Computers & Education 105 (2017) 44–56

Contents lists available at ScienceDirect

Computers & Education

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

Scientific modeling with mobile devices in high school physics labs

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A R T I C L E I N F O

Article history:
Received 12 March 2016
Received in revised form 3 November 2016
Accepted 6 November 2016
Available online 9 November 2016

Keywords:
Architectures for educational technology system
Teaching/learning strategies
Improving classroom teaching
Pedagogical issues
Applications in subject areas

A B S T R A C T

Scientific modeling is thought to help students understand the world and scientific phenomenon. Science laboratory in school should provide well-designed activities to promote students' model building skills. Thus, this study aims to propose microcomputer based labs with several data acquisition tools and a modeling tool, which can assist students to collect and visualize data in faster and fancier ways, and generate mathematical models to fit the data, thus exercising their skills of scientific modeling. Thirty-two high school students participated in the science laboratory courses within two semesters for four labs. Results showed that students' overall success rates of model building were approaching 50%; the duration of participants' modeling time decreased with the increase of the experimental labs; the benefits of doing physics labs with smartphones were confirmed by the success rates, personal preferences, and students' feedback. Regarding students' spontaneous model building behavior in the first lab, almost 90% of the participants fitted data with linear equation; most participants adjusted coefficients to fit the data, instead of changing the highest degree of equation; and different strategies were used by successful participants and the others. These results indicated that the combination of modern data acquisition tools and fitting data with a modeling tool would provide an alternative and meaningful approach to doing physics labs at high school.

1. Introduction

Traditional physics labs in high school have two major problems. First, following step-by-step lab instructions, students focus almost entirely on fitting experimental data to known theories. Few instructors ask students to produce scientific models to fit the data. Second, most of the data logging methods are slow, resulting in low sampling rate and precision. In

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http://dx.doi.org/10.1016/j.compedu.2016.11.004
0360-1315/

other words, science teachers focus too little on the training of scientific inquiry while too much on memorizing textbook knowledge. As a result, students are generally weak in inquiring in, explaining, formulating scientific issues and in gathering evidence to support scientific hypotheses. This calls for changes in science education. Past research results clearly indicate that learning by doing experiments enhanced learners' skills of science laboratory work (Hart, Mulhall, Berry, Loughran, & Gunstone, 2000; Lumpe & Oliver, 1991).

In laboratory practice, scientific modeling is a critical activity and powerful strategy for meaningful learning (Schwarz et al., 2009; Wu, Wu, Kuo, & Hsu, 2015). Mediating between theories and the real world, model building is to abstract and transform representation of a system (Davis et al., 2008), allowing model builders to create theories, test hypothesis, analyze data, and make predictions. However, scientific modeling is rarely incorporated into high school science laboratory. Traditionally, students are told the theory with given equations in a science lab. So their job is simply to collect data to confirm the given equations.

In 2012, Chen et al. proposed an approach of Microcomputer based laboratories (MBL) to solve challenging problems in traditional laboratory work, including low sampling rate and low precision of data acquisition tools, limited time of science classes, and the lack of teaching resources. This approach uses small and mobile tools of data acquisition with embedded microprocessors, which reduce the time in data collection and graph plotting (Kelly & Crawford, 1996; Srisawasdi, 2012; Tortosa, 2012). In this way, students can focus their attention in explaining the relationship among the data variables (Russell, Lucas, & McRobbie, 2004). This approach sets an excellent, realistic example of technology-assisted learning.

However, the laboratory tools of MBL can be quite expensive (Tortosa, 2012), leading to its limited use in school teaching (Chen et al., 2012). Given that students in MBL can propose their research hypothesis and conduct multiple trials to examine the cause and effect relationships, they do not build an explicit mathematical model that relates a dependent variable to one or more independent variables. Hence, this study proposes to combine some new, inexpensive data acquisition tools with a software that enables students to experience explicit model building in science laboratory work. With these technologies, students are asked to do experiments and collect data without any given equations. One of the most common and accessible tools is smartphones, which are getting smarter and cheaper every year. In order to evaluate the learning results with smartphones, this study also used Lego Mindstorms NXT and digital video camera for the sake of comparison. For most students, these common electronic toys are taken as a robotic kit or as an entertaining device like PlayStation but seldom thought as tools for scientific investigation like a microscope. In addition, this study has adopted a modeling tool called InduLab for data analysis, visualization, and the discovery of mathematical relationship among data variables (Wong, Chao, Chen, Lien, & Wu, 2015). Using the collected data plotted in InduLab, students are asked to express a dependent variable as a function of an independent variable. In short, this study investigates two aspects of science laboratory work: the feasibility of using InduLab as a model building tool as well as the spontaneous model building behaviors of students.

2. Literature review

2.1. MBL and related studies

Laboratory training is a critical component of science education. Several meta-analysis studies pointed out that laboratory work can improve learners' science process skills and content knowledge (Shymansky, 1989; Stohr-Hunt, 1996). Regarding the motivation aspect, without any corresponding laboratory work, lecturing on scientific concepts and theory in a traditional classroom can be monotonic and boring (Tortosa, 2012). Moreover, laboratory work offer opportunities for students to work in group and to communicate their ideas verbally (Hofstein & Mamlok-Naaman, 2007). Unfortunately, with limited time and resources, laboratory teachers often over-rely on the laboratory manuals. Thus the experiments supposed to be exciting and innovative often turn into cookbook-style, order-following procedural steps with little excitement (Chen et al., 2012). To address some of these issues, MBL succeeds in reducing the time in data collection and visualization and helps students with graph plotting and problem solving, which brings laboratory work closer to the experiences of scientists in the real world (Krajcik, Mamlok, & Hug, 2001). In addition, the actual inquiry-based experiences that MBL provides can promote learners' conceptual understanding (Gunhaart & Srisawasdi, 2012). This approach allows students to interact directly with physical phenomena or with data gathering from the phenomena (Pyatt & Sims, 2011), which further promotes effective scientific learning (Hofstein & Lunetta, 2004). Therefore, MBL could be used as a cognitive tool in enhancing the understanding of scientific concepts.

MBL uses new technologies such as smartphones, personal digital assistants, Bluetooth or geographical information system in experiments. As pointed out by many studies, MBL has several advantages. First, students can experience a realistic process of scientific inquiry (Mokros & Tinker, 1987). Second, by saving much time in data collection and data plotting (Kelly & Crawford, 1996; Srisawasdi, 2012; Tortosa, 2012), students can devote more time and efforts to analyzing and explaining experimental results (Lavonen, Juuti, & Meisalo, 2003; Russell et al., 2004; Tortosa, 2012). Third, the acquired experimental data can be presented in various representations (Mokros & Tinker, 1987; Zbiek, Heid, Blume, & Dick, 2007). Fourth, selected variables can be plotted and studied almost instantaneously (Brungardt & Zollman, 1995; Pierri, Karatrantou, & Panagiotakopoulos, 2008; Russell et al., 2004; Tortosa, 2012), which provides prompt feedback for students to adjust their hypothesis and to establish links between a physical phenomenon and the associated data plots (Aksela, 2012; Linn & Songer, 1991) which further improves in-depth understanding of scientific concepts (Dori & Sasson, 2008) and higher order thinking skills (Barnea, Dori, & Hofstein, 2010; Friedler, Nachmias, & Linn, 1990; Lavonen et al., 2003).

Several empirical studies examined the advantages of MBL. In physics classes, Russell et al. (2004) found that learners did experience a realistic process of scientific inquiry with MBL. After the first MBL session, students were asked to explain their findings and to examine it later by showing graphic data collected from students' answers which were prepared by teachers with an overhead transparency. During the process, students could discuss and clarify the cause and effect relationships between variables with the entire class after each lab. In addition, the study of MBL by Kaberman and Dori (2009) indicated significant improvement in learners' higher order thinking skills in chemistry classes through their laboratory portfolio and questionnaire. Another study pointed out the improvement of learners' in-depth understanding of scientific concepts with the assistance of MBL in physics classes through questionnaire (Gunhaart & Srisawasdi, 2012).

Besides, several studies compared MBL with other technological tools to examine its effectiveness. Brungardt and Zollman (1995) compared the effect of MBL's simultaneous data visualization and that of delayed visualization on learning. In the latter approach, the data plots were drawn some time after the data were collected. But in the former approach, the plots were drawn almost immediately during data collection. Four classes later, the researchers interviewed the learners and tested them with a test on graphs. And they found no significant differences between the two groups. But the test on graphs showed that the average score of the MBL group was higher than that of the control group. The results of interviews indicated that the MBL group was more motivated with more discussions and less confused on physics concepts in general.

In another study, Chen, Chang, Lai, and Tsai (2014) compared a group of learners with simulation-based laboratory (SBL) and another group with MBL in a 11th grade class on Boyle's law. The researchers developed their own tests with a pretest and a posttest on physics concepts which included multiple-choice questions and open questions. During the experiments, the learners had to answer all the questions listed in their lab books. Students had to generate their own research hypothesis, conduct experiments, collect data, and interpret findings. Then the answers would be reviewed to check their performance in scientific inquiry. Students were allowed to make different predictions and repeat experiments to figure out the relationships between variables in a period of time. Afterward, the researchers also conducted structural interviews with the learners. Results indicated no significant differences between the two groups. Nevertheless, the MBL group performed better on exploration, experiment design, and explanation of experimental data. In addition, the MBL group showed more positive learning attitudes and greater interests in the laboratory work.

From the above discussion, many studies supported MBL's advantages and flexibility in teaching. However, they focused more on exploring the cause and effect relationships of the scientific phenomenon in inquiry activities rather than on explicit model building and fitness checking of each model. In addition, MBL teaching usually involves expensive experiment equipment (Chen et al., 2012; Tortosa, 2012), resulting in its underuse. Addressing the cost issue in MBL, this study uses low-cost electronic hardware with reasonable precision together with the scaffolding-based InduLab modeling tool to enhance learners' experiences in model building and scientific inquiry. Furthermore, noting that previous MBL studies did not compare different hardware tools (Brungardt & Zollman, 1995; Chen et al., 2014; Gunhaart & Srisawasdi, 2012; Kaberman & Dori, 2009; Russell et al., 2004), this study compares the feasibility and the effects of several electronic devices on learning.

2.2. Scientific modeling

In traditional laboratory work, learners generally spend much time in data collection while do only simple manipulation and analysis of data (Chen et al., 2014). Addressing these issues, various forms of technology-assisted laboratory work emerged, including MBL and simulation-based laboratory (SBL) (Manlove, Lazonder, & De Jong, 2009; Jaakkola, Nurmi, & Veermans, 2011). Advantages of SBL include controllability, safety, cost-effectiveness, non-pollution, flexibility, extensibility, and time-saving. However, this tactile experience of learning might produce naïve expectation and mistaken explanation in learners. Such experience would be insufficient to train learners in practical experimental design (Chen et al., 2014), and weaker in training critical thinking in comprehending the experimental results (Olson, Clough, & Vanderlinden, 2007). As a consequence, laboratory work with MBL is still considered to be the most effective approach (Chen et al., 2012). Students are able to manipulate the experimental data instantaneously (Nicolaou, Nicolaidou, Zacharia, & Constantinou, 2007; Pierri et al., 2008). It saves time in data collection and manipulation (Kelly & Crawford, 1996; Srisawasdi, 2012; Tortosa, 2012) and in presenting model prediction and experimental data side by side. In short, MBL is thought to have an edge over both traditional laboratory work and SBL.

Scientific reasoning involves skills in identifying patterns in experimental data, confirming the patterns, and generalizing the patterns into a rule that explains the patterns (Devlin, 1994; Steen, 1988). After generalization, learners should be able to construct a mathematical model and relate it to the knowledge and concepts of science. Model building constructs and refines representations/models of physical phenomena in a reiterative way (Hestenes, 1992). As a signature of scientific research (Nersessian, 2008), model building is the core activity of real scientists' daily work (NRC, 2012), which forms and justifies new scientific knowledge (Halloun, 2006; Koponen, 2007). Besides, model building also develops individuals' scientific literacy by providing an easier way to define, visualize, understand and engage with the physical world (Hernández, Couso, & Pintó, 2015; Lehrer & Schauble, 2012; Louca & Zacharia, 2015; Mendonça & Justi, 2014). In science education, students' involvement of model building activity was found to promote their cognitive ability (Bell, 1995; Harrison & Treagust, 1996).

However, model building activity is rarely included in high school science classes. Even being introduced, model building is usually used as an illustration rather than a lab assignment (Windschitl & Thompson, 2006). To address this issue, a variety of modeling media emerged as technological extensions to traditional hands-on laboratory work (Bowen, DeLuca, & Franzen, 2016; Louca & Zacharia, 2015), including simulation modeling (Ernst & Clark, 2009; Jaakkola et al., 2011). With many advantages in incorporating simulation modeling into the lesson, an unrealistic and vacuum context might also result in learners' difficulty in transferring the acquired model building skills to other contexts (Haverty, Koedinger, Klahr, & Alibali, 2000). Thus, it would be appropriate to design a concrete, scientific context with MBL support for learners to participate in model building activities. Scaffolding support includes modeling tools that relate physical attributes mathematically and represent their relationship with graph plots. This might help students practice their scientific modeling skills, closing the gap between the learning context and real life situation.

In this study, learners are instructed to use familiar modern electronic products (e.g., smartphones) to collect data in self-exploratory physics experiments. This flexible and open-ended approach might help learners relate abstract physical concepts to their concrete daily experiences.

2.3. MBL with model building for physics labs

In a study, Gunhaart and Srisawasdi (2012) integrated MBL and computer simulation (actual and virtual experimentation) as a cognitive tool to improve students' conceptual understanding in physics classes of 11th grade. They directly adopted MBL tools designed by Vernier Software & Technology which produces sensors and graphing software for use in science education. Another study developed MBL activities in a predict–observe–explain format to support students' understanding of physics (Russell et al., 2004). The equipment of MBL was designed by the researchers for data logging and graphing. However, the details of their MBL setting was not presented clearly and many questions remained unanswered. For example, how much time did students spend on plotting the data acquired by different sensors used in MBLs? In addition, the difficulty of developing MBL tools or the price tags of commercial tools may drive teachers away from using MBL in their classes.

This study proposes a new approach to run science labs in high school by combining several data acquisition tools with a modeling tool. There are several special features in this approach. First, several low-cost, modern electronic devices including Lego Mindstorms NXT, smartphones, and digital video camera, are used to serve as data acquisition tools. These electronic devices have much higher precision than traditional equipment used in a common high school science lab in Taiwan. Second, a modeling tool called InduLab is adopted to let students freely propose and revise models to fit the experimental data with immediate feedback of a visual plot as well as a numeric measure of the error of modeling (Wong et al., 2015). Third, several physics experiments are designed to investigate everyday kinematic phenomena with common electronic devices. One of the critical differences between other MBL studies (Fig. 1) and our work (Fig. 2) is that, instead of only exploring the cause and effect relationships, students can experience a model building process with InduLab. In our work, students only collect data in

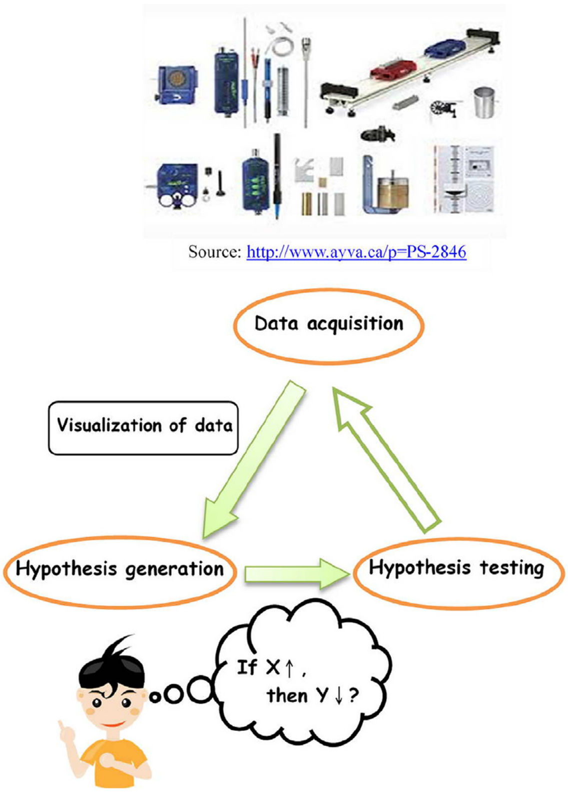

Fig. 1. Cause-effect inquiry of MBL.

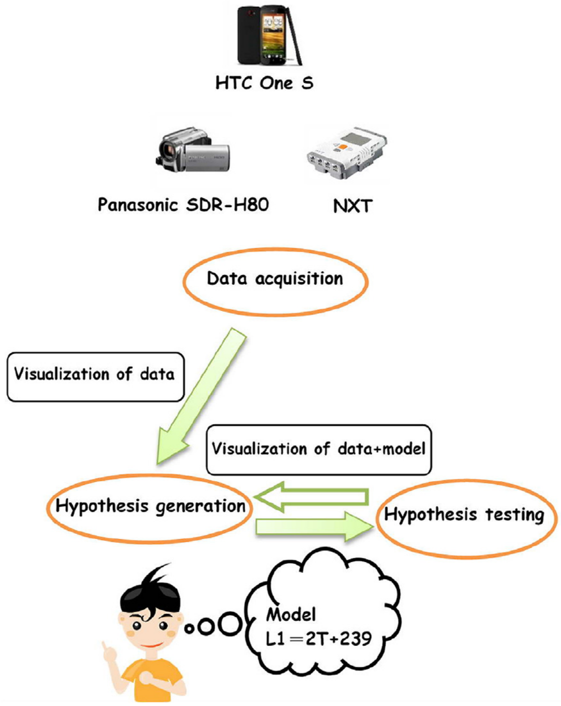

Fig. 2. Model inquiry of MBL.

the stage of data acquisition during the experiment. Then they get into the cycle of hypothesis generation and hypothesis testing with InduLab until they are satisfied with their models.

2.4. Research questions

To assist students in scientific modeling in physics laboratory, this study adopted some new, inexpensive technologies with good precision and our modeling tool InduLab. The study addresses issues in two directions. The first is about the feasibility of data acquisition tool and the modeling tools of InduLab for students to do scientific inquiry in high school. For example, we want to find out which devices, among the ones used in this study, are more beneficial to students' performance in scientific modeling, and how effective InduLab is as a modeling tool. The second is to investigate the patterns in students' spontaneous model building, including their initial hypothesis and model modifying strategies.

3. Method

3.1. Participants

The participants were 32 10th-grade students (aged 16–17) at a private high school in Taiwan. These students were enrolled in the "physics and technology applications" class. Regarding the gender ratio, female students accounted for 25% of the total population. However, one student was absent in a couple of labs due to illness and so there were only valid data from 31 subjects for the empirical results.

One of our colleagues and a school teacher supervised the four labs in this study. The colleague was a doctoral student in electronic engineering and one of the developers of the modeling tool InduLab. He oversaw the technical aspects of the data logging devices used in the experiments, instructed students on how to use experimental tools, and collected raw experimental data and questionnaires from students. The school teacher, holding a Master degree in physics, had 4-year experience teaching physics. He was responsible for dealing with students' questions concerning physics theory and explaining the math of physical phenomenon after each lab. We collected the teacher's feedback after all labs were done.

3.2. Course design

The objective of the four labs is to assist students in building scientific models to explain the physical phenomena. In all of the labs, students participated in two stages. Firstly, students had to collect the raw data by conducting hands-on experiments. Next, students would propose their scientific models with InduLab. As the two stages were completed, the teacher would explain the math of the physical phenomenon.

The participants did four labs in two semesters. The data logging devices used included smartphones, digital video recorders, and Lego Mindstorms NXT. Smartphone was used in all labs. DV was used in free fall and projectile motion. NXT was used in pendulum motion and slope motion. In the first lab of pendulum motion, smartphones and NXT equipped with gyros were used to record the changing angles of the pendulum. In the labs of free fall and projectile motion, smartphones and digital video recorders were used to record videos of a free-fall object against the background of a scale. In the final lab of slope motion, smartphones were used to record the videos of a moving object and NXT equipped with ultrasonic sensors were used to record the positions of the moving object.

3.3. Modeling with InduLab

After experimental data are acquired, students propose a mathematical model to fit the data. The task of modeling, illustrated with the pendulum lab, is to express one variable as a polynomial function of another variable. In this lab, students need to relate the period T of pendulum motion and the length L of the pendulum arm, and to express L as a polynomial function of T.

In order to collect the raw data, students are required to connect gyros to NXT (Fig. 3), which can record the time and the changing angles of the pendulum simultaneously. The plot shows a harmonic motion with damping effect. Then the students need to obtain a period as the distance in the *x*-axis between two neighboring maxima (or minima). They record manually ten such periods for each pendulum length L (mm) and repeat this procedure for five lengths. Then they enter the data in InduLab, where the average T (ms) of the ten periods would be computed automatically. For example, one data set of (L, T) obtained by a student was {(410, 1313), (430, 1347), (770, 1756), (920, 1992), (330, 1150)}. With the five data points, InduLab would show a data plot (diamonds in the plots of Fig. 4) of length versus period and then the students can work on the mathematical models to explain the data. The plot is chosen to be L against T rather than T against L because InduLab restricts the plot to be a polynomial function. Mathematically speaking, $L = f(T)$ is a quadratic function whereas $T = f^{-1}(L)$ is not a polynomial function.

After a student ran an experiment, collected data, and entered the data into InduLab, she must propose an initial model that expresses one variable as a function of another. Some student might choose a linear model while others might choose a quadratic model or another polynomial function. Once a model is committed, InduLab would show the model plot (rings in the plots of Fig. 4) on the background of data plot (solid diamonds in the plots). The y-value of each ring was computed with the model with the x-value of one diamond.

In the top figure of Fig. 4, the model $L = T^*T/2200$ was chosen. The rings were clearly above the diamonds. This resulted in an error of 460.797, computed by InduLab. The error was defined as the average of all vertical absolute distances between all corresponding pairs of ring and diamond. So one sensible strategy in improving the model was to reduce the coefficient 1/

Fig. 3. Experimental tools of pendulum motion in the lab. The time and the angle of a swinging pendulum are recorded by and stored as CSV files in a smartphone simultaneously. About 38 data points are recorded per second.

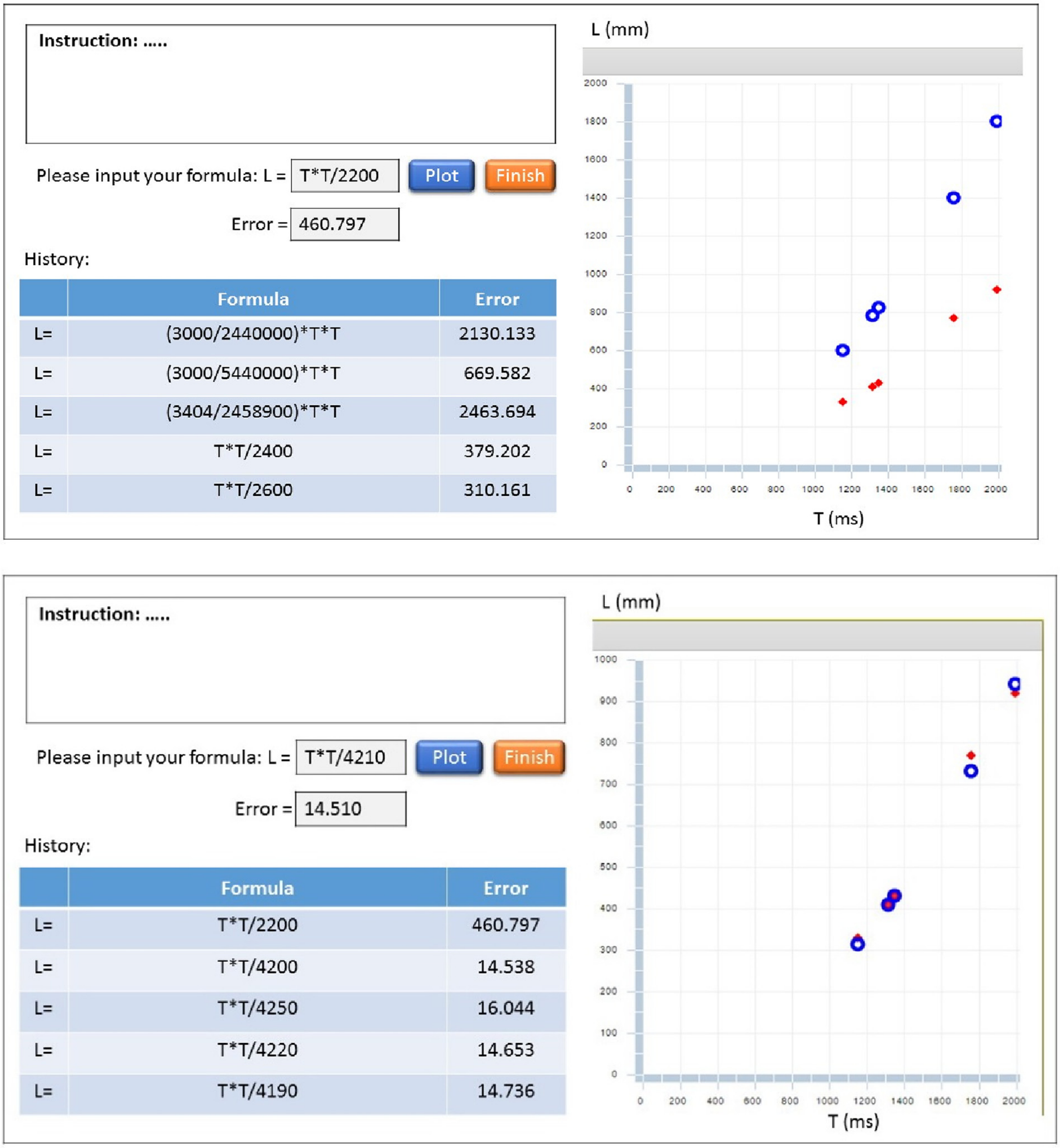

Fig. 4. Finding an ideal formula in InduLab.

2200. After several trials, the student entered the model $L = T^*T/4210$ and the resulting plot showed that the rings were closer to the diamonds with an error of 14.510. Completed in 20 min by one student, this process of model revisions showed that she was careful in choosing models that gradually reduced the error of modeling. This was a data-driven strategy, in contrast to a traditional experiment where students tried to fit the experimental data to a correct theoretical model known in advance.

3.4. Questionnaire

3.4.1. Course feedback questionnaire

There were 25 items in the course feedback questionnaire. The first eighteen items adopted a five-point Lickert scale, aiming to understand their preferences towards various parts of the course as well as the skills they had learned from the labs.

One item asserts “I like the practical hands-on experiences in this lab.” Another item says “I think I have acquired the skills used in this lab”. The 19th to the 25th items were open-ended questions. One question is “Which data acquisition device did you prefer in this lab? Why?” Another is “In this lab, I wish more can be done …” In order to check whether students exercised care in filling the questionnaire, two negative items were added.

3.5. Procedure

The four labs were done in two semesters. Each lab took about nine hours. All students participated in the course for two hours per week. The experiments were conducted in a science laboratory. In the first week of each lab, students were given the instruction of the lab and the hardware and software tools of Arduino, Bluetooth modules and a sensor. They were also instructed on how to use Excel to plot experimental data. Then they tried to set up the equipment in the lab, sometimes with their own improvement in specific ways. For example, they found two different ways to mount a pendulum, i.e. on the wall or by the window. In the second week, they set up the lab equipment and acquire data in groups. In the third week, they repeated the experiment with a different logging device. In the fourth week, they discovered patterns and made inferences with InduLab. Finally, the teacher would explain the math involved in the physical phenomenon of the experiment.

For data collection, half of the participants conducted hands-on experiments with peers using smartphones, and the other half used other technologies. Next, students exchanged the hardware tools to conduct the same experiments. After collecting data with different logging devices, each student worked to find an ideal equation relating the two given variables with InduLab in 20 min. Each experiment was done twice, each time with a different logging device. If a student used device A first and then device B to conduct an experiment, the two data sets collected would be used for modeling in this order. Finally, students were asked to fill out a course feedback questionnaire after each lab was completed.

4. Results

There are two ways to evaluate the results in this study. The first evaluation is about the feasibility of the labs indicated by students' model building performances and the feedback of students and teacher. The second one is to explore students' spontaneous model building behaviors.

4.1. The evaluation of the labs' feasibility

4.1.1. The overall success rate of model building

A model is considered successful if two conditions are both met: (1) Student's model is quadratic and (2) The value of error proportion is less than 10%. Error proportion is defined as

$$\frac{E_t}{(E_t + P_t)} \times 100\% \tag{1}$$

or

$$\sum \frac{|P_i - S_i|}{\sum |P_i - S_i| + \sum P_i} \times 100\% \tag{2}$$

P_t is the sum of observed data points P_t = sum of P_i (where $i = 1, 2, \ldots, n$), E_t is the sum of errors, and each error is the absolute value of observed data (P_i) minus the corresponding predicted value (S_i) of a model. The average modeling error in the four labs among all students who produced successful models at the end were 5.71%, compared to 83.16% among those who failed to produce successful models.

The overall success rates of model building in the four labs were 42%, 75%, 22%, and 50%. In order to assess whether there was a general trend between the success rates and the four labs, we conducted trend analysis. The error rate of this trend analysis was α/c, then the alpha for each comparison was 0.05/3 = 0.017. This means that F ratio would have to reach an alpha of 0.17 to be declared significant. Result showed a significant cubic trend, $F(3, 116) = 37.35$, $p < 0.001$, $r = 0.49$, showing almost a large effect size. According to the Cohen’s (1988) conventions, small, medium and large effects are defined for r values of 0.1, 0.3, and 0.5, respectively. It indicated that the trend had two inflection points, meaning that it changed direction twice. Although the first lab was where the participants encounter model building the first time, the success rate was better because the lab was the least difficult. Later on, as they became more familiar with model building, their low success rate was due to the greater difficulty of projectile motion. With the increasing frequency of the experiments, their mastery of InduLab and model building also improved. Hence, the participants' overall success rate of model building increased in the last lab.

4.1.2. Length of modeling time

To understand whether students spent less time finding successful model with the progress of experimental labs, that is, whether they became more familiar with model building, we conducted descriptive statistics and trend analysis of students' modeling time. Since students would use two data logging devices in every experimental lab, we averaged their modeling time to conduct trend analysis. The average modeling time in the four labs were 18.77 min, 18.31 min, 17.78 min, and 12.58 min respectively, indicating that the time spent would decrease with the increase of the experimental labs. In order to assess whether the decreasing trend was significant, we conducted another trend analysis. The alpha for each comparison was $0.05/3 = 0.017$. Results showed a significant linear trend, $F(3, 124) = 46.21$, $p < 0.001$, $r = 0.52$, and a quadratic trend, $F(3, 124) = 14.22$, $p < 0.001$, $r = 0.32$, both showing medium to large effect sizes. It indicated that modeling time decreased with more lab experiences, but the tendency of decrease slowed down. It can be seen that learners need to have sufficient practice to get familiar with model building.

4.1.3. Comparison in the benefits of using smartphones with other technologies

Fig. 5 showed that the success rate of model building using smartphone was higher than those of DV and NXT in every lab except for projectile motion. Thus, we conducted McNemar's test to examine whether the differences among the three data logging devices were statistically significant. Results indicated that the success rate of smartphone was significantly higher than that of DV in free fall ($p = 0.01$) and that of NXT in slope motion ($p = 0.001$). However, the success rate of smartphone was not significantly higher than that of DV in pendulum ($p = 0.09$) or that of NXT in projectile motion ($p = 0.23$). Moreover, no significant difference was found between the success rate of DV and that of smartphone in projectile motion, showing the floor effect caused by the high difficulty of the labs. To sum up, though the success rate of each hardware tools could be influenced by the difficulty levels of the labs, smartphone was a clear winner in model building.

To understand students' preferences among the three data logging devices, we conducted McNemar's test. Result indicated that the preference for smartphone was significantly higher than that for DV in projectile motion ($p < 0.001$) as well as those for NXT in pendulum ($p = 0.02$) and in slope motion ($p < 0.001$). Although no significant difference was found between smartphone and DV in the free fall ($p = 0.17$), students' preference for smartphone was obvious. The result was similar to the feedbacks to the open questions of the questionnaire. Many students preferred to use smartphones with reasons such as "data of greater precision", "easy to handle", "plots of data with smooth curves", "smaller errors" and "abundant data."

4.1.4. Feedback of students and teacher

To assess students' attitude towards the course, we asked them to fill out a course feedback questionnaire after each lab. The questionnaire included 18 five-point Likert-scale items and seven open-ended questions. For the 18 Likert-scale items, the average scores of 31 participants were about 4 (pendulum = 3.99; free fall = 4.02; projectile motion = 4.00; slope motion = 4.00). One-sample t-test showed that every item was significantly higher than 3 (the intermediate value of five-point scale) ($p = 0.00–0.04$), indicating that participants had positive attitude toward the labs. However, the nonsignificant result of trend analysis showed that participants' positive attitude did not increase with the progress of the four labs, $F(3, 123) = 0.02, 0.12, 0.53$, $p = 0.89, 0.73, 0.47$, $r = 0.01, 0.03, 0.07$.

The qualitative part of the questionnaire, namely the seven open-ended questions, was designed to evaluate students' learned abilities and favorite activities. Each item was shown with the percentage of students who had mentioned this concept (Table 1 and Table 2). The participants believed that they acquired the abilities of setting up hardware tools, collecting data, and analyzing data. They enjoyed not only the hands-on activity but the pleasure of science learning. In addition, over 50% of the participants suggested that the finding of formula play a meaningful role in science laboratory. About 70% of the participants liked the activity of formula finding, which stimulated thinking and enhanced science learning.

Feedbacks from the teacher were very positive. First, he agreed that students acquired hands-on skills to conduct experiments. Secondly, students learned how to measure and analyze large amount of data. Thirdly, students tackled problems independently and cooperated with peers to solve problems in the labs. Finally, he observed that though students lacked prior knowledge of how to use these technologies, their learning motivation seemed to increase as their lab experiences accumulated.

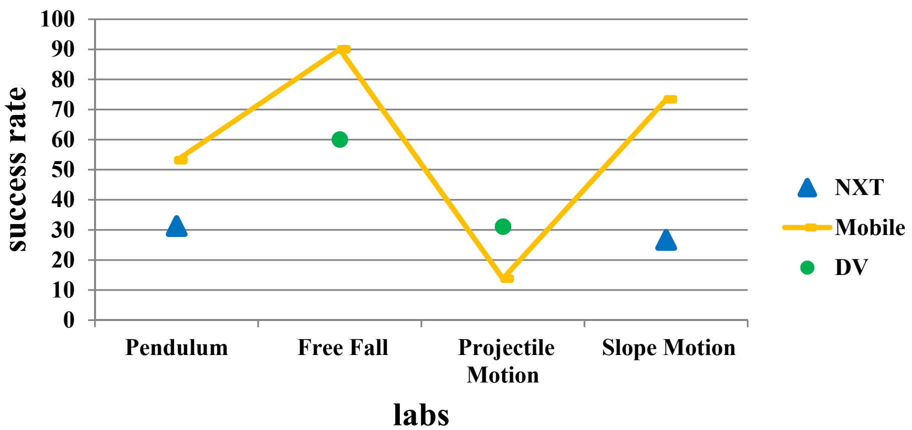

Fig. 5. The success rates of model building using three hardware tools.

Table 1
The learned abilities of participants' report in experimental group.

Learned abilities	Percentage (%)
Setting up hardware tools and collecting data	100
Inducing formulas from data	53
Using familiar tools for data collection	38
Plotting	6
Enhancing spatial reasoning	16
Acquiring the knowledge of physics	50
Collaborating with peers	53
Maintaining their interest and persistence in science subjects	6

Table 2
The favorite activities of participants' report in experimental group.

Favorite content	Percentage (%)
Conducting hands-on experiments	100
Finding formulas from data	72
Using familiar tools for data collection	34
Plotting	6
Collaborating with peers	31
Acquiring the knowledge of physics	3

4.2. Students' spontaneous model building behaviors

Since the teacher would explain the math formula and physical phenomena for students after each lab, students might propose and modify their models with what they learned in the following labs. To examine their model building patterns and performances, we only analyze students' spontaneous model building behaviors with the data from the first lab. With the raw data collected by 32 participants using two data logging devices - smartphones and NXT, 64 conditions were adopted to explore students' model building behaviors.

4.2.1. Initial hypothesis

For the initial hypothesis, about 89% (57/64) of the students proposed linear models after seeing the graph plots of the experimental data in InduLab. There are two possible explanations. First, students had difficulty transferring what they had learned in school to their model building activities. Secondly, the graph plots of our data looked more linear than quadratic. In order to check the second explanation, we invited two raters to categorize all of the graph plots in 64 worksheets as parabola, linear or others. Results showed that only 25% of the graph plots were categorized as linear. Hence the second explanation does not look correct. In conclusion, having difficulty transferring their knowledge to model building, students are more inclined to select the simple linear model as their initial hypothesis.

4.2.2. Model modifying strategy

Some interesting pattern was found in students' modeling strategies. In the pendulum experiment, each student proposed an average of 78 models to fit the experimental data, where 33 (42%) of these models were linear. More surprisingly, seven students used only linear models. In short, students tended to mildly adjust a model instead of changing the highest degree of the model equation.

4.2.3. Reaction to increased fitness error when changing a linear model to a quadratic one

Researchers noticed that the modeling error would increase dramatically as the equation of the model changed from linear to quadratic. The dramatic increase of modeling error might weaken some students' faith in a quadratic model. Thus, we hypothesize those students who showed more faith with their quadratic model by trying different coefficient values with more patience and persistence are more likely to build a successful model. The Mann-Whitney *U* test, a non-parametric test, was conducted to examine whether there was a significant difference in the number of trials in quadratic model between students who failed and those who built successful models.

The results of the Mann–Whitney *U* test ($\alpha = 0.05$) indicated that the number of trials was greater for successful students ($Mdn = 32$, mean rank $= 46.54$, $n = 25$) than for non-successful students ($Mdn = 3$, mean rank $= 23.50$, $n = 39$), $U = 136.5$, $z = -4.84$, $p < 0.001$, $r = 0.61$, indicating a large effect size. According to Cohen's (1988) conventions, small, medium and large effects are defined for r values of 0.1, 0.3, and 0.5, respectively. Regarding why successful students undertook more trials with quadratic model than failed students, we think that an explanation could be their differences in prior knowledge. With the prior knowledge of parabola, the successful students demonstrated great patience and persistence to improve a model even with increased modeling error in quadratic models. On the other hand, the non-successful students tended to abandon the quadratic model and switched back to linear models once the modeling error increased.

In order to get a more realistic estimate of the average modeling error, we also calculated the average error rate as the tested equation was changed from linear to quadratic. Firstly, the data of those students who proposed only one type of model (i.e., linear or quadratic) from the beginning to the end were excluded. For each student who had modified a linear model into a quadratic one for one or more times, the average quotient of dividing the error of the quadratic model by that of the linear model was computed. Then with an average quotient from each student, the overall average of all such students was computed. Result showed that the average error rate increased by 284,877 times as the highest degree of equations changed from linear to quadratic. Thus, the unexpected abrupt increase might have scared many students away from continuing with quadratic models.

5. Discussion and conclusions

In the new era when creativity and innovations cannot be overemphasized, the ability of scientific modeling is especially critical in science learning. Although many researchers adopted MBL as a powerful tool in guiding inquiry and improving learners' higher order learning skills, few of them emphasize the ability of proposing explicit mathematical models to explain the data acquired from experiments. In addition, the experimental equipment of MBL can be quite expensive, resulting in its low accessibility for teachers. To address these issues, the current study adopted several less expensive but not less precise data acquisition tools as well as InduLab to improve MBL and enhance scientific modeling skills. Mobile phones, NXT, and DV can be used to simplify data logging and improve the accuracy of the raw data. Moreover, InduLab can visualize the data as graph plots. With immediate visual and fitness error feedback, students can see the corresponding graphs with the mathematical models they proposed. With these cues, students are able to revise and improve the model by reducing the fitness error, thus exercising their scientific modeling skills. The physics labs with the above hardware and software tools help to create a realistic context of scientific inquiry at a school setting. The learners could really experience some of the pains and joys of doing scientific experiments like a scientist.

In this study, the students obtained successful models with a rate close to 42% in the first lab and the success rates ranged from 22% to 75% in the four labs. One explanation of this pattern was the difficulty levels of the labs. In general, the average success rate was 50%. On the other hand, the time the students spent in modeling decreased as they became more experienced. This indicated students' increasing familiarity with the InduLab environment. In addition, the success rate of model building using smartphones was significantly higher than those of DV and NXT in the second and fourth labs. This indicates that the high sampling rate and the high precision of data logging of a smartphone could be important features for finding successful models. Moreover, students preferred smartphones to DV and NXT as data logging devices. For them, the lab procedure of data collection with smartphones was friendlier. The feedbacks of both the students and the physics teacher also indicated that this approach of MBL and model building was feasible and beneficial for students' learning. Though the overall success rate of model building was not as high as the researchers expected, which revealed the difficulty of building a successful model to explain scientific phenomena, the feasibility of such labs was confirmed.

In addition, students demonstrated several patterns of scientific modeling. First, the mathematical concepts the students had learned in school might not be transferred to this context of model building. Even though the students had learned the concepts of quadratic functions, when constructing a model to fit parabolic data, most of them still began with a linear model instead of a quadratic one. Second, on revising their models to reduce the modeling error, they tended to mildly adjust the coefficients of a polynomial model, instead of changing the highest degree of the model. Third, the students who succeeded in building a quadratic model at the end and those who failed differed in one aspect, i.e., the number of trials they undertook to revise a quadratic model. The successful students persisted to revise a quadratic model even when fitness got worse, probably because they believed fitness could be improved with the right choices of coefficients or because they had prior knowledge of parabola. In contrast, for the students whose final models were not successful, when they found that revising a linear model into a quadratic one increased the fitness error, they tended to give up the quadratic model immediately. The study showed that students might not transfer the mathematical concepts they had acquired in classes to real physical laboratory work automatically. Moreover, few students kept trying to revise their models regardless of the increased modeling errors. It revealed the necessity of integrating technology and the contents of mathematics and science in a realistic context. In this way, students should be better equipped to transfer their acquired knowledge in the real world.

This study conducted a new, innovative, and practical design of low-cost friendly data acquisition tools and a modeling tool in a scientific context, where students were looking for a function relating two variables with obvious physical meanings. By participating in the cycle of generating and testing hypotheses with InduLab, students experienced explicit model building in science laboratory work. Such design enables students to exercise their ability of relating abstract physical concepts to concrete mathematical functions. Our ultimate goal is to provide effective tools for all educators around the world to develop appropriate science inquiry classes in a realistic context.

As for future research inspired by this study, the following five directions are suggested. Firstly, as smartphones were the students' favorite choices as a data logging device in this empirical study, future studies could consider using smartphones or tablet PCs for other physics experiments. And this calls for more software development, which enables tablet PCs and iPads to plot the data in real time during data acquisition. Secondly, qualitative approaches should be employed to investigate in depth the learners' behaviors and experiences during the entire scientific inquiry process, thus providing a guideline for the design and improvement of approaches in teaching physics. Thirdly, lab manuals should be developed for teachers to make the technology-supported experiments more manageable. Fourthly, the current study focused only on some physical phenomena. Future studies could provide different contents of science laboratory work to expand the breadth and depth of scientific inquiry learning. Finally, in response to different contents of science laboratory work, the number of variables to be manipulated by the students should also be increased.

Acknowledgements

This study is supported by the Department of International Cooperation and Science Education, Ministry of Science and Technology, Taiwan under contracts 101-2511-S-224-001- and 102-2511-S-224 -002 -MY2.

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