Implementation a Context-Aware Plant Ecology Mobile Learning System

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Abstract
Mobile devices are becoming ubiquitous methodologies and tools, providing application for learning and teaching field. On the basis of the widespread use of wireless devices and mobile computing technology, this study proposes a context-aware plant ecology learning system (CAPELS) based on context-aware technology; adapting deep neural networks (DNN) and leaf vein and shape identification algorithm which can identify plant leaves, this system automatically provides relevant botanical and growth environment knowledge to the learners. Therefore, during outdoor education, it can assist learners in accurately obtaining the required relevant botanical and growth environment knowledge. The experimental results indicate that students who used CAPELS performed better learning about plant ecology than those who did not. We also delivered questionnaires to those who used CAPELS and analyzed the results by using the partial least squares (PLS) method. The results have shown that CAPELS can encourage student’s learning motivation and thus improve their learning effectiveness. Thus, CAPELS provides a new educational platform for promoting ecology learning approach and effectively improves student learning efficiency and motivation.

Keywords
plant ecology, mobile learning, context-aware, image judgment, learning effectiveness

Introduction
Due to the popularity of wireless devices and progress in mobile computing technology, mobile devices are becoming ubiquitous tools in everyone’s life. Innovation, design, and creating new technology interfaces are developing a theoretical conception of potential mobile devices to inspire new forms of learning and engagement in the scholars of different fields (Land et al., 2015). Digital education learning from mobile technology not only has the potential to enhance the immersion and participation of learners in the actual settings where the knowledge being learned is to be applied, but also experiences real-world or pursued by learners across setting goal (Land et al., 2012).

In recent years, the field of digital education has progressed from e-learning to mobile learning (m-learning). Students are also becoming increasingly familiar with using mobile devices to search for information and learn. m-Learning is defined as using a new platform for e-learning (J. L. Shih et al., 2011). Therefore, as long as mobile devices, whether mobile phones or portable computers, can be integrated using specific context-aware mechanisms for learning purposes in a specific subject, it can be called m-learning.

In Taiwan, outdoor education is well known because it is especially in science learning which can not only be aimed at answering simple choice questions to know “what” and “when” but also “why” and “how.” More teaching style and learning processes closing practical design and exercises should be provided by the school’s teacher (Sambodo et al., 2018). m-Learning can help increase practical exercise to build scientific skill processes, broadening students’ scientific perspectives, and help teachers effectively used at outdoor education teaching sites (Wulandari et al., 2013). Because m-learning is highly mobile, it provides learners with access to learning objects and resources distributed around them, thus achieving the objectives of learning from life anytime and anywhere. Learners can interact with the real world through a three-dimensional virtual platform and are no longer limited to two dimensions because it is more realistic; thus, teaching sites become more diverse (Y. S.
Chen et al., 2003). In addition, a virtual platform close to a realistic world can encourage learners to walk out of their typical classroom and interact with the real world to obtain specific learning experiences. Therefore, the trend of continual progress in mobile technology encourages updating the teaching mode at the education sites and transforming the current situation in which PCs are only used as supplemental digital learning teaching tools to the current ever-present m-learning, and analyzing how to apply information technology in assisting outdoor teaching has become a popular research topic in the recent years (Y. M. Huang et al., 2012; T. T. Wu & Huang, 2010).

However, most challenges to make use of the mobile device in the teaching site have been considered, that is, how to attract students’ full attention to engage in learning activities. In the past, m-learning platforms have mostly focused only on using mobile devices for extracting useful web-based platform teaching tools (M. J. Huang et al., 2007; Tsai, 2009; Q. Wang, 2009). Education experts anticipate that if the emphasis is placed only on the utility of the platform but activities that connect with the real world are lacking, students cannot truly understand problems in the real world (Baloian et al., 2011; Chu et al., 2010). Particularly, in the botanical ecology educational field, lack of real-world interactions and exploration would make it difficult for the students to develop an emotional attachment and interest in ecology.

In the past, teachers usually applied m-learning methodology to teach plant ecology (Liu, Tan et al., 2009), which required to import all the plant-related information at the ecological pool into the database. Then the learners used the laptop as the mobile device to access websites to learn about plant ecology. Lin and Chen (2008) proposed the use of smartphones equipped with radio-frequency identification (RFID). Learners could receive the correct information about the plant via the following steps. The learners use the smartphone to detect RFID Tag, and then it will match up with the database and then send the corresponding information back to the mobile devices. Carmine (2012) and G. H. Hwang et al. (2012) proposed to use QR code (quick response code) technology, which allows students to quickly receive corresponding information after scanning the QR code. However, these methods are limited by the learning place, for example, the learners can’t receive the correct information once the RFID Tags or QR code labels are damaged, or if there is a delay in updating the database.

Therefore, the direct image identification of objects is the most effective method to help learners. Researchers typically propose using mobile devices that incorporate context-aware technology, thus providing learners with different learning experiences through mobile devices that provide learners with knowledge that corresponds to the context, allowing learners to closely interact with and be immersed in the actual objects they are learning about and their learning environment and to receive instant feedback and seamless assistance and guidance (Chu et al., 2010). On the contrary, many psychologists and pedagogues have pointed that individual learning behavior and psychological and physiological feedback have been impacted by positive emotion. Thus, to combine m-learning and context-awareness to provide a highly interactive dynamic learning environment, appropriate individualized learning subjects and content can be provided without any limitation on time, space, or location. Besides, it also incorporates learning in the real living space, encouraging real situation learning and accumulating and constructing knowledge and skills that can improve the passive learning attitudes and efficiency of students (Hall & Bannon, 2006).

The present study focused on the outdoor education needs of a university forestry department and constructed a set of context learning–based individualized plant ecology m-learning systems termed as the context-aware plant ecology learning system (CAPELS). In addition to investigating the viewpoints of education experts for the system, we also analyzed learners’ behaviors before and after they used the system. The study mainly analyzed whether the system can strengthen learner motivation and learning efficiency when used in outdoor plant ecology teaching.

**Literature**

**m-Learning**

m-Learning refers to a learning platform where learners can use wireless internet and mobile devices, including mobile phones, personal digital assistants, smartphones, and digital audio players, anywhere and anytime. m-Learning allows users to exchange data by using the platform and deposited education resource databases to improve the traditional mode of learning. Therefore, with progressing m-learning technology, the pervasive characteristics of m-learning have made it a reliable supplementary educational tool (C. C. Chen & Huang, 2012; Y. M. Huang et al., 2012).

The independence and high mobility of mobile devices provide an e-learning environment that can begin anywhere and that students and teachers can both use time outside school to finish homework and prepare for classes, respectively (Virvou & Alepis, 2005). While e-learning took learning away from the classroom, m-learning is taking learning away from a fixed location (Y. S. Wang et al., 2009). Motiwalla (2007) speculated that m-learning can add value to the current learning model, thereby playing a crucial role in the digital learning environment. m-Learning motivates the learner to easily integrate words and vivid pictures and get additional resources to communicate with peer learners by freedom of choice. This can help the learner make the conjunction of auditory and visual information about botany, which is considered to lead to deeper and more meaningful learning about plants and thus to increased appreciation (Balas & Momsen, 2014). Education researchers and
practitioners have been exploring the use of mobile devices to enhance learning environment diversity in the real world as a natural place for science (Crompton et al., 2016; Kamarainen et al., 2013; E. Tan & So, 2011; Zimmerman et al., 2014); to enable observation, data capturing, data sharing of the outdoor setting (T. Y. Liu, Tan, & Chu, 2009); to increase social interaction (Crompton, 2013); and to make use of reality-based educational game to improve students’ learning attitudes (G. J. Hwang et al., 2016). All of these studies on m-learning have the potential to revolutionize teaching and learning in science in the future.

**Context-Aware Learning**

Although m-learning has substantial developmental potential, it faces numerous challenges such as the small screen size, limited processing power, fewer input functions, and the problem of the external data connection. Because of the need to obtain context-specific data connection, particularly during outdoor education, we speculate that the lack of information access causes obstacles in applying m-learning in teaching. Therefore, traditional context-based methods are also gradually becoming popular in the teaching field.

The traditional techniques of the recommender system, such as collaborative, content-based, knowledge-based, and hybrid recommender systems, have been applied in numerous fields. Context-aware information is one of the famous technologies of the recommender system. The most commonly cited definition of “context-aware system” is

> Any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves. (Abowd et al., 1999)

Such contextual information can be obtained in numerous ways (Verbert et al., 2012):

a. Explicit context capturing relies on manual inputs from users. Registration modules are typically used to capture user information, or rating modules are used to retrieve interests and preferences.

b. Implicit methods automatically capture contextual information from the environment, for instance, by obtaining the current location and device type.

c. Contextual information can also be inferred by analyzing user interactions with tools and resources, for instance, estimating the current task of the user.

Advocates of contextual learning consider that human cognitive activities of daily life are typically controlled by social situations. Therefore, after interacting with the actual context, problem-solvers invent efficient strategies for solving problems, and this is called context learning (Brown et al., 1989). Learning is a process of establishing knowledge. By adding context-awareness functionality to m-learning, learners can detect situations in their environment, including time, location, and weather, for learning (Kawahara et al., 2003).

In the past, related research on m-learning with context-aware system (G. J. Hwang et al., 2009) instrument operation in the laboratory, ascending science assists students to use the instrument quickly and familiarly. Chang et al. (2011) applied this concept toward teaching outdoor activities to help students think about learning the content in an outdoor context. More recently, G. Z. Liu et al. (2018) designed contextual themes to improve the English listening comprehension of college students in fitness centers. Earlier, S. L. Wang et al. (2015) had used context and ontology to construct a knowledge map with context-awareness, which significantly helped learners to construct knowledge. In addition to the information context, this can provide information on the location in conjunction with the development of GPS technology. Sun and Chang (2016) provided teaching materials at the learning site, where learners immerse themselves in real-life situations to learn English and improve their English learning effectiveness.

m-Learning with context-aware system provides not only personalized learning but also collaborative learning with other learners. Y. M. Huang et al. (2011) applied this concept to elementary school students to learn about butterflies in the park and interacted with each student to construct information situations. More recently, Ştefan et al. (2018) allowed students to collect information and learn how to cooperate, be self-aware, empathize, and work out conflicts. In yet another recent research, to strengthen timely learning, Asad et al. (2019) designed a cloud-supported machine learning system that provides immediate and appropriate suggestions based on the student’s learning context and increases the skills of the students in learning programming.

Based on the above-mentioned information, it can be deduced that this study would aim at learning about plant ecology and constructing a plant ecology m-learning with context-aware system. This system can provide appropriate information about plant ecology with the help of sensors and, according to the situation factors at any given time, can be implemented in a wireless network environment.

**Identifying Plant Leaves**

We provide a brief account of earlier studies on plant leaf identification. Du et al. (2006) adopted the Douglas–Peucker approximation algorithm and created a sequence of invariant attributes. For the original leaf shape, a modified dynamic programming algorithm was adopted to identify the leaves of 25 plants with an accuracy of up to 92.3%. However, when the leaves of a plant have a similar shape, the recognition effect becomes different. Therefore, Zhao et al. (2015) extracted the pyramid histograms of plant leaf features with
oriented gradients such as color, hue, saturation, value, wavelet, and texture features and evaluated them using the ImageCLEF 2012 plant identification database, which contains the data of 126 tree species from the French Mediterranean region. The intersection of the histograms was used to predict the class with an accuracy of 89%.

In addition to enhancing the characteristics of leaves, plant identification algorithms have been integrated into machine learning models. Muammer and Davut (2019) applied Fourier descriptors (FD) and gray-level co-occurrence matrix methods for identifying plant leaf characteristics such as color and vein features, divided the plant leaves into two or four components, and then extracted the features separately, rather than extracting the entire leaf. Using the extreme learning machine classifier algorithm and the Flavia plant leaf database established by S. G. Wu et al. (2007), the accuracy was tested and found to be 99.10%. In a recent research, Yigit et al. (2019) extracted plant leaves using leaf picture database. The randomly selected 536 leaves corresponded to 80% of all leaves for training, and the remaining 134 leaves were used for testing and were identified by using the SVM model with 92.53% accuracy.

Deep learning technology has advanced in the past 2 years. Saleem et al. (2019) used the Flavia plant leaf database (S. G. Wu et al., 2007) to extract a feature set consisting of 11 shape features, seven statistical features, and five venation features (and FD), using AlexNet, a Convolutional Neural Network with two classification methods. Using Flavia plant leaf database as training data, and self-collecting plant pictures as test data, the training result reaches 98.75% plant recognition accuracy. It can reach 97.25% plant recognition accuracy on the self-collected data set.

At present, these plant identification technologies generally use pictures in the plant database as test data; however, at the actual teaching site, the plant data set must be extremely diverse, and the images are collected in the natural environment, indicating the need for a high-precision and generalized classifier. Due to this reason, in addition to the above-mentioned plant leaf characteristics, this study uses deep learning for identification.

System Design and Architecture

In this study, the learning topic of the system was botanical ecology, which is the science of various plants and their mutual relationships with their environmental conditions. We chose eight plants for the experiment. Considering the domain knowledge obstacle, the plant information was reviewed by the expert panel that we recruited in this study before the experiment. The expert panel included three senior teachers from a botany department and three practical forestry workers; all six people were experts in plant identification with advanced professional knowledge. The expert panel designed the CAPELS knowledge content and test questions and suggested appropriate rules for judging the model. In addition, after the system was constructed, the expert panel evaluated the CAPELS. Only after the system design quality was optimal, the teaching efficiency was evaluated. The CAPELS contains three modules as discussed in the following sections.

The m-learning module (MLM) was mainly included for learners to interact with the course content. On the basis of the knowledge target, the course content has to be delivered through the wireless mode, and an appropriate transfer mechanism has to be established to allow the learners to easily obtain the required information for different situations. The MLM allows learners to retrieve the history data and adjust the plant identification functions, thus allowing teachers and learners to receive instant knowledge feedback. Figure 1 shows the MLM operation system architecture.

First, teachers must input an image for comparison and the related information in the database for system learning. Our system assesses the image and the context captured by a sensor in the MLM reader of the handheld devices that are used by learners to take pictures of specific plant leaves. Then, the system runs several programs including dyadic transformation, noise elimination, edge detection, and area calculation and comparison. Finally, if the results and database pair up successfully, the system displays the corresponding plant content in the database. If this fails, the system suggests that the user retakes the photo and pairs up with the appropriate results again. After three unsuccessful pair-up results, the system automatically begins browsing to perform the data pair-up process. The pair-up success percentage is recorded in the database as a reference for the teachers to alter the database again. The details of the image judgment mechanism are as follows:

a. Learners capture pictures of plant leaves at the learning site and then send the images to the context-aware server. The system begins executing the identification
function, which uses the deep neural network (W. Liu et al., 2017). This architecture primarily replaces the sigmoid function of the neural network with ReLU (rectified linear unit), which helps in overcoming the problem of vanishing gradients, thereby achieving deep learning (Agostinelli et al., 2014). It also provides rapid learning (Chandra & Sharma, 2016). There is a good effect on image recognition (He et al., 2016).

Furthermore, K. B. Lee and Hong (2013) used the leaf vein and shape identification algorithm for the selection of plant features, which primarily consists of the following five steps:

1. Grayscale conversion: The system automatically converts the obtained image into a grayscale image with 300 × 375 pixels.
2. Noise elimination: The system eliminates noises in the original image to prevent them from affecting the retrieval of the plant leaf length and width ratio; therefore, M-mask covers every element on the indicated image, and convolution is performed as shown in Formula 1, where $m(-s, -t)$ represents the mask, $p(i + s, j + t)$ represents the indicated image, and $s$ and $t$ represent the corresponding primitive values:

$$
\sum_{s=-1}^{1} \sum_{t=-1}^{1} m(-s, -t)p(i + s, j + t).
$$

3. Sobel edge detection: The system calculates the first derivative for the image blocks whose grayscale shows dramatic changes and obtains a vertical Sobel matrix equation with a standard formula matrix. These two matrices are used to perform convolution on the images, that is, separately calculating the vertical direction and level direction gradient, and the gradient for each primitive value can be obtained using Formula 2.

$$
\nabla f(x, y) \approx G_x |+| G_y |
$$

4. Plant width-to-length ratio calculation: After performing edge detection on the images for analyzing the outlines of the plant leaves, the system analyzes the image. It subtracts the maximal and minimal $x$ values to obtain the leaf width. In the vertical direction, it subtracts the maximal and minimal $y$ values to obtain the leaf length. Finally, it divides the leaf width by the leaf length and uses the absolute value to obtain the length-to-width ratio of the plant leaf.

5. Plant comparison: After calculating the average length-to-width ratio of each type of plant leaf, the data are saved in the database. After the image is sent to the system, the system executes the same calculation steps and calculates the length-to-width ratio and subtracts it from the length-to-width ratio of every type of plant in the database to obtain the absolute value. The smallest difference represents the identification result.

b. In addition to the physiological structure of the plant, the location, the temperature, and the humidity of the environment in which the plant grows are important factors. For learners, information about the plant growth environment can be used to link other similar plant ecological elements. Therefore, when learners use mobile devices to access CAPELS, a GPS analyzes the location coordinates of learners and sends this back to the context-aware server. The system then searches for the environment sensor that is closest to the user and transmits the temperature, humidity, and illumination data to the context-aware server. The system adopts a single-chip wireless transmission environment monitoring system, which mainly includes a chip thermometer to measure parameters such as humidity, temperature, pressure, and illumination, and Wi-Fi, GPRS, and a 3.5G network to transmit the data to the MS SQL Express database of the context-aware server. Next, the system identifies plant function and compares it with the plant ecology database of the context-aware server, then sends the plant ecology knowledge of the textbook, as well as the temperature, humidity, and illumination results back to the mobile devices to be sure whether the identified plants are getting the right answer. Last, depending on our system, learners can compare the knowledge from the textbook and the real plant in the world.

c. After the comparison process, the questions about related plant knowledge were also retrieved from the database and pushed into the interface of the system. The goal of the function is to be sure whether the students understand the related growth background and knowledge procedures of the identified plant. If students fail to follow the incomplete work, then they cannot pass the question presented in the system. This design had led students to really understand the field of the practical procedure. Therefore, an efficient, accurate, practical exercise guide of our system would help students in conducting connect the plant in the real world with the ecology knowledge in the books.
Prototype System Display and Testing

After accessing the CAPELS (Figure 2(a)), users click on the “take the photo” button to activate the device’s built-in camera and take pictures of the plant leaves (Figure 2(b)). After photographing, the system allows the users to examine the shooting results. If the picture taken is not ideal, the user can use the return key to retake the photo. The gallery button can be clicked to choose the plant leaf image that one wants to identify from the mobile album. After photographing the plant leaf, the enter key is pressed to send the image to the server for processing. The identification results and temperature and humidity data are sent to the client end (Figure 2(c)). Furthermore, on the top-right corner of the results interface, a search option is provided, which can help the users to automatically use the browser to search for relevant information on the plant. If the system cannot identify the plant image, it displays a detection error and asks the user to retake the picture (Figure 2(d)).

To understand the plant identification quality of the CAPELS, this study chose eight plants for conducting the leaf identification test. The identification process was mainly conducted by the researcher and assistants, a total of six people, using the ASUS Zenfone 5 mobile device, obtaining images for five leaves of each of the eight plants and conducting five identification processes for each plant. Therefore, a total of 150 tests were performed for each plant.

The plant leaf database of this system is collected at the teaching site by themselves, and hence the plant leaf identification test is also performed at the teaching site. Therefore, the accuracy of the test is inferior to that of the current research using the plant picture database. The primary reason is that under different weather conditions, and under light and dark conditions, the three-dimensional changes in the shape of the leaves, the chromatic aberration of the leaves, and the changes in the shooting posture and direction will increase the difficulty of identification.

In general, the identification accuracy was higher than 80%, and the overall average identification accuracy was 95.25% (Table 1). Some inaccurate identifications in our experiment were caused by the inconsistent learning samples of each plant. Overall, the average identification accuracy rates in our experiment proved that the CAPELS identification quality was of a high standard.

Teaching and Evaluation Module

This study assessed the CAPELS, and the process was mainly divided into three stages. First, we invited botanical teaching experts to preliminarily evaluate the system quality, information quality, learning motivation, and learning willingness. Second, we conducted a teaching experiment focusing on the learners and compared their effectiveness in...
learning plant ecology. Finally, we adopted the technology acceptance model (TAM) to analyze learner acceptance of this system.

**Expert Evaluation**

This study consulted six plant ecology teaching experts and invited them to experience this system and preliminarily evaluate the learning functions and quality of this system. The experts evaluated the system mainly using one of the questionnaires adopted from G. J. Hwang et al. (2010) or W. C. Shih et al. (2012), which had 11 items in total. The main purpose was to understand whether the system developed in this study contributes to the teaching practice.

**Teaching Experiment**

To understand the learning efficiency and acceptance of learners using the CAPELS, this study adopted the single-factor complete between-subjects experimental design and the independent variable was the context-aware plant ecology system and textbook sample and item bank of every chapter for students’ learning. The experiment involved the research group randomly picking eight plants for the students to learn, four for the CAPELS study group, and four for the textbook sample group. The main objective was to understand whether the context-aware system can effectively improve learning efficiency. Hence, the after-test grades were the dependent variables in this study.

The samples for evaluation were obtained by 61 technology college forestry department freshmen; all students had received basic botany course knowledge when using this system during an outdoor educational field trip. After the experiments, a questionnaire survey was administered to evaluate the effectiveness of the CAPELS in improving student learning motivation and effectiveness. The CAPELS study group performed the outdoor education experiment at an experimental woodland, whereas the control group performed the teaching experiment in the plant sample laboratory of the classroom. Every participant had to perform two sets of experiments, and four types of the plant had to be learned in the experiment every time. The pretest and posttest time was approximately 10 min each, and the actual learning time was set to 20 min. The experiment order was adapted from the ABBA method, simultaneously executing two sets of experiments.

In addition to comparing the learning effectiveness, this study further investigated the learner acceptance of this system. An increasing number of studies have reported that the TAM can be applied in different groups based on technology implementation factors, and the research results were highly consistent (Hu et al., 1999; Y. Lee, Kozar, & Larsen, 2003). The CAPELS is a new technology that changes the current habits of learners. Therefore, we adopted and modified the TAM, which has been commonly used for the issue of “behavioral intention regarding the acceptance of information technology,” as the theoretical foundation to build the research framework of this study (Figure 3).

The items of the perceived usefulness dimension of the learner learning behavior scale were modified from the scales of P. H. Wu et al. (2012); P. H. Wu et al. (2013); and Lu et al. (2014). The items of the system quality dimension were modified from the study of Liu et al. (2009), and the items of the information quality dimension were adopted from the study of T. T. Wu et al. (2011). The items of reuse and use intention dimensions were adopted from the study of

![Figure 3. Path analysis.](image-url)
Lu et al. (2014). Finally, the items of the learning motivation dimension were modified from the evaluation scale of P. H. Wu et al. (2013). All the items were scored using a Likert-type scale, and the main purpose was to investigate learner-perceived feelings after using this system. The following hypotheses were also proposed:

- **Hypothesis 1 (H1):** Information quality is significantly related to perceived ease of use.
- **Hypothesis 2 (H2):** Information quality is significantly related to perceived usefulness.
- **Hypothesis 3 (H3):** System quality is significantly related to perceived ease of use.
- **Hypothesis 4 (H4):** System quality is significantly related to perceived usefulness.
- **Hypothesis 5 (H5):** Perceived ease of use is significantly related to willingness to reuse.
- **Hypothesis 6 (H6):** Perceived ease of use is significantly related to learning motivation.
- **Hypothesis 7 (H7):** Perceived usefulness is significantly related to willingness to reuse.
- **Hypothesis 8 (H8):** Perceived usefulness is significantly related to learning motivation.
- **Hypothesis 9 (H9):** Learning motivation is significantly related to learning effectiveness.

### Evaluation Results and Discussion

#### Expert System Evaluation

Table 2 shows the statistical results of the survey of the CAPELS evaluation by the six experts. The responses indicated that the CAPELS can assist in enhancing student learning motivation and help students learn plant ecology ($\mu > 3.5$). Second, regarding the system functional design, both interface and operation designs were satisfactory ($\mu > 3.5$).

#### Learning Effectiveness Evaluation

This study adopted plant ecology knowledge for evaluating learning effectiveness. Plant ecology test questions were based on the teaching content and were in the multiple-choice format. After the experts edited the questions, 40 questions were set for each type of plant, of which 20 were for the pretest and 20 for the posttest. In addition, comparing the experimental group and control group questions and their difficulty levels revealed that the average difficulty levels of the learning efficiency questions were 0.5 and 0.54, the average degrees of distinctiveness were 0.51 and 0.54, Cronbach’s credibility values were .77 and .79, respectively; hence, each set of questions complied with the credibility and reliability assessment.

This study used an experimental design for nonequivalent groups. Therefore, the preliminary plant ecology knowledge of the students belonging to the two groups had to be tested to understand whether the two groups of learners had a similar degree of knowledge on plant ecology in the experiment. We conducted a pretest for the experiment on these eight plants, and an analysis of variance (ANOVA) revealed that the pretest scores for these eight plants did not exhibit statistically significant differences ($F = 0.961, p = .459 > .05$), indicating that students had similar average preliminary knowledge scores for these eight plants.

Table 3 shows the mean grades and standard deviations of evaluation for each learning activity. The experimental group adopted the CAPELS, whereas the control group adopted the traditional sample, textbook learning. The experimental results revealed that the scores of the experimental group ($8.89 \pm 3.45$) were significantly higher than those of the control group ($6.77 \pm 3.26$) and reached statistical significance ($t = 3.48; p < .000$). This indicates that compared with the traditional textbooks, samples, and oral teaching methods, the use of the CAPELS for teaching is more favorable.

### Table 2. Statistical Results of Questionnaire.

| Items                                                                 | n  | $\mu$ | $\sigma$ |
|-----------------------------------------------------------------------|----|-------|---------|
| This teaching model is able to enhance the learning motivation.       | 6  | 4.33  | 0.82    |
| This teaching model is able to enhance the learning efficiency.       | 6  | 3.67  | 0.82    |
| This teaching model is able to help students understand the characteristics and development of plants. | 6  | 4.17  | 0.75    |
| This system has a high feasibility.                                   | 6  | 3.67  | 0.52    |
| This system can help teachers reduce their teaching loads.           | 6  | 3.50  | 1.05    |
| The image and text used in this system are consistent.               | 6  | 4.00  | 0.89    |
| The functions in this system are easy to find.                       | 6  | 4.50  | 0.84    |
| It is easy to use this system to switch to different pages.          | 6  | 4.50  | 0.84    |
| The text colors, sizes, and icons of this interface design are easy to identify. | 6  | 4.00  | 0.89    |
| The messages provided by this system are clear and to the point (concise). | 6  | 4.33  | 0.82    |
| The overall operation of this system is easy.                        | 6  | 4.33  | 0.82    |
Furthermore, to analyze whether the freshman background in the vocational school influenced the learning effectiveness of the CAPELS, we divided the subjects into three groups, namely, the National Hualien Vocational High School of Agriculture (HLAHS) forestry department, with an HLAHS background but not from the forestry department, and not from the HLAHS. Comparing the learning effectiveness of students from these three backgrounds with these two sets of learning strategies (Table 4) revealed that among all the three groups, the mobile context-aware learning strategy was more effective than the textbook samples. The study further analyzed whether the two groups of different experiments differed. The ANOVA revealed that the six groups differed significantly, $F(5, 116) = 9.13, p < .05$ (Table 5). The least significant difference (LSD) post hoc comparison revealed that in terms of using the context-aware mobile system, their learning effectiveness differed because of their background (HLAHS forestry department > HLAHS nonforestry department > non-HLAHS). As for the HLAHS nonforestry department and non-HLAHS background students, the performance with using the context-aware mobile system was similar to that of the HLAHS forestry students using textbook samples.

**Analysis of the Measurement Model**

This study also developed and tested an implementation CAPELS factor model and performed a cross-sectional verification of the model by using opinions from the learners. We analyzed the data to test the hypotheses through partial least squares (PLS) path modeling by using Smart PLS 3.0. PLS can be used both to specify structural relationships among latent variables and develop and test conceptual models (Fornell & Bookstein, 1982; Shim et al., 2010). First, we conducted a PLS factor analysis to examine the measurement model according to the indices such as factor loadings, item reliability, convergent validity, and discriminant validity. Second, we employed the PLS modeling technique to execute a bootstrap resampling method (for 500 resamples) to examine and assess the significance ($t$ values) of the path coefficients in the path model.

To evaluate the constructs of the questionnaire, we performed confirmatory factor analysis (CFA) by using PLS. To obtain the CFA results, we analyzed the reliability, convergent validity, and discriminant validity of multiple-item scales. This procedure was conducted according to guidelines provided in the literature (Fornell & Larcker, 1981; Hutchinson et al., 2009). These results are reported in Table 6.

Composite reliability is used to assess the internal consistency of constructs. According to Fornell and Larcker (1981) and Nunnally (1978), composite reliability should be more than 0.7 for achieving internal consistency in measurements. The composite reliability in our study was 0.873 to 0.963, indicating a high internal consistency in our measurement model.

Convergent validity refers to multiple variables in the same construct being measured precisely. Convergent validity is measured in terms of factor loadings and average variance extracted (AVE). The AVE of every construct should be higher than 0.5, and factor loadings for every item should be higher than 0.7 (Fornell & Larcker, 1981; Nunnally, 1978). The factor loadings of all the items were higher than 0.7. The AVE was 0.669 to 0.766, suggesting adequate convergent validity.

Discriminant validity tests the variables for different degrees of discrimination between constructs. The relevance of each construct is measured to ensure that its relevance is higher than the correlation coefficients for the correlations between the construct and all the other constructs. The square root of the AVE of each construct should be higher than the covariance between the construct and all the other constructs in the model (Chin, 1998). Table 7 lists the inter-construct correlations and square roots of AVEs off the diagonal of the measurement model.

**Table 3. Mean Grades and Standard Deviation of Posttest Evaluation.**

| Groups            | n  | Test score | T test |
|-------------------|----|------------|--------|
| Experimental group| 61 | 8.89 ± 3.45| 3.48** |
| Control group     | 61 | 6.77 ± 3.26|        |

**Table 4. Mean Grades and Standard Deviation of Posttest Evaluation for Different Backgrounds.**

| Identity                   | Experimental group score | Control group score | t      |
|----------------------------|--------------------------|---------------------|--------|
| HLAHS—Forestry department  | 11.11 ± 2.42            | 9.05 ± 2.78         | 2.57*  |
| HLAHS—Nonforestry department| 7.87 ± 3.24            | 5.90 ± 3.06         | 4.51*  |
| Non-HLAHS                  | 7.91 ± 3.94             | 5.27 ± 2.621        | 2.96*  |

Note. HLAHS = National Hualien Vocational High School of Agriculture.

*p < .05.
Table 5. Posttest Post Hoc Comparison for Different Backgrounds.

|                      | Square sum | Degree of freedom | Average square sum | F test | Significance | LSD post hoc comparison |
|----------------------|------------|-------------------|-------------------|--------|--------------|-------------------------|
| Between groups       | 419.36     | 5                 | 83.87             | 9.13   | 0            | 1 > 2, 3, 4, 5, 6        |
| Within groups        | 1,066.02   | 116               | 9.19              |         | 2 > 5, 6     | 3 > 6                   |
| Total sum            | 1,485.39   | 121               |                   |         |              |                         |

Note. 1. HLAHS forestry experiment; 2. HLAHS nonforestry experiment; 3. non-HLAHS experiments; 4. HLAHS comparison; 5. HLAHS nonforestry comparison; 6. non-HLAHS comparison. HLAHS = National Hualien Vocational High School of Agriculture; LSD = least significant difference.

Table 6. Results of Measurement Model, Convergent Validity, and Reliability.

| Factors                              | M ± SE         | Factor loading |
|--------------------------------------|----------------|----------------|
| Factor 1: Perceived Usefulness (CR = 0.941, AVE = 0.669, α = 0.928) |                |                |
| The guidance of plant identification learning system can clearly and efficiently help me understand the learning contents and steps. | 3.74 ± 1.01    | 0.80           |
| With the guidance of plant identification learning system, I could acquire the plant knowledge. | 3.93 ± 0.89    | 0.78           |
| The combination of plant identification learning system and real context is conducive to learn. | 3.98 ± 0.92    | 0.90           |
| The plant identification learning system of mobile identification technology provides a convenient learning environment. | 4.26 ± 0.79    | 0.84           |
| Using identification technology makes the plant identification learning smoother. | 3.74 ± 0.95    | 0.79           |
| Using plant identification system leaning and observing plant ecology under real context is useful for me. | 3.85 ± 0.91    | 0.88           |
| I think using plant identification system leaning method allows me to learn better about plants. | 3.67 ± 0.96    | 0.72           |
| This set of system can save my learning time. | 3.97 ± 1       | 0.82           |
| Factor 2: Information Quality (CR = 0.939, AVE = 0.794, α = 0.913) |                |                |
| The system buttons are clear and easy to use. | 4.51 ± 0.77    | 0.94           |
| The instructions of plant identification system are clear and easy to use. | 4.57 ± 0.67    | 0.87           |
| The colors of plant identification system are clear and easy to identify. | 4.26 ± 1       | 0.82           |
| The messages of plant identification system are easy to understand. | 4.46 ± 0.79    | 0.93           |
| Factor 3: System Quality (CR = 0.912, AVE = 0.722, α = 0.871) |                |                |
| Using the plant image identification system in outdoor learning is helpful for me to increase real context knowledge. | 3.98 ± 0.87    | 0.84           |
| Using plant image identification system in outdoor learning is helpful for our group to collect data. | 3.92 ± 0.94    | 0.89           |
| Using Google Search links in outdoor learning is helpful for the width of plant ecology information. | 4.31 ± 0.74    | 0.79           |
| Using plant image identification system in outdoor learning is helpful for completing the assigned work. | 3.92 ± 0.9     | 0.88           |
| Factor 4: Perceived Ease of Use (CR = 0.963, AVE = 0.766, α = 0.956) |                |                |
| It is easy to operate the interface of plant identification system. | 4.59 ± 0.80    | 0.77           |
| Reading the information on the screen of plant identification system is easy. | 4.49 ± 0.74    | 0.82           |
| Information system operation process is clear and simple for me. | 4.66 ± 0.66    | 0.82           |
| The buttons and functions in the system are easy to understand. | 4.66 ± 0.63    | 0.93           |
| The user interface is easy to use. | 4.69 ± 0.62    | 0.92           |
| I can quickly learn how to plant identification learning system. | 4.70 ± 0.64    | 0.91           |
| In the overall learning activities, operating the plant identification learning system is not difficult for me. | 4.72 ± 0.58    | 0.92           |
| The interface of plant identification learning system is easy to use. | 4.70 ± 0.61    | 0.89           |
| Factor 5: Learning Motivation (CR = 0.873, AVE = 0.696, α = 0.783) |                |                |
| After participating in this learning activity, I am happy to learn about identifying and distinguishing trees. | 3.77 ± 0.76    | 0.83           |

(continued)
The correlation coefficients for the correlation between any two constructs are lower than the square roots of the AVEs of their corresponding constructs. The results indicated adequate discriminant validity.

Hypothesis Testing

To estimate the path coefficients, we used PLS path modeling and executed the bootstrap resampling method as suggested by Bollen and Stine (1992). However, the PLS method does not provide estimations of goodness-of-fit statistics. Chin (1998) clarified that the goodness-of-fit test is related not to the predictive power of latent variables but to the estimated parameters and sample covariance. Therefore, $R^2$ was the main indicator for identifying the goodness-of-fit of the models in our study.

We performed a behavior analysis to analyze whether learners use this system (Figure 3). First, regarding learner-perceived ease of use, information quality was significantly related to system quality, and the explanation of variance was 68.3%. Among them, information quality ($\beta = 0.652, t = 10.122, p < .05$) and system quality had direct influences, supporting H1 and H3. Moreover, information quality was highly related to learner-perceived ease of use. Thus, if the system is easy to operate, and the interface design is friendly and easy to understand, learners can easily use this system.

Second, regarding learner-perceived usefulness, information quality was significantly related to system quality, and the explanation of variance was 57.5%. Among them, information quality ($\beta = -0.059, t = 0.837, p > .05$) had no significant influence; thus, H2 was rejected. System quality ($\beta = 0.782, t = 11.891, p < .05$) had a direct influence, thus supporting H4. In addition, learner-perceived usefulness was related to system quality. Thus, if the system can help learners collect information and increase knowledge, its functional quality will be useful for learners.

Third, regarding the willingness of learners to reuse, learner-perceived ease of use was significantly related to perceived usefulness, and the explanation of variance was 64.6%. Among them, perceived ease of use ($\beta = 0.206, t = 3.529, p < .05$) and perceived usefulness had direct influences, thus supporting H5 and H7. Moreover, system quality ($\beta = 0.612, t = 10.842, p < .05$) indirectly affected willingness to reuse. In general, if the system is conducive to

| Factors | $M \pm SE$ | Factor loading |
|---------|------------|----------------|
| I want to know more about trees in the real living environment. | 4.05 ± 0.96 | 0.87 |
| I will actively search more information and learn about forestry. | 3.80 ± 0.83 | 0.80 |
| **Factor 6: Reuse Willingness ($CR = 0.939, AVE = 0.702, \alpha = 0.921$)** | | |
| I would be willing to continue to use this system in the future. | 4.10 ± 0.94 | 0.88 |
| I want to use other similar systems in the future. | 4.15 ± 0.83 | 0.78 |
| I would do my best to complete the assignment required by teachers with this system. | 3.89 ± 0.97 | 0.77 |
| When my classmates are using this system, I would want to use it too. | 4.20 ± 0.81 | 0.88 |
| I hope teachers to use this set of system in the curriculums of plant identification. | 3.92 ± 0.94 | 0.89 |
| I would recommend the plant identification learning system to other classmates. | 4.08 ± 0.94 | 0.87 |

Table 6. (continued)

| Table 7. Inter-Construct Correlations. |
|----------------------------------------|
| Variable Source | Reuse willingness | Learning motivation | Learning effectiveness | Perceived ease of use | Perceived usefulness | System quality | Information quality |
|-----------------|-------------------|---------------------|-----------------------|-----------------------|---------------------|-----------------|---------------------|
| Reuse willingness | .85 | | | | | | |
| Learning motivation | .31 | .83 | | | | | |
| Learning effectiveness | .08 | .29 | 1.00 | | | | |
| Perceived ease of use | .46 | .35 | −.02 | .88 | | | |
| Perceived usefulness | .77 | .35 | .00 | .36 | .82 | | |
| System quality | .72 | .33 | −.07 | .58 | .76 | .85 | |
| Information quality | .43 | .29 | −.02 | .78 | .28 | .44 | .89 |

Note. CR = composite reliability; AVE = average variance extracted; $\alpha$ = Cronbach’s alpha.

matrix. The correlation coefficients for the correlation between any two constructs are lower than the square roots of the AVEs of their corresponding constructs. The results indicated adequate discriminant validity.

Hypothesis Testing

To estimate the path coefficients, we used PLS path modeling and executed the bootstrap resampling method as suggested by Bollen and Stine (1992). However, the PLS method does not provide estimations of goodness-of-fit statistics. Chin (1998) clarified that the goodness-of-fit test is related not to the predictive power of latent variables but to the estimated parameters and sample covariance. Therefore, $R^2$ was the main indicator for identifying the goodness-of-fit of the models in our study.

We performed a behavior analysis to analyze whether learners use this system (Figure 3). First, regarding learner-perceived ease of use, information quality was significantly related to system quality, and the explanation of variance was 68.3%. Among them, information quality ($\beta = 0.652, t = 10.122, p < .05$) and system quality had direct influences, supporting H1 and H3. Moreover, information quality was highly related to learner-perceived ease of use. Thus, if the system is easy to operate, and the interface design is friendly and easy to understand, learners can easily use this system.

Second, regarding learner-perceived usefulness, information quality was significantly related to system quality, and the explanation of variance was 57.5%. Among them, information quality ($\beta = -0.059, t = 0.837, p > .05$) had no significant influence; thus, H2 was rejected. System quality ($\beta = 0.782, t = 11.891, p < .05$) had a direct influence, thus supporting H4. In addition, learner-perceived usefulness was related to system quality. Thus, if the system can help learners collect information and increase knowledge, its functional quality will be useful for learners.

Third, regarding the willingness of learners to reuse, learner-perceived ease of use was significantly related to perceived usefulness, and the explanation of variance was 64.6%. Among them, perceived ease of use ($\beta = 0.206, t = 3.529, p < .05$) and perceived usefulness had direct influences, thus supporting H5 and H7. Moreover, system quality ($\beta = 0.612, t = 10.842, p < .05$) indirectly affected willingness to reuse. In general, if the system is conducive to
learning, provides a convenient learning environment, and effectively assists learners in understanding plant ecology, learners will be willing to reuse this system.

Fourth, regarding the learning motivation of learners, learner-perceived ease of use was significantly related to perceived usefulness, and the explanation of variance was 18.3%. Among them, perceived ease of use ($\beta = 0.26$, $t = 2.932$, $p < .05$) and perceived usefulness ($\beta = 0.258$, $t = 2.618$, $p < .05$) had direct influences, thus supporting H6 and H8. Moreover, information quality ($\beta = 0.154$, $t = 2.238$, $p < .05$) and system quality indirectly affected learner motivation. Thus, system design and functions that provide plant image identification knowledge and plant ecology knowledge search are the factors that encourage learners to use this system for learning plant ecology.

Finally, the learning effectiveness of learners was significantly related to learning motivation, and the explanation of variance was 7.5%. Learning motivation ($\beta = 0.275$, $t = 2.643$, $p < .05$) had a direct influence, thus supporting H9. Thus, if learners have strong motivations to use the plant ecology m-learning system for learning plant ecology, their learning effectiveness will be higher.

**Conclusion**

Currently, most courses are taught indoors in classrooms, and few course activities are taught outdoors, preventing interaction with the environment. Therefore, researchers have proposed that mobile devices combined with context-aware technology can provide learners with different learning experiences. This research focused on the plant ecology teaching design and developed a set of context-aware plant ecology learning systems, named CAPELS. This system mainly connects user mobile device, location, climate temperature and humidity, and plant identification by using a wireless network to connect to Google, thus enabling learners to learn plant ecology.

In the past, most of the study topics about plant image identification only focus on the technology of the image processing; the CAPELS directly uses photographs of plant leaves taken on-site instantly for identification to be the teaching strategies at education sites which compensates for the research gap of the education field. To understand CAPELS identification quality, this study also conducted an identification experiment, in which the eight types of plant were tested 150 times; the overall accuracy was higher than 95%.

The range of application of the plant leaf identification technology of this system is not limited by plant species, and as long as the leaf has its own characteristics, it can be identified. However, the problem encountered in the current plant identification method is the feature extraction of plant leaves. Because plant leaves grow in different environments, the three-dimensional style (curl, etc.) of the leaves and the color of the leaves are different even for the same plant. Therefore, one of the first important directions of future research should be to focus on how to increase the plant leaf characteristics. In addition, an identification technology can be incorporated into the deep learning model (long short-term memory [LSTM]), which can strengthen the identification effect and provide more complete ecological information about the entire plant ecology.

Second, to understand the system quality and teaching effectiveness, this system first asked the experts to evaluate the system. The investigation results indicated that they approved the CAPELS quality and used the system as a complementary teaching tool for enhancing the learning motivation of learners.

Third, after applying the CAPELS to on-site teaching, the study proved that context-aware mobile teaching can effectively improve traditional sample learning and oral teaching methods. The study also compared learner backgrounds and proved that although they influenced learning effectiveness, the CAPELS improved their learning results irrespective of the background.

Finally, this study analyzed the TAM and proved that the CAPELS can be used as a learning tool. The results indicated that learning effectiveness is subject to learning motivation, and learning motivation is affected by the perceived ease of use, perceived usefulness, and system quality. Moreover, the willingness of learners to continue using the CAPELS is affected by perceived usefulness and system quality.

In general, improving the quality of the whole m-learning system is the key factor for enhancing learning motivation. Moreover, learning effectiveness will be substantially improved if learning motivation is enhanced. In addition, we must increase the effectiveness of using the m-learning system for encouraging learners to continue using mobile devices for learning.

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