raised in the butterfly-ecology garden of that school. The learning activity aims to guide the students to observe the ecology of butterflies (e.g., how a larva grows and becomes a butterfly) and to recognize the food plants for various butterflies. Before conducting the learning activity, the teacher was asked to complete the repertory grid that describes the features of each plant in the butterfly-ecology garden. Table 3 shows the repertory grid of the plants, where $E1$, $E2, \ldots, E18$ represent "Aristolochia heterrophylla", "Aristolochia Zollimgeriana", …. "Castor Seed", respectively. From Table 3, the relevance between each pair of plants can be determined by calculating the similarity degree between the columns of data.

Table 4 shows the relevance degrees between each pair of learning objects by applying the relevance analysis formula (Eq. (2)), according to which the learning paths for individual students were determined.

Twenty-five students who participated in this course needed to have an individual learning path arranged for them to learn the course content effectively. By applying the proposed Heuristic Algorithm for 40,000 iterations, the final best learning path for each student is derived in 35 s and the result is shown in Table 5.

To conduct the learning activities in the butterfly-ecology garden, a context-aware ubiquitous learning environment was implemented, in which the butterfly host plants were labeled with RFID tags. Moreover, a mobile device equipped with an RFID reader and wireless communication facilities was provided to each student. That is, the mobile device can communicate with a computer server, and the system can detect the location of individual students.

Table 3
Repertory grid of the plants in the butterfly-ecology garden.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17	E18	
Plant of Papilionidae	1	1	1	1	1	1	1	1	1	5	5	5	5	5	5	5	5	5	Non-Plant of Papilionidae
Plant of Dadaidae	5	5	5	5	5	5	5	5	5	1	1	1	1	1	5	5	5	5	Non-Plant of Dadaidae
Plant of Pieridae	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	1	1	5	Non-Plant of Pieridae
Plant of Nymphalidae	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	Non-Plant of Nymphalidae
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Cordate	5	2	1	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	Non-Cordate
Digitate	5	5	5	1	5	5	5	5	5	5	5	5	5	5	5	5	5	1	Non-Digitate
Ovate	5	5	5	5	1	5	5	5	5	2	1	2	5	4	5	2	5	5	Non-Ovate
Oblong	5	5	5	5	5	1	2	1	5	2	5	5	5	5	1	5	1	5	Non-Oblong
Lanceolate	5	5	5	5	5	5	2	5	1	5	5	2	1	5	5	5	5	5	Non-Lanceolate
Obovate	5	5	5	5	5	5	5	5	5	5	5	5	5	1	5	2	5	5	Non-Obovate
Orbicular	5	5	5	5	5	5	5	5	5	2	5	5	5	5	5	5	5	5	Non-Orbicular
Oval	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	2	5	5	Non-Oval

Table 4
Relevance degrees between each pair of plants (%).

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17	E18
E1	**100**	88	88	91	83	83	80	83	83	68	74	72	74	73	74	68	74	74
E2	88	**100**	98	88	79	79	77	79	79	65	71	68	71	70	71	65	71	71
E3	88	98	**100**	88	79	79	77	79	79	65	71	68	71	70	71	65	71	71
E4	91	88	88	**100**	83	83	80	83	83	68	74	72	74	73	74	68	74	83
E5	83	79	79	83	**100**	91	89	83	83	75	83	78	74	75	74	75	74	74
E6	83	79	79	83	91	**100**	96	91	83	75	74	72	74	73	83	68	83	74
E7	80	77	77	80	89	96	**100**	87	87	73	72	76	78	71	78	66	78	72
E8	83	79	79	83	83	91	87	**100**	83	75	74	72	74	73	83	68	83	74
E9	83	79	79	83	83	83	87	83	**100**	68	74	78	83	73	74	68	74	74
E10	68	65	65	68	75	75	73	75	68	**100**	92	90	86	78	75	707	75	68
E11	74	71	71	74	83	74	72	74	74	92	**100**	96	91	84	74	75	74	74
E12	72	68	68	72	78	72	76	72	78	90	96	**100**	96	82	72	73	72	72
E13	74	71	71	74	74	74	78	74	83	86	91	96	**100**	82	74	68	74	74
E14	73	70	70	73	75	73	71	73	73	78	84	82	82	**100**	73	76	73	73
E15	74	71	71	74	74	83	78	83	74	75	74	72	74	73	**100**	86	91	74
E16	68	65	65	68	75	68	66	68	68	70	75	73	68	76	86	**100**	77	68
E17	74	71	71	74	74	83	78	83	74	75	74	72	74	73	91	77	**100**	74
E18	74	71	71	83	74	74	72	74	74	68	74	72	74	73	74	68	74	**100**

Table 5
Best learning path derived by the Heuristic Algorithm.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15	E16	E17	E18
S_1	6	8	16	11	10	12	13	14	15	17	7	5	9	1	3	2	4	18
S_2	10	12	13	14	11	16	3	2	9	1	5	7	6	8	4	18	15	17
S_3	12	13	14	5	7	8	18	4	3	2	9	6	17	15	16	10	11	1
S_4	10	11	13	12	14	16	15	17	18	4	1	9	3	2	7	6	5	8
S_5	2	1	3	4	18	11	5	7	6	17	16	14	10	12	13	9	8	15
S_6	7	8	1	2	9	13	12	11	10	14	18	17	15	16	4	3	5	6
S_7	5	12	18	4	2	3	15	17	16	14	11	10	8	7	6	1	9	13
S_8	15	18	9	7	6	8	1	4	11	10	12	13	14	16	17	5	3	2
S_9	3	2	4	18	15	1	8	6	14	16	17	7	9	5	11	12	13	10
S_{10}	17	15	16	14	8	9	13	10	11	18	5	6	1	3	2	4	7	12
S_{11}	3	5	14	13	18	7	6	8	17	15	4	1	2	9	12	11	10	16
S_{12}	6	7	5	11	13	14	4	1	8	3	2	9	12	10	16	17	15	18
S_{13}	13	11	2	3	1	9	7	5	10	12	14	18	4	6	8	15	16	17
S_{14}	11	16	17	6	4	18	9	13	12	1	3	2	7	8	15	10	14	5
S_{15}	14	10	15	16	17	6	7	5	4	3	2	1	8	9	12	13	11	18
S_{16}	2	4	18	9	16	12	10	11	5	7	6	8	1	13	14	15	17	3
S_{17}	8	3	2	1	5	7	14	9	13	11	18	4	6	17	15	16	12	10
S_{18}	18	14	11	12	13	15	17	8	2	3	1	4	5	7	9	6	10	16
S_{19}	9	13	12	10	7	4	2	3	1	5	6	15	16	14	18	17	8	11
S_{20}	4	6	7	8	15	17	16	11	10	12	13	18	14	5	1	3	2	9
S_{21}	15	17	6	1	4	3	2	14	16	13	10	11	12	18	5	7	9	8
S_{22}	14	1	7	6	17	5	9	18	4	15	16	12	13	11	10	8	2	3
S_{23}	1	2	17	15	16	10	11	12	13	9	8	14	18	4	3	5	6	7
S_{24}	16	15	10	13	12	11	14	18	7	8	9	3	17	6	5	2	1	4
S_{25}	13	9	5	17	3	2	4	1	7	6	15	16	11	12	10	8	18	14

Fig. 4 depicts the interface of the mobile device for guiding individual students to a series of planned learning objects by showing the map of the butterfly-ecology garden and pointing out the location of each target object to them. As soon as the learning system detects the student's arrival at the target location, the corresponding learning activity will be activated.

While visiting a target learning object (a host plant or a specified butterfly-ecology area), the students are guided to observe the features of the plant or the specified ecology phenomenon. Fig. 5 shows the interface of the mobile device for guiding the students to observe the butterfly caterpillars. Several versions of such learning materials and activities have been developed for meeting the special ecological phenomena in different seasons.

5. Experiments and analysis

To evaluate the effectiveness of the innovative approach, a series of experiments has been conducted, including interviewing the teachers who have experienced the learning environment, analyzing the learning achievements of the students who participated in the learning activity of a butterfly-ecology course, and comparing the performance of the proposed algorithm with that of other approaches based on a set of testing data.

5.1. Feedback from the teachers

In the first stage, two experts (experienced teachers who had taught the butterfly course for above 5 years) were interviewed. The first expert, coded TA, had 8 years of experience teaching butterfly-related courses. The second expert, coded TB, had 5 years experience. The

Fig. 4. Illustrative example of guiding a student to the target learning object.

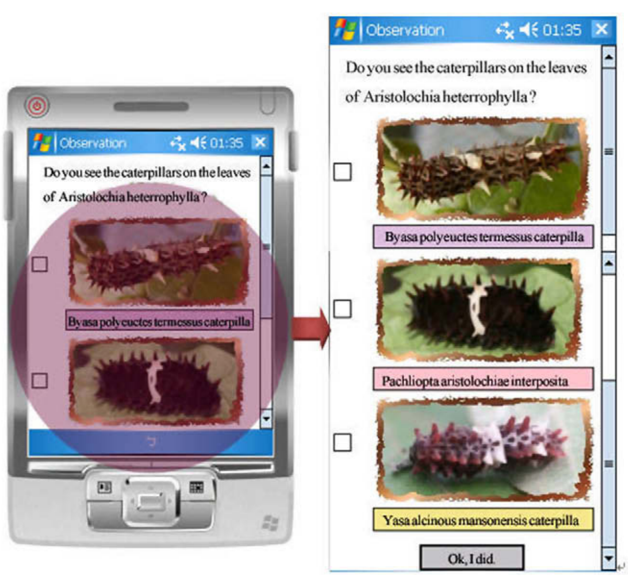

Fig. 5. Interface of guiding the students to observe butterfly caterpillars.

experts were required to comment on the usefulness and quality of the innovative learning approach in comparison with the conventional instructional approach in terms of three aspects: (1) motivation for learning; (2) learning management; (3) effectiveness of learning.

Table 6
t-Test results of pre-test for the students in the experimental group and the control group.

Group	n	Mean	SD	t
Experimental group	25	72.68	13.149	.559
Control group	25	70.56	12.316	

Table 7
t-Test results of post-test for the students in the experimental group and the control group.

Group	n	Mean	SD	t
Experimental group	25	80.00	9.979	.023*
Control group	25	72.56	12.316	

* $p < .05$.

- *Motivation for learning*

TA stated, "The mobile device certainly increases students' interest due to the diversity of the learning materials shown to them." Moreover, what impressed her was that the students seemed very happy and looked forward to operating the mobile devices; meanwhile, the students' interest and efficacy were also promoted by the u-teaching strategy in contrast to the conventional instruction. In addition, in comparison with the traditional instruction, TB also mentioned the "continuous concentration" manifested by the students when the mobile device guided them during the learning process. He stated, "It is amazing that the students concentrated on the learning activities for a longer time than I ever expected.".

- *Learning management*

The two teachers both agreed about the benefits of the u-learning system. TA mentioned, "With the innovative system, we can browse individual student's learning process. This even allows us to immediately trace their real-world learning status during the learning activity. It is convenient for teachers to offer timely and appropriate assistance to students." Meanwhile, TB also expressed, "The learning status including the browsed pages, time for observation, and learning paths were all recorded in the system, which can not only be regarded as a reference for analyzing students' efficacy and improving teachers' instruction, but can also help us to adjust teaching materials and strategies based on the collected data.

- *Effectiveness of learning*

As for the guidance strategy mentioned in the study, TA brought up the "immediacy" aspect of the system, which TB also agreed with, "A guidance strategy can guide students to an appropriate location in the u-learning environment, and provides timely and appropriate help to solve the problems they meet. Thus, such a guidance strategy is an appropriate way for students. It works like a tutor for each student." Thus, the two teachers both stated, "Not only is students' efficacy promoted, but they are also given an insight into the butterfly-based course".

5.2. Learning achievements and student feedback

To evaluate the effectiveness of the innovative approach, a learning activity was conducted. Fifty elementary school students from two classes participated in the learning activity. The students in one class were assigned to the experimental group ($n = 25$) and those in another class were the control group ($n = 25$). Those students were aged 10 or 11. Before conducting the learning activity, the students received a pre-test, which consisted of 20 multiple-choice items, to ensure that both groups of students had equivalent basic knowledge concerning the plants and the butterflies. Table 6 shows the *t*-test results of the pre-test scores for the experimental group and the control group, from which it can be seen that there was no significant difference between the scores of the students in the two groups ($t = .559$, $p > 0.05$).

To avoid affecting the experimental results, the two groups of students were arranged to visit the butterfly-ecology garden for the learning activity (120 min) at different times. Each student had a hand-held device (PDA) equipped with wireless network access and an RFID reader. Each target learning object to be observed had an RFID tag on it. By detecting the RFID signals, the u-learning system was able to know the location of individual students and guide them to learn via the PDAs. The students in the experimental group were guided by the u-learning based on the personalized learning paths generated by the innovative approach. For those in the control groups, the u-learning system only provided corresponding supplemental materials and instructions when the students walked close to the learning objects.

After participating in the learning activity, individual students were arranged to take a test on identifying the features of the plants and the butterflies in the butterfly-ecology garden. Each student needed to write down their answers to the questions while being led to the plants by the teaching assistant. The post-test contained 18 short-answer questions. Table 7 presents the *t*-test results of the post-test, showing that the students in the experimental group had significantly better achievement than those in the control group ($t = .023$. $p < 0.05$).

Five participants in the experimental group, coded as *S*1, *S*2, *S*3, *S*4 and *S*5, were selected for one-to-one semi-structured interviews. At the time, all these students were in fourth grade.

When the students were asked the question, "What are the differences between learning by mobile device and learning by conventional instruction?" they variously characterized the system as an "interesting," "interactive," and "immediate" learning assistant. *S*1 found that the teaching strategy of the u-learning system was more interesting and interactive than conventional instruction in the classroom. He also stated that students could read more detailed materials consisting of text and pictures, and compare them with the real-world learning objects in the garden, which motivated his learning. Moreover, he also stated, "I can go over the learning path repeatedly in the garden with the mobile device, and search for solutions without asking the teacher again and again. Such a learning method has relaxed me in the learning process". *S*2 thought, "The butterfly-based course has become more interesting and successful. It integrates the similar learning objects to make observation easier for students. Meanwhile, mobile devices equipped with a u-learning system seem like a guide providing proper materials to us step by step, and make learning more fun." In addition, it is worth noting that both *S*4 and *S*5 raised the point that their use of mobile devices would enable them to access data when needed during the learning process, a function that heightened their interest in the course. Thus, the proposed system not only features a friendly and easy-to-use interface, but also provides adaptive and appropriate materials for students in the u-learning environment.

In terms of the "effectiveness" perspective, these participants all viewed the system with a positive attitude. For example, when asked about how the learning guidance function worked, four students (*S*1, *S*2, *S*3 and *S*4) commented, "The system is immediate and convenient." S3 expressed, "The mobile device can guide us or suggest a learning path, and this makes me feel like a teacher explains it to me. Thus, I would rather learn with this system than with a teacher." From these comments, it can be seen that the learning paths generated for individual students were helpful to them.

Furthermore, five participants in the control group, coded as SC1, SC2, SC3, SC4 and SC5, were interviewed. In the aspects of "interesting," "interactive," and "immediate", the feedback from those students was similar to that from the experimental group. The major differences however, were the "inefficiency" and the "ineffectiveness" problems addressed by those control group students. For example, all of the five students complained about the difficulty observing some learning objects owing to them being crowded by learners. SC2 expressed, "The observation activities were interrupted several times, because too many classmates crowded in the same location." SC4 expressed, "I was forced to observe other learning objects owing to the crowded people."

5.3. Performance evaluation of the Heuristic Algorithm

In this section, simulations are conducted in order to analyze and evaluate the performance of the proposed heuristic approach and other methods. The platform of the experiments is a personal computer with a Pentium Dual-Core 2.0 GHz CPU, 2 GB RAM and 250G hard disk with 7200-RPM access speed. The programs were coded in C# Language.

- *Sensitivity analysis*

We first conducted the sensitivity analysis on the variants of the proposed Heuristic Algorithm. As previously noted, seven types of perturbation operations (A, B, C, AB, AC, BC, and ABC) can be embedded in the Heuristic Algorithm. Another parameter that may affect the performance is the perturbation rate. We applied each variant 20 times on a simulated problem instance with 50 learning objects and 100 students. Each time the executed variant was performed with a different perturbation rate ranging from 0.05 to 1.0 with an increment of 0.05. Fig. 6 shows the box plot of the sensitivity analysis. The top and bottom lines of the box represent the Q3 and Q1 quartiles of the fitness distributions of the 20 runs. The bold horizontal line within the box and the horizontal lines above and below the box indicate the median, maximum, and minimum of the fitness values, respectively. The small circle is the identified outlier according to the density analysis. It is seen that Heuristic Algorithm C, which embeds the inversion perturbation operation, is the most robust variant against different perturbation rates.

Furthermore, we implemented a genetic algorithm as a competing counterpart. The genetic algorithm applies roulette wheel selection, partially matched crossover (PMX), and the inversion mutation for the same number of fitness evaluations as that consumed by the Heuristic Algorithm. We first applied GA-FixM where the mutation rate was fixed to 0.1 and the crossover rate varied among 10 levels

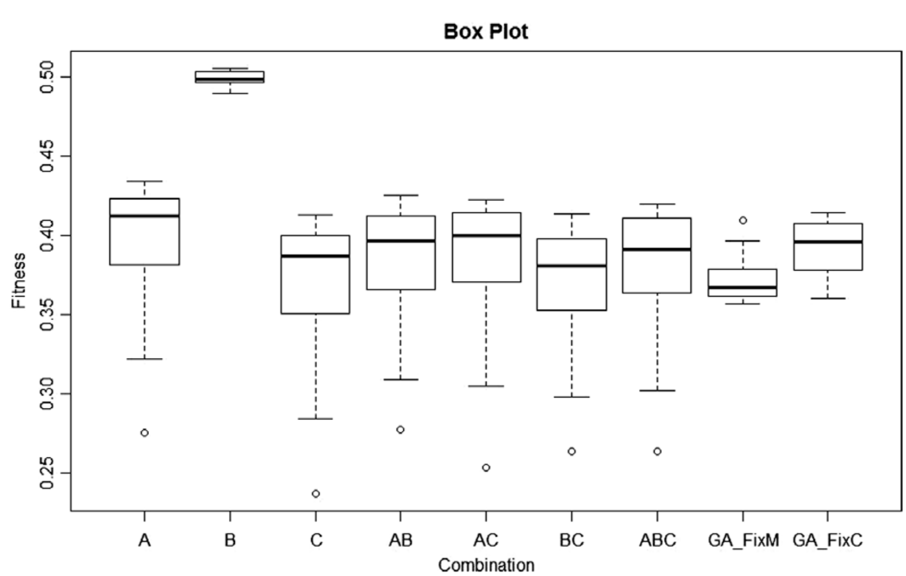

Fig. 6. Sensitivity analysis of seven heuristic variants and a genetic algorithm.

Table 8
Sensitivity analysis for the influence on Heuristic Algorithm C using varying values for the parameters α and β.

	α								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Fitness	0.39	0.35	0.31	0.27	0.24	0.20	0.17	0.13	0.10

$\beta = 1 - \alpha$.

Table 9
Comparative performances between Heuristic Algorithm C, the Random Search, and GA-FixM.

Parameters		Heuristic Algorithm C					Random Search		GA-FixM	
m	n	Average	Standard deviation	Best	Worst	Time (s)	Average	Time (s)	Average	Time (s)
20	20	0.24	0.005	0.23	0.25	47	0.54	53	0.31	52
20	40	0.23	0.002	0.23	0.24	85	0.54	98	0.36	95
20	60	0.24	0.002	0.24	0.25	123	0.54	143	0.39	130
50	50	0.20	0.002	0.20	0.21	1492	0.48	1533	0.32	1567
50	100	0.23	0.001	0.23	0.23	2817	0.49	2928	0.36	2974
50	150	0.25	0.002	0.24	0.25	4269	0.49	4450	0.39	4392
80	80	0.26	0.001	0.25	0.26	9157	0.50	9363	0.38	9628
80	160	0.29	0.001	0.29	0.29	18,095	0.50	18,484	0.41	19,495
80	240	0.31	0.001	0.31	0.31	29,486	0.50	29,668	0.43	30,234

(0.1, 0.2, ..., 1.0). For each combination of various mutation and crossover rates, 20 runs of GA-FixM on the same simulated problem instance were conducted, and each run was associated with a different perturbation rate selected from (0.05, 0.1, 0.15, ..., 1.0). Therefore, the box plot for GA-FixM shown in Fig. 6 corresponds to the fitness distributions for 200 repetitive runs. The simulation for GA-FixC was conducted analogously by instead fixing the crossover rate to 1.0 and varying the mutation rates in (0.1, 0.2, ..., 1.0). We observe that GA-FixM is more robust than GA-FixC against varying conditions. However, the best heuristic variant C is still significantly better than GA-FixM.

Next, we conducted sensitivity analysis for the influence on Heuristic Algorithm C using varying values for the parameters α and β employed in the objective function (Eq.(1)). As the parameters satisfy $\alpha + \beta = 1.0$, we only needed to vary the value of α and then compute the value of β accordingly. Table 8 shows that as the value of α increases (by decreasing β simultaneously) the obtained optimum fitness is smaller. This means that the minimization objective related to the difference between the numbers of students attending various learning objects is easier to achieve, while the other objective to minimize the relevance loss incurred in successive learning objects is strongly dependent upon the characteristics of the learning activities.

- *Comparison with other approaches*

In order to simulate the environment adapting to various context-aware U-learning applications, a dataset with the number of learning objects set to 20, 50, and 80, respectively, was created. For each specified number of learning objects, the number of participating students was set to one, two, and three times the object number. Therefore, there were totally nine problem instances in our dataset. The parameter setting covers a broad range of U-learning applications encountered in the real-world. To justify the performance of our method, the best way is to compare the obtained result with the exact optimal solution. However, even the smallest problem instance ($m = 20$, $n = 20$) is intractable for an exact method such as Branch-and-Bound. Alternatively, we implemented the previously noted GA-FixM and a Random Search method for comparison. The Random Search method initially produced a feasible learning path solution by generating n sequences of random m-permutations. The Random Search method was allowed to produce the same number of fitness evaluations as that consumed by Heuristic Algorithm C and GA-FixM (this number was set to 40,000 in all the experiments), and the best solution observed overall was output.

Table 9 shows the comparative results obtained using Heuristic Algorithm C, the Random Search, and GA-FixM, respectively. Each algorithm was executed for five independent runs. It is seen that the average fitness value obtained by the Random Search is about two times larger than that derived by Heuristic Algorithm C over all problem instances. GA-FixM also derives better results than the Random Search; however, the fitness values obtained by GA-FixM are worse than those of Heuristic Algorithm C. Moreover, the best and the worst fitness values obtained by Heuristic Algorithm C are very close to each other among the five independent runs, resulting in low standard deviation values, disclosing the fact that Heuristic Algorithm C is robust against the problem size, and its performance is relatively independent of the initial seed used to generate random numbers. Finally, the computational time consumed by Heuristic Algorithm C and the Random Search is comparable, while GA-FixM needs a slightly longer time to finish the evolution process because GA-FixM involves more complex operations for performing selection, crossover and mutation.

Fig. 7 shows the best fitness values for the largest problem instance with $m = 80$ and $n = 240$ that can be obtained using Heuristic Algorithm C as the number of fitness evaluations increases. The algorithm starts the search course with a random initial solution whose fitness value is evaluated as 0.51. As the number of fitness evaluations increases, we observe that Heuristic Algorithm C continually improves the best fitness value obtained by iteratively applying the embedded inversion operation. Upon the termination criterion of the program where 40,000 trial solutions have been generated, Heuristic Algorithm C reports the best fitness value observed overall as 0.31. This reveals that the proposed Heuristic Algorithm C can effectively construct a learning path for each participating student in the context-aware U-learning environment.

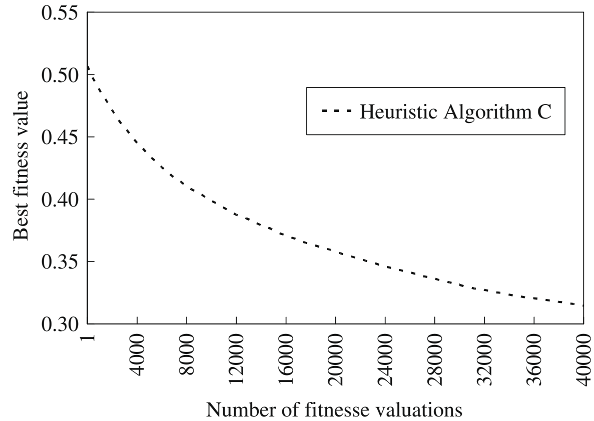

Fig. 7. Best fitness value obtained as the number of fitness evaluations increases.

6. Conclusions

Although previous research on personalized learning has taken many factors into consideration, the relevance between learning objects is seldom discussed, especially while guiding the students to learn in a real-world environment. In this paper, an optimization problem that models the objectives and criteria for planning personalized learning paths consisting of a set of real-world learning objects to maximize the learning efficacy for individual students is formulated. A Heuristic Algorithm is proposed to cope with the problem, and a learning environment has been implemented to evaluate the innovative approach.

The experimental results from learning activities conducted in an elementary school show the benefits of this innovative approach. The experts and students who experienced the learning scenario showed positive perceptions with respect to the motivation, interactivity and effectiveness issues. In addition, both of the experts agreed that the mobile device's learning guidance (in the context of the real-world learning environment) was essentially helpful to the students. These reactions point to the effectiveness of this innovative training approach. Furthermore, the system enabled the teachers to keep track of the students' learning status (e.g., the arrival time at each target learning object, the observation time for each target and the answers to the questions asked by the system), as well as facilitating the teachers' individualized instruction. Overall, the teachers expressed the following praise, "Such a learning system not only saves time and reduces our workload, but can also promote students' efficacy. In addition, the students' status during the learning process is recorded in detail in the system, which can be used as a reference for teachers to adjust their instruction. Based on these data, teachers can offer students adaptive help at the right time, in the right place." In addition, all the students stated, "We are excited and curious about the butterfly-based course conducted using the context-aware u-learning system". From these comments and feedback, it can be seen that the generated learning paths do meet the requirement of guiding students to learn to observe relevant objects while considering the criterion of maintaining learning quality.

This innovative approach can be applied to most real-world learning activities concerning natural science and ecology observations; in addition, it can also be applied to cultural learning activities in museums or temples. There are more factors that can be taken into account in practical applications, such as the personal features of students (e.g., knowledge level, learning style, cognitive style) and the features of the learning environment (e.g., the available space of individual learning objects, the time for walking from one location to another, and the time needed to observe individual learning objects), depending on the practical needs. While using this algorithm in other settings, the researchers need to adjust those constraints and the objective functions in the optimization program; moreover, for each application, the teachers will need to provide a repertory that states the relevance of the learning objects.

To apply this innovative approach to more complex learning activities or to learning environments with larger spaces (e.g., museums), more constraints and parameters need to be considered while formulating the optimization problems. Furthermore, for some applications, the time needed to complete the learning-missions could be quite different. In that case, the assumption that each learning stage has identical expected time will need to be revised, and the path optimization problem will need to be enhanced as well.

Acknowledgement

This study is supported in part by the National Science Council of the Republic of China under Contract Nos. NSC 96-2628-S-024-001-MY3 and NSC 98-2631-S-024-001.

References

Araujo, I. S., Veit, E. A., & Moreira, M. A. (2008). Physics students' performance using computational modelling activities to improve kinematics graphs interpretation. *Computers & Education, 50*(4), 1128–1140.
Chen, Y. S., Kao, T. C., & Sheu, J. P. (2003). A Mobile Learning System for Scaffolding Watching Learning. *Journal of Computer Assisted Learning, 19*(3), 347–359.
Chen, C. M. (2008a). Intelligent web-based learning system with personalized learning path guidance. *Computer & Education., 51*(2), 787–814.
Chen, C. M. (2008b). Ontology-based concept map for planning personalized learning path. *British Journal of Educational Technology*.
Chen, C. M. (2009). Personalized E-learning system with self-regulated learning mechanisms for promoting learning performance. *Expert Systems with Applications, 36*(5), 8816–8829.
Chen, C. M., Lee, H. M., & Chen, Y. H. (2004). Personalized e-learning system using Item Response Theory. *Computers & Education, 44*(3), 237–255.
Chu, H. C., & Hwang, G. J. (2008). A delphi-based approach to developing expert systems with the cooperation of multiple experts. *Expert Systems with Applications, 34*, 2826–2840.

Chu, H. C., Hwang, G. J., Huang, S. H., & Wu, T. T. (2008). A knowledge engineering approach to developing E-libraries for mobile learning. *The Electronic Library, 26*(3), 303–317.
Chang, A., Chang, M., & Heh, J. S. (2007). Implementing a context-aware learning path planner for learning in museum. In *6th WSEAS international conference on E-ACTIVITIES*, Tenerife, Spain, December 14–16.
Cardellini, L. (2004). Conceiving of concept maps to foster meaningful learning: van interview with joseph d novak. *Journal of Chemical Education, 81*(9).
Din, F. S. (2009). The functions of class size perceived by Chinese rural school teachers. *National Forum of Applied Educational Education Research Journal, 22*(3).
Grabe, M., & Grabe, C. (2007). *Integrating technology for meaningful learning* (5th ed.). New York: Houghton Mifflin Company.
Hwang, G. J. (2003). A concept map model for developing intelligent tutoring systems. *Computers & Education, 4*(3), 217–235.
Hwang, G. J. (2006). Criteria and strategies of ubiquitous learning. In *Proceedings of the IEEE international conference on sensor networks, ubiquitous, and trustworthy computing* (Vol. 2, pp. 72–77). Washington, DC, USA: IEEE Computer Society.
Hwang, G. J., Wu, T. T., & Chen, Y. J. (2007). Ubiquitous computing technologies in education. *Journal of Distance Education Technology, 5*(4), 1–4.
Hwang, G. J., Tsai, C. C., & Yang, S. J. H. (2008). Criteria, strategies and research issues of context-aware ubiquitous learning. *Educational Technology & Society, 11*(2), 81–91.
Hwang, G. J., Yang, T. C., Tsai, C. C., & Yang, J. H. S. (2009). A context-aware ubiquitous learning environment for conducting complex experimental procedures. *Computers & Education, 53*(2), 402–413.
Jonassen, D. H. (1995). Supporting communities of learners with technology: A vision for integrating technology with learning in schools. *Educational Technology, 35*(4), 60–63.
Kelly, G. (1955). *Principles of personal construct psychology*. New York: Norton.
Kevill, E., Shaw, M., & Goodacre, E. (1982). In-service diploma course evaluation using repertory grids. *British Educational Research Journal, 8*(1), 45–56.
Liu, T., Chu, Y., Tan, T., & Chang, C. (2007).RFID-based ubiquitous learning environment for outdoor learning. In *Proceedings of the seventh IEEE international conference on advanced learning technologies* (pp. 675–677). Arquivo.
Liu, C. L., Wu, S., Chang, M., & Heh, J. S. (2008). Guiding students to do remedial learning in school campus with learning objects' spatial relations. In 16th *international conference on computers in education conference*, 27–31 October 2008 (pp. 249–256).
Limongelli, C., Sciarrone, F., Vaste, G., & Temperini, M. (2008). Lecomps5: A web-based learning system for course personalization and adaptation. In *IADIS international conference e-learning*, Amsterdam, The Netherlands, 22–27 July 2008.
Maas, J. D., & Leauby, B. A. (2005). Concept mapping – Exploring its value as a meaningful learning tool in accounting education. *Global Perspectives on Accounting Education, 2*, 75–97.
Mladenovic, N., & Hansen, P. (1997). Variable neighborhood search. *Computers and Operations Research, 24*, 1097–1100.
Murakami, T. (2003). *Establishing the ubiquitous network environment in Japan*. Nomura Research Institute Papers (p. 66).
Novak, J. D. (1998). *Leaning, creating and using knowledge*. Lawrence Erlbaum Associates, Inc.
Ogata, H., & Yano, Y. (2004). Context-aware support for computer-supported ubiquitous learning. In *Proceedings of the 2nd IEEE international workshop on wireless and mobile technologies in education (WMTE'04)*, 27–34. JungLi, Taiwan: IEEE Computer Society.
Reinelt, G. (1994). *The traveling salesman–computational solutions for TSP applications*. Berlin: Springer-Verlag.
Rogers, Y., Price, S., Randell, C., Fraser, D. S., Weal, M., & Fitzpatrick, G. (2005). Ubi-learning integrating indoor and outdoor learning experiences. *Communications of the ACM, 48*(1), 55–59.
Schiaffino, S., Garcia, P., & Amandi, A. (2008). ETeacher: providing personalized assistance to e-learning students. *Computers & Education, 51*(4), 1744–1754.
Wu, T. T., Yang, T. C., Hwang, G. J., Chu, H. C. (2008). Conducting situated learning in a context-aware ubiquitous learning environment. wireless, mobile, and ubiquitous technology in education, *WMUTE 2008.* In *Fifth IEEE international conference*, 23–26 March 2008 (pp. 82–86).
Westerlund, J. (2008). Class size and student evaluations in Sweden. *Education Economics, 16*, 19–28.
Zahorik, J. A. (1999). Reducing class size leads to individualized instruction. *Educational Leadership, 57*(1), 50–53.