Learner Expertise and Mathematics Different Order Thinking Skills in Multimedia Learning

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Abstract

This experimental study used an instructional visual aid for algebra to investigate whether different order thinking skills – remembering, understanding and analyzing – affect the expertise reversal effect. One hundred and twenty-three secondary school students were assigned to an experimental condition, either with or without the aid. In the experiment, an aid that was designed for novice learners, and the materials were developed using multimedia learning principles to maximize the use of learner cognitive capacity. The results showed that the expertise reversal effect occurred in understanding (retention, more-structured), but not in remembering (transfer, more-structured) and analyzing skills (transfer, less-structured). A plausible explanation is less-structured environments that require heavier process of searching and/or selecting increased demand of cognitive load imposed. We suggest that designing adaptive environments should take order thinking skill, instructional format and learner expertise into account.

Keywords: Learner expertise, multimedia learning, adaptive learning, mathematics

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Multimedia presentations should display images and words simultaneously for learning (Mayer, 2009, 2014). Such presentations benefit novice (less knowledgeable) learners more than advanced (more knowledgeable) learners (Ayres & Paas, 2007; Leslie, Low, Jin, & Sweller, 2012), which was explained by the expertise reversal effect (Kalyuga, 2007). The effect suggests that multimedia presentations designed for novice learners may interfere with the learning of advanced learners by reducing their available cognitive capacity (Kalyuga, 2014; Leslie et al., 2012, Liu, Lin, & Paas, 2013; Rey & Fischer, 2013; Spanjers, Wouters, Van Gog, & Van Merrienboer, 2011). In most expertise reversal effect empirical studies for multimedia learning the retention test measured remembering (Level 1 in revised Bloom taxonomy in Anderson, Krathwohl, & Bloom, 2001) and the transfer test measured understanding (Level 2) or a mixed order thinking skill. Most of their results showed that the effect occurred for transfer, but not retention; and a few of them occurred for both tests, which suggests there are causal relationships between learner expertise and different order thinking skill. Two plausible explanations are that the degree of integrative cognitive processes is associated with different order thinking skill (Chiu, 2016; Mayer, 2009, pp21) and that higher order thinking skill development involves more cognitive processes (Jones & Idol, 2013; Verhoeven, Schnotz, & Paas, 2009).

It is necessary to understand how different instructional formats support different expertise level learners (Kalyuga, 2014) for different order thinking skills in multimedia learning. This would help us understand expertise reversal effect more, and make its principle more complete. The present study aims to investigate how different order thinking skills affect the effect. We used three order thinking skills from Bloom's Taxonomy to measure learning outcomes, and used more- and less-structured formats to facilitate the lower order thinking skills – remembering and understanding – and the higher order thinking skill – analyzing.

Cognitive load theory and expertise reversal effect

Cognitive load theory developed by Sweller (1998, 2003, 2010) can explain expertise reversal effect (Kalyuga, 2013). The theory is based on the architecture of human memory and distinguishes two types of memory. Working memory is limited and processes all the organized information, while long-term memory is large and stores the information that can be retrieved. The theory further suggests that cognitive capacity available in working memory critically influences the effectiveness of instructional designs and information presentation formats. Accordingly, the cognitive load theory is one of the most influential theories in the area of instructional design (Jong, 2010; Ozcinar, 2009). In learning processes learners search and/or select relevant multimedia messages from presentations, organize them into a mental structure, and finally integrate them with relevant prior knowledge retrieved from long-term memory (Mayer, 2009). The processes consume cognitive load. According to the theory, cognitive load comprise three components. Intrinsic load refers to working memory demands imposed by processing relevant information that are essential for learning. Extraneous load is imposed by processing unnecessary information to achieve the learning objectives. Germane load refers to the memory used to make sense of the essential information during learning. Since learner prior knowledge plays an important role in human cognitive architecture for effective learning, learner expertise levels are essential in predicting the cognitive load demand (Kalyuga, 2013).

The expertise reversal effect refers to a reversal in the relative effectiveness of designs on learners with differing levels of expertise (Kalyuga, 2007; Kalyuga, Rikers, & Paas, 2012). The designs are beneficial for novice learners, but may be redundant or even detrimental for more knowledgeable learners. As processing the designs unnecessarily consume additional resources in working memory, more knowledgeable learners may be imposed an extraneous cognitive load. This results in less cognitive capacity available for other processes that are relevant for learning, which is more important for learners as their expertise increases. According to the effect, novice learners often benefit from more-instructured designs that often explain how to learn with the activities by providing procedures, steps and explanations, such as worked examples, direct help/cues, visual aids and integrated words (Kalyuga, 2014), see Figure 1. For more knowledgeable learners who may have the information provided by the designs in their long-term memory, processing the designs may generate an extraneous cognitive load. Therefore, levels of prior knowledge and the process of recalling directly influence the effectiveness of the integration process or the acquisition of new knowledge. Novice learners, in many situations, cannot recall prior knowledge effectively, but advanced learners can. Therefore, while instructional designs that present/activate prior knowledge are often more effective for novice learners, they may become a burden to advanced learners. Consider as an example, students learning mathematics, who are presented with a graph and an equation. Novice students may find it difficult to recall what they already know (prior knowledge). It would take more time or steps (heavier extraneous cognitive load) than advanced learners to identify learning messages and see the connections between the graph and the equation, i.e. the relationships between the intercepts and coefficients. If a direct cue, such as an explanation and procedure, was presented, novice learners would be able to see the connections more easily (less extraneous load), but advanced learners would still need to process the cue they already know. This process would be unnecessary and would occupy their cognitive capacity, which could have been used for intrinsic and germane loads. Accordingly, the main recommendation is that instructional designs should be adjusted to help learners acquire more knowledge in a specific domain, which refers to as the expertise reversal principle (Kalyuga, 2014). The principle advocates many multimedia learning designs, that are more effective for novice learners, but may lose effectiveness or have a negative impact when used by advanced learners (Kalyuga, 2014) for a specific domain (Mayer, 2009). The principle can be treated as another form of the redundancy principle of Kalyuga and Sweller (2014) or the coherence principle of Mayer (2009).

Numerous experimental studies support the expertise reversal effect in multimedia learning (Kalyuga, 2014; Kalyuga et al., 2000; Leslie et al., 2012; Rey & Fischer, 2013; Spanjers et al., 2011). Their experimental materials were designed for novice learners, and included additional instructional designs, such as presenting aids audibly and/or visually, and controlling the pace of learning. Their designs showed that learning steps with images presented on screen worked best for novice learners, but not for advanced learners (Kalyuga et al., 2000); visual representations helped younger children (less prior knowledge) learn science, but not older children (Leslie et al., 2012); segmented animations were more effective than continuous animations for less knowledgeable learners (Spanjers et al., 2011); and adding expository examples and illustrations was more beneficial for weaker undergraduate students than stronger students when developing the statistical transfer skill (Rey & Fischer, 2013). The studies suggested that the designs helped novice learners understand the images and words presented. The designs helped provide information or environments to guide novice learners to connect images and words presented, thereby easing cognitive processes for searching or recalling (less extraneous load). In contrast, advanced learners may have found the information was duplicated or the environment was discouraging. Therefore, for advanced learners, the designs became redundant and unneeded for learning (heavier extraneous load). In multimedia learning, instructional designs also often benefit novice learners but not advanced learners. Most studies concerning the expertise reversal effect used retention and transfer tests in their experiments (Leslie et al., 2012; Rey & Fischer, 2013, Spanjers et al., 2011). Their results indicated that the expertise reversal effect occurs for the transfer skill, but not for the retention skill. In their experiments, the retention tests assessed ability to store factual information and recall or recognize the information later, but the transfer tests assessed learning outcomes in different ways. In the transfer tests, Leslie and colleagues used understanding the information and applying the information in a new context; Rey and Fischer (2013) used applying the information in a new context; and Spanjers and colleagues (2011) used problem-solving skills that may include many different thinking skills, i.e. a mixed order. A few studies, however, have found instructional methods can benefit both novice and advanced learners in some situations (Nievelstein et al., 2013; Stylianou & Silver, 2004; Sullivan & Puntambekar, 2015). For example, visual representations were useful for university mathematics novices and experts in learning graphical topics and solving problems respectively; and worked examples were more effective for both novice and advanced university law student learning of problem-solving skills. Hence, incorporating instructional design in multimedia representations was effective for both novice and advanced learners on retention skill, but was effective for novice learners only on transfer skill, when learned from presentations. This demonstrates a causal relationship between the expertise reversal effect and different order thinking skill in multimedia learning.

Orders of thinking skills and mathematics

Bloom's Taxonomy can be used to develop assessment items in mathematics learning (Vidakovic, Bevis, & Alexander, 2003). The Bloom's Taxonomy categorizes skills into six cognitive process dimensions (Anderson et al., 2001). The taxonomy suggests six orders of thinking skill – remembering, understanding, applying, analyzing, evaluating and creating. Remembering requires learners to retrieve, recognize and recall relevant knowledge from long-term memory; understanding requires them to construct their knowledge by way of classifying, summarizing and comparing; applying requires learners to implement procedures; analyzing requires learners to determine how parts relate to each another and to an overall idea; evaluating requires students to make judgments and explain their decisions; and creating requires students to reorganize what they have understood into a new pattern. For example, "What color are the different types of grapes in the multimedia presentation?" is remembering; "Are green fruits always grapes?" is understanding; and "How many green fruits and vegetables can you get for $10?" is analyzing.

In mathematics, there are two types of knowledge: procedural (mechanical) knowledge is the ability to follow procedure with understanding (know-how); and conceptual (relational) knowledge is the ability to symbolize mathematical concepts and their relationship with each other (Rittle-Johnson, Schneider, & Star, 2015; Skemp, 1976; Tessmer, Wilson, & Driscoll, 1990). In other words, procedural knowledge concerns condition-action rules while conceptual knowledge concerns hierarchies of cognitive units, i.e. connections and relations (Skemp, 1976; Tessmer et al., 1990). Procedural knowledge typically requires less thinking or conscious work and is often routine in nature, while conceptual knowledge is knowledge of internal representations that is relational, dynamic, and transferable in nature (Skemp, 1976; Tessmer et al., 1990). Star (2005) further suggested that procedural knowledge can be either superficial (e.g. follow or copy steps) or deep (e.g. understand how the steps are interrelated). Deep comprehension of procedures cannot exist without understanding relationships between each step). Deep procedural knowledge depends on at least a degree of conceptual knowledge (Baroody, Feil, & Johnson, 2007; Rittle-Johnson et al., 2015). Accordingly, superficial procedural knowledge is seen as lower order thinking skills while deep procedural and conceptual knowledge is higher order thinking skills.

Orders of thinking skills and structures of learning environments

Different order thinking skills require different structures of internal representation. A higher order thinking skill requires a more complete and complicated internal representation (Berger & Torner, 2002). Representation for higher order skills is often less-structured and network-like, while that for lower is more-structured (Anderson et al., 2001). Different internal representations should be facilitated by different learning designs. These designs can be categorized into more- and less- structured (e.g. Nievelsten et al., 2013). More-structured designs have a clear goal and logical path – using instructions, rules, methods and procedures. For example, learners are presented with steps that instruct them how to operate computer-based learning material to understand relationships between a table and a graph, see Figure 1 (adapted from Kalyuga, Chandler, & Sweller, 2000). Less-structured designs have no specific and clear goal (visual representations); for example, the presentation of pictures and words allows learners to select messages they need for their learning, see Figure 2 (adapted from Chiu & Churchill, 2015b). Many studies suggest different less-structured instructional methods to promote higher order thinking skills in mathematics (Chiu, 2016; Chiu & Churchill, 2015a; Ogden et al., 2014;

Springer et al., 1999). Chiu and Churchill (2015a) used an exploring approach using a digital educational material in learning algebra concepts; Odgen and colleagues used flipped classrooms with discussion in teaching algebra concepts; and Springer and colleagues (1999) used a small-group approach in learning mathematics concepts. The tasks in these studies correlates with the premise that "*too much structure on a task that involves higher-order thinking skills is dysfunctional because it impedes conceptually oriented interactions*" (Cohen, 1994, p20). Too much structure on a task often restricts student thinking, resulting in a more-structure internal representation. More-structured tasks are less likely to encourage students to see connections between learning messages. For example, a teacher may use a drill-and-practice approach to teach a student several methods to solve an equation. This approach does not facilitate comparison between methods or the introduction of other possible methods during learning, and the student is unlikely to develop an internal representation showing interrelationship among the different methods. This shows that the use of less-structured learning materials is more effective for developing higher order thinking skills in mathematics.

Less-structured learning environments often require learners to select relevant information for thinking. According to the cognitive theory of multimedia learning, essential processing involves searching and selecting messages from presentations (Mayer, 2009, 2014). More-structured instructional designs better instruct learners on how to learn with images and words (see Figure 1), requiring less time in the selecting process (reduce extraneous load). These designs require less intrinsic load than less-structured designs. In less-structured environments, however, learners would need more help to maximize cognitive capacity by reducing intrinsic load. . An instructional design tailored for novices may be more helpful for advanced learners to maximize cognitive capacity in less-structured environments. In other words, the expertise reversal effect of an instructional design that occurs in more-structured environments may not occur in less-structured environments.

Higher order thinking skill development requires heavier intrinsic load. Learners more effectively develop higher order thinking skills when they remember and recall basic knowledge from long-term memory (Jones & Idol, 2013); for example, acquiring procedures of reassigning variables in an algebraic equation can facilitate improving solving conventional problems. Developing a higher order thinking skill can involve different types of thinking/cognitive processes of its own and/or other lower order thinking skills (Jones & Idol, 2013). Learners need to select from their relevant lower order thinking skills, reducing intrinsic cognitive load. Thus, as with less-structured learning environments, developing higher order thinking skills requires heavier intrinsic cognitive load.

Instructional design for presentation – algebra

An important factor in expertise reversal effect studies is the additional instructional design in the experiments. Providing appropriate and relevant learning messages for a specific-domain in an instructional way is beneficial for learners (Chiu & Churchill, 2015a, 2015b; Pang et al., 2016; Stylianou & Silver, 2004; Papanikolaou, Makrh, Magoulas, Chinou, Georgalas, & Roussos, 2016). Generally, instructional methods for mathematics learning include providing worked examples, explanations, answers and procedures (e.g. Kalyuga et al., 2000). Different mathematics domains have their own focus for effective teaching methods, for example, geometry pays more attention to shapes, while algebra focuses more on numbers, symbols and their relationships.

In algebra teaching, numerous studies have been conducted on presenting various forms of learning information for students. Rittle-Johnson and Star (2007, 2009) endorse comparing and contrasting solution methods, holding that students learn better by comparing an equation and its different solution methods, or by comparing different forms of an equation and solution method. Students understand concepts better by seeing and experiencing different algebraic forms and solving methods simultaneously (Mok, 2009). This is supported by a study of Mok and Lopez-Real (2006) describing an effective secondary school algebra lesson that adopted variations in the teaching content. To foster concept learning, classroom activities should be designed to help students understand connections among different forms of the same problem (Gu, Huang, & Marton, 2004; Mok & Lopez-Real, 2006). Moreover, learner prior knowledge had an impact on the effectiveness of the variation in content (Guo & Pang, 2011; Rittle-Johnson & Star, 2009). Students with lower prior knowledge benefited more when they learned by comparing various messages in mathematics.

In addition to advocating teaching strategies that evolve from content variation, the National Council of Teachers of Mathematics (NCTM) (2000) suggests that mathematics concepts should be presented in four forms simultaneously – numerical, graphical, algebraic and descriptive – to ensure effective algebra learning and teaching. Such representation aims to help students perceive relationships and associations between conceptual and procedural knowledge, and is supported in the literature. Images facilitate learning of novice learners, but interfere with the learning of advanced learners when the subject matter is visualized (Schnotz & Bannert, 2003). Novice learners benefit more from images and words, since advanced learners can construct their mental understanding by reading text only (Ayres, 2015; Mayer, 1997). Therefore, in algebra learning, the instructional design should (1) enable learners to see and experience a learning message in different ways (Pang et al., 2016; Mok, 2009; Mok et al., 2002) – and (2) present a learning message numerically, graphically, algebraically and descriptively simultaneously (NCTM, 2000). Overall, this design is more effective for novice learners in perceiving the relationships and associations between the messages presented (NCTM, 2000). This was further confirmed by the experimental study of Chiu and Churchill (2015b).

The present study

Most expertise reversal effect empirical studies in multimedia learning used retention and transfer tests (e.g. Leslie et al., 2012; Rey & Fischer, 2013; Spanjers et al., 2011). In their experiments, the additional designs were not developed for a specific domain and their overall designs did not focus on maximizing the use of a learner cognitive capacity; the instructional format of the additional design was either more- or less-structure; and the questions in the transfer tests either included one order thinking skill or a mixed order thinking skill. Understanding how instructional formats affect different expertise level learners (Kalyuga, 2014) for different order thinking skills in multimedia learning environments (Mayer, 1997, 2009) would contribute to completeness of the expertise reversal principle.

In this study, we investigated whether the three orders of thinking skill – remembering, understanding and analyzing – affect the expertise reversal effect using different instructional formats in the context of a digital multimedia learning environment. In the experiment, the learning topic was secondary school quadratic equation graphic representation skills. The students were required to understand the relationships between a quadratic equation and its graphic representation. Learner prior knowledge was linear equation graphic representation skills. Learning tasks for the remembering and understanding skills were more-structured, while that for analyzing skill was less-structured. The additional design that was tailored for novices was a visual aid.

We hypothesized that the expertise reversal effect would not occur for remembering, but for understanding (Leslie et al., 2012; Rey & Fischer, 2013; Spanjers et al., 2011). As discussed previously, instructional designs tailored for novices have potential benefits for advanced learners in developing higher order thinking skills in less-structured tasks due to possible increased essential processing. We also hypothesized that the expertise reversal effect would not occur for analyzing.

Method

Participants and design

We used a stratified procedure to select classes from a Hong Kong government-subsidized school to increase the validity of the study. As learner expertise is the key to this experiment, we invited strong and weak classes, but not the average one, in the school. Five classes agreed to participate, comprising 140 senior secondary level students aged from 16 to 18 years. Two of the classes (72 students) had good performance in mathematics, and were much stronger than the other three classes (68 students). One hundred and twenty-nine students accepted the invitation and 123 (around 60% male) completed the experiment. We also invited two teachers in the school to participate in this study. One of the teachers had more than 25 years of teaching experience in mathematics, and the other had more than 10 years. The students were assigned to one of the experimental conditions – with and without the aid. This resulted in 2 experimental conditions – 61 students learning with the aid and 62 students learning without the aid.

More-structured environments that frame learning resources are likely to be an obstacle to constructing interrelationships among messages (Cohen, 1994, p21). Internal representations are more likely to be more structured when developed in more-structured environments. These more-structured representations are better for remembering and understanding, but not analyzing (Skemp, 1976). Therefore, our learning activities were more-structured when learning the two lower order thinking skills – remembering (retention) and understanding (transfer) – which require more-structured internal representations. The activities were less-structured when developing the higher order thinking skill, analyzing, which requires less-structured internal representations.

Materials

This study included learning materials, worksheets and assessment materials. The learning materials, see Figure 2, were developed using Mayer multimedia learning design principles including coherence, signaling, redundancy, spatial contiguity, temporal contiguity, segmenting, pre-training and multimedia. The design aims to maximize the use of learner cognitive capacity.

In our experiment, the visual aid, presented different forms of a quadratic equation and its different solving methods, and the four-section presentation – graph, equation, solving method and description (i.e. the bottom two sections). The description and solving method sections demonstrated the relationships between the graph and equation sections. Other than these two sections, color matching and changing, and the names of solving methods were provided on the presentation to help students identify/select messages. This design acted as an instructional visual aid to help novice students connect the graph and the equation for learning.

Appendix A shows learning activities in student worksheets for the experiment. There are two types of learning activities: more-structured and less-structured. In more-structured activities, the students were required to manipulate the material and see how values of discriminants and roots relate to the graphs. In other words, the learning messages are related. The students only need to understand how to identify values of roots and signs of discriminants from graphs. In less-structured activities, not all the learning messages are related, for example, the value of coefficient a is not related to the values of roots. The students were required to determine how parts relate were required to each another and to an overall idea. They manipulated the materials to learn how coefficients, discriminants, directions, and the values of a, roots and x-intercept(s) relate to the graphs. In the worksheets, sets of data including variables a, b and c, roots and relevant information were given to ensure both groups have same learning messages.

The assessment materials included a quiz, posttest and questionnaire. The quiz measured prior knowledge (i.e. graphic representation skills of linear equations); the posttest measured graphic representation skills of quadratic equations, and the questionnaire measured mental effort invested in the learning process. The questions in the materials were in a multiple choice format and assessed graphic representation skills. Questions in the assessment materials were designed using the study of Schneider and Stern (2005) and Sangwin (2007) on algebra learning performance, and were used in the experimental study of Chiu and Churchill (2015a), which examined whether the design of learning objects improved procedural and conceptual knowledge of quadratic equations. We used three measures: a lower order thinking skill (more-structured) for each of the retention and transfer tests, and a higher order thinking skill (less-structured) for the transfer test. The questions assessed remembering (retention, level 1 in the revised Bloom's taxonomy), understanding (transfer, level 2) and analyzing (transfer, level 4). According to Vidakovic, Bevis, and Alexander (2003), assessments items for remembering measure skills of recalling some facts and symbols, item for understanding measure skills of identifying, distinguishing and predicting, items for analyzing measure skills of breaking down information into its constituent parts and considering their relationships.

During the development of the materials, the two teachers confirmed that the questions in the posttest would evaluate what the students learned from the materials and matched the different order thinking skills. They learned the learning materials and finished the tests to make sure (i) the participants are able to answer the questions and (2) the questions are relevant to the learning activities. confirmed the group formation was appropriate for the experiment.

The teachers also provided model answers to the questions for scoring purposes. The quiz questions were able to assess student skills on their graphic representation of linear equations, see Appendix B. For the questions designed to assess remembering, students were required to choose x-intercept and y-intercept from a graph (two answers for each of the questions); for the questions assessing understanding, students were asked to identify their graph using the values of x and y provided; and in the analyzing questions, students were required to decide if the graph related to an equation. Each of the skills was scored out of 4.

Questions in the posttest tested student skills on the graphic representation of quadratic equations, see Appendix C. Table 1 shows how the questions are categorized into the Bloom's Taxonomy. For the questions assessing remembering, students were required to choose the value(s) of roots and the discriminant of a graph; for those of understanding, the students were asked to compare and identify the graph(s) of a quadratic equation or a condition; and in the analyzing questions, students were required to consider two pairs of statements or expressions and decide whether they were related (true) or not related (false). Each of the questions in all the skills was scored out of 1; and each skill was scored out of 12.

To answer the remembering and understanding questions, the students could use the description section to connect an equation and its graph; to answer the analyzing questions, the students could use the solving method and description sections. In this way, the learning tasks for remembering and understanding were more-structured (reading the description section of the material), and the task for analyzing was less-structured (selecting relevant messages in the material). Remembering and understanding may contribute to the development of the analyzing skill, but are not prerequisite.

In the questionnaire, we used the question developed by Paas (1992) to measure invested mental effort for learning with a 9-point subjective rating scale. The scale ranged from very, very low mental effort (1) to very, very high mental effort (9). The invested mental effort reflects the actual cognitive capacity that is allocated to accommodate processing on the learning task. This question is detailed here:

Please respond to the following question using the scale.

In the learning material just finished, I invested (1). very, very low mental to (9). very, very high mental effort

Procedure

We first got the ethical approval from Human Research Ethics Committee in our university before conducting this study in the schools where the students studied. We first talked to the school principal about the purpose of the study and received consent to conduct the study. Then, we explained the procedure of the experiment to the two teachers and students, and received their consent. We also sent the students' parents paper-based passive consent forms to seek their approval. The students had rich experience completing tests and questionnaires on their school intranet called “IT-school”. They did at least one reading exercise or test every week and one questionnaire every semester. All online activities were conducted on the intranet. The time allowed for the learning tasks and tests was determined by a pilot study. A week before the experiment, students completed an online, ten question, multiple-choice quiz (time allocated was 10 minutes) in a computer room of their school. Students with scores of not less than 7 points were randomly divided into the ‘with aid’ (31 students) and the ‘without aid’ (30 students) groups; those with scores of less than 7 points were similarly divided (median is 6; the “with aid” and “without aid” groups had 30 and 32 students respectively). The two teachers who taught all the students confirmed the groups represented different learner expertise levels using the results of two multiple choice examinations as reference. They used the examination results to cross check the quiz scores. We conducted the experiment in a computer room on two consecutive school days with either one of the teachers. The two sessions for the ‘without aid’ groups were held on the first day; and the two sessions for the ‘with aid’ groups were held the next day. This arrangement was intended to avoid any treatment effects from one group to the other (diffusion), which might unintentionally affect the results of the study.

In each session, the students were randomly assigned to an individual seat in front of a personal computer without internet access. At the beginning of the experiment, we thanked them all for their participation. Thereafter, we briefed them on the procedure of the experiment, distributed the worksheets, as well as explained how to control the materials and what they would learn from the learning activities. The students had 40 minutes to manipulate the multimedia materials assigned After the experiment, the students were given 5 minutes to log on to the intranet and complete the online questionnaires, and another 30 minutes to complete the posttests.

Breaking the participants into two groups, as with a median split, results in a loss of analysis power (Cohen, Cohen, West, & Aiken, 2013).Therefore, we chose to perform moderated multiple regressions using prior knowledge and visual aid use as predictors.

Result

Table 2 shows the descriptive statistics for prior knowledge, remembering, understanding, analyzing and mental effort. Moderated multiple regression analyses on remembering, understanding and analyzing skills were executed. Two models for each of the skills were examined. In Model 1, only prior knowledge and aid use were entered. In Model 2, the interaction term prior knowledge X aid use entered simultaneously as predictors were added in the model. Comparison of the two models and examination of the beta values of the predictors in Model 2 allow us to determine interaction effects occur for the skills and mental effort. We used grand mean to center prior knowledge to avoid problems with multicollinearity (Aiken & West, 1991). Aid use was coded as 0 for the material with the aid and 1 for the material without the aid to examine the presence of an interaction between prior knowledge and aid use. To conduct follow-up tests on significant interactions, we examined the specific effect of prior knowledge in each of the aid use groups independently. To further test the interactions, we tested the regression coefficients (simple slope analyses) at one standard deviation below (lower prior knowledge) and above (higher prior knowledge) the mean in the models to examine the significance of the difference between the regressions lines for lower and higher prior knowledge students (Aiken & West, 1991). In addition, we also used simple slope analyses to confirm the visual aid that was beneficial to the novices in remembering, and examine the effects of the aid in analyzing.

Model 1 for the dependent variable remembering had a significant R^2 , R^2=.449, $F(2,120)=48.97$, $p<.001$. There was no significant increase in R^2, indicating that the interaction was not a significant predictor of remembering, $p=.076$. Positive slopes of the regression lines indicated the student with higher prior knowledge resulted in better remembering when learning both materials. A simple slope analysis showed that at one standard deviation below mean, the novice group benefited more from the aid, $\beta=-0.91$, $t(119)=-3.02$, $p<.001$.

For the dependent variable understanding, Model 1 had a significant R^2 , R^2=.355, $F(2,120)=32.96$, $p<.001$. There was a significant increase in R^2, showing that the interaction was a significant additional predictor of understanding ($\triangle R^2$= .05, $F(1,119)=9.89$, $p=.002$). Figure 3 depicts the interaction between prior knowledge and aid use on understanding. In Model 2, the interaction were significant, $\beta=3.15$, $t(119)=3.14$, $p=.002$. The simple slope analyses revealed that at one standard deviation below, the material with the aid benefited more than without the aid, $\beta=-1.19$, $t(119)=-3.76$, $p<.001$; and at one standard deviation above, the materials had no significant effects on understanding, $\beta=.25$, $t(119)=.76$, $p=.78$.

Model 1 for the dependent variable analyzing had a significant R^2 , R^2=.27, $F(2,120)=21.83$, $p<.001$. There was no significant increase in R^2, indicating that the interaction was not a significant predictor of analyzing, $p=.80$. Simple slope analyses showed that with the aid significantly benefited the students, at both one standard deviation below, $\beta=-1.36$, $t(119)=-4.36$, $p<.001$, and above, $\beta=.-1.25$, $t(119)=-4.21$, p<.001.

For the dependent variable mental effort, Model 1 had a significant R^2 , R^2=.48, $F(2,120)=56.16$, $p<.001$. There was significant increase in R^2, indicating that the interaction was a significant additional predictor of mental effort ($\triangle R^2$= .07, $F(1,119)=19.75$, $p<.001$). Figure 4 depicts the interaction between prior knowledge and aid use on mental effort during learning. In

Model 2, the interaction were significant, β=-0.49, $t(119)$=-4.44, p<.001. The simple slope analyses revealed that at one standard deviation below, the students significantly invested less mental effort when learning without the aid, β=2.07, $t(119)$=6.29, p<.001; and at one standard deviation above, there was no significant difference in the mental effort invested, β=.07, $t(119)$=.20, p=.84.

Overall, the analyses indicated that (a) understanding scores depended on both the existence of visual aids and the level of prior knowledge, but remembering and analyzing did not; (b) the aid is beneficial to the novice group in understanding; (c) the aid benefited the learners when developing the analyzing skill.; and (d) the lower prior knowledge students invested less mental effort during learning and disappeared at higher levels of prior knowledge.

Discussion and Conclusion

Discussion

The experiment reported in this paper was designed to investigate the effect of using an instructional visual aid – variation theory and four-section representation – in digital multimedia learning environments for students with different levels of expertise on the different order thinking skills – remembering, understanding and analyzing skills. The goal of this study was to investigate whether the expertise reversal effect occurs in the acquisition of these skills in different instructional formats. As predicted, student prior knowledge has an impact on the effectiveness of multimedia designs. According to the expertise reversal principle (Kalyuga, 2014), instructional designs that effectively help novice learners may be ineffective for advanced learners in multimedia learning. In line with the studies of Leslie and colleagues (2012), and Rey and Fischer (2013), our results show the expertise reversal effect occurs for developing understanding, but not remembering. For understanding, novice students who received the aid designed for novices outperformed those novices who did not receive the aid. In contrast, advanced students who received the aid performed less well than advanced learners who did not receive the aid. These results suggest that the aid did help novice students see the relationships between the equation and the graph, to better understand the properties of the graph. The description section in the instructional design, which may be seen as an explanation, directly described the relationship between the graph and equation. In accordance with the expertise reversal effect, this section appeared to be redundant for advanced learners who may have stronger graphic property skills. Processing the aid increased extraneous processing in working memory and thereby reduced cognitive capacity available for other processing (Kalyuga, 2007, 2014; Kalyuga & Sweller, 2014). This demonstrates that for novice students, the understanding of graphs and equations might be facilitated by the inclusion of a visual instructional aid that reduces extraneous processing to maximize their available cognitive capacities. The negative consequence of the same visual aid for advanced students was also demonstrated (Kalyuga, 2014).

The expertise reversal effect did not occur for remembering multimedia messages. All the students effectively remembered what they had seen or learned from the multimedia presentations with or without the aid. This may be because understanding skill development requires heavier cognitive processing than remembering skill development (Rasch & Schnotz, 2009; Schnotz & Heiß, 2009).

Furthermore, our results suggest that the aid helped not only novice but also advanced learners to develop analyzing skills – the expertise reversal effect did not occur. The literature suggests that developing higher order thinking skills, i.e. analyzing (less-structured knowledge representation), often happens in a less-structured learning environment (Chiu & Churchill, 2015a; Cohen, 1994, p21; Nievelstein et al., 2013; Ogden et al., 2014; Springer et al., 1999). Less-structured learning environments offer more freedom to students to select relevant messages for their learning. Such environments facilitate the construction of interrelationships among messages (Cohen, 1994, p21), resulting in the development of less-structured internal representations. These presentations may be more transferrable to the analyzing skill whose nature is dynamic and relational (Skemp, 1976). However, the less-structured environment required learners to choose their relevant messages, resulting in heavier cognitive load for searching and/or selecting (Mayer, 2009). In our experiment, the task was more-structured (sequential) when the students remembered and understood multimedia representations, whereas the task became less-structured when the students connected more multimedia messages to develop their analyzing skills. For example, to answer the questions of remembering, the students were required to experience the “critical” phenomena – no roots, two distinct roots and equal roots – to remember the properties of the graph. To answer the understanding questions, the students were required to figure out the relationships between the graph and coefficients of the equations. These can be facilitated by trying the values and reading the information from the aids – reading the descriptions to understand an equation and its graph. In other words, the students were required to choose their values, and then read the description to connect the values and the graph. However, the analysis questions required the students to justify any relationships between pairs of statements. The students were required to select relevant multimedia messages from all four sections to see the connections among most multimedia messages. The task became less-structured. Therefore, a plausible explanation is that the learning task for analyzing skill became less-structured and involved more demand of cognitive load. This requires increased intrinsic and germane load, and learners would need more help to construct a more complete understanding. The aid that provides essential information facilitates the selecting process for advanced learners.

Overall, the findings showed that the expertise reversal effect occurs for understanding skill in multimedia learning, but not on remembering and analyzing skills, and also that the visual aid may be useful (by helping to better manage essential processing) for advanced learners when developing analyzing skills in less-structured tasks.

Implications and suggestions

The current findings provide much needed evidence to include different order thinking skills into the expertise reversal effect in multimedia learning. Our findings also demonstrated that multimedia materials were more effective when designed for learners of different levels of expertise (Kaluga, 2014, Mayer, 1997, 2009) and different order thinking skills. The study has three implications. First, the findings confirmed that the visual instructional aid format (variations and multiple representations) was more effective for novice learners when developing their understanding skill. The aid explained the relationships between graphs and equations, and thereby helped novice learners better understanding algebra (see Leslie et al., 2012; Rey & Fischer, 2013) in multimedia learning. Second, if not carefully orchestrated in different order thinking skills, the multimedia materials may not be the best for novice or advanced learners. The learners may not receive the best design for a specific order thinking skill. In our experiment, for novice students, the aid was more effective in understanding compared to analyzing and remembering. There may be better designs for remembering and analyzing skill development. As discussed before, numerous experimental studies support the expertise reversal effect in multimedia learning, but most of them did not consider the orders of thinking skills. Our findings suggest that the order of thinking skills could influence the expertise reversal effect of the instructional design in multimedia learning. Third, less-structured tasks would cause heavier essential processing. Designs that are ineffective for advanced learners in more-structured tasks may become effective for them in less-structure tasks.

The results also afford two suggestions. First, we suggest that in multimedia learning, instructional designs should consider the order of thinking skills when tailoring to learners of different expertise levels (Mayer, 1997). Instructional designers should use different order thinking skills to identify instructional formats offered to learners. For example, for the remembering skill, providing images and words only (without explanations) could be enough; for the analyzing skill, the materials should also provide aids that help the process of selecting messages. Second, in choosing instructional formats, less-structured task should be provided in multimedia learning, when the intended learning outcomes require relational and dynamic internal representation; more-structure tasks can be used when the outcomes require routine and less conscious work.

In conclusion, the findings could contribute to the completeness of the expertise reversal principal of Kalyuga (2014) in multimedia learning. One multimedia learning design cannot fit all learners of all different expertise levels (Kalyuga, 2008, 2014; Mayer, 2009). The findings suggest that instructional designers should take different order thinking skill, instructional format and learner expertise into account when designing multimedia learning environments.

Limitations and Future Directions

There are limitations in this study and six are noted here. First, while this study appears to support the effects of instructional designs and learner expertise level on different order thinking skill, more studies are needed to validate the finding. The results of the present experiment could also be extended by additional studies on other higher order thinking (evaluating and creating) or in other subject domains to refine the expertise reversal principle. Second, this study did not consider ongoing learning process measures, such as processing time (Sánchez & García-Rodicio, 2013) and performance in different phases. Future research should be conducted using longitudinal design including learning time and scores. Third, more- and less-structured tasks were used to develop understanding and analyzing skills. No effects of more-structured tasks on analyzing and less-structured task on understanding were investigated. Factors in future studies should be task structure, order thinking skill and learner expertise. Fourth, the advanced learner scores for remembering were relatively high. This may suggest a ceiling effect at which the treatment no longer has an effect on the measure. Questions for remembering should be more difficult or conducted in a shorter time. Fifth, one question was used to measure mental effort in the experiment, which did not distinguish between different types of cognitive load. Future studies could adopt questions from the studies of Leppink and colleagues (2014) to understand how intrinsic, extraneous and germane cognitive load affect learning. The final limitation is that the experiment was conducted over different sessions. Environmental factors, for example, weather, noise and temperature, may influence student motivation for learning, which lead to differences between conditions. The experiment should be done in parallel sessions in future.

There are two suggested future directions: adaptive learning environments and mathematics education. First, the present findings are also relevant to adaptive digital multimedia learning environments. Multimedia learning will be used in many adaptive learning environments (Van Merrienboer & Sweller, 2005) in the future. Most studies suggest using learner behavior, characteristics and expertise (Chen, Huang, Shih, & Chang, 2016; Kalyuga, 2006, 2008; Kayuga et al., 2003) to modify the environment or to give personalized feedback to learners. This present study suggests that the adaptive environment should include order thinking skills and learner expertise to identify multimedia presentations or tasks for delivery to promote individual learning. Future research on adaptive learning environments should focus on cognitive processing, and interactions among learner prerequisites, multimedia presentations and learning outcomes. Second, our findings suggest that intrinsic cognitive load demand depends on instructional design and prior knowledge during learning different degrees of mathematics knowledge. We suggest another future work should be done on cognitive conflict in mathematics leaning and teaching.

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Appendix A

Learning tasks in the worksheets.

Note:

- If the discriminant △ = 0, one equal real roots
- If the discriminant △ > 0, two distinct real roots
- If the discriminant △ < 0, no real roots

Solving methods

- Quadratic formula $x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$
- Taking square $(a\,x + \frac{b}{2})^2 = \frac{\triangle}{4}$
- Factorization $(x - \alpha)(x - \beta) = 0$

Remembering and understanding

1) Change the values of a, b and c. Use the following table and manipulate the materials to learn how △ and the values of roots relate to the graphs.

a	b	c	△	values of roots	x-intercepts
1	2	1	0	-1, -1	-1, -1
1	-2	1	0	1, 1	1, 1
2	2	0	-4	0, -1	0, -1
-1	2	3	16	-1, 3	-1, 3
1	1	1	-3	No real roots	No
2	2	2	-12	No real roots	No
-2	1	-2	-15	No real roots	No

Analyzing

2) Change the values of a, b and c. Use the following table and manipulate the materials to learn how coefficients, △, directions, and the values of a, roots and x-intercept(s) relate to the graphs.

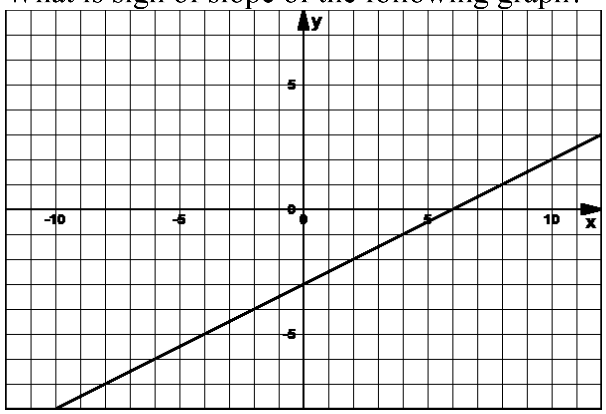
a	b	c	△	values of roots	x-intercepts	y-intercepts	direction	Value of a
1	2	1	0	-1, -1	-1	1	upwards	1
1	-2	1	0	1, 1	1	1	upwards	1
2	2	0	-4	0, -1	0, -1	0	upwards	2
-1	2	3	16	-1, 3	-1, 3	3	Downward	-1
1	1	1	-3	No real roots	No	1	upwards	1
2	2	2	-12	No real roots	No	2	upwards	2
-2	1	-2	-15	No real roots	No	-2	downwards	-2

Appendix B

Sample questions in the pretest.

What is the value of x-intercept of the following graph?

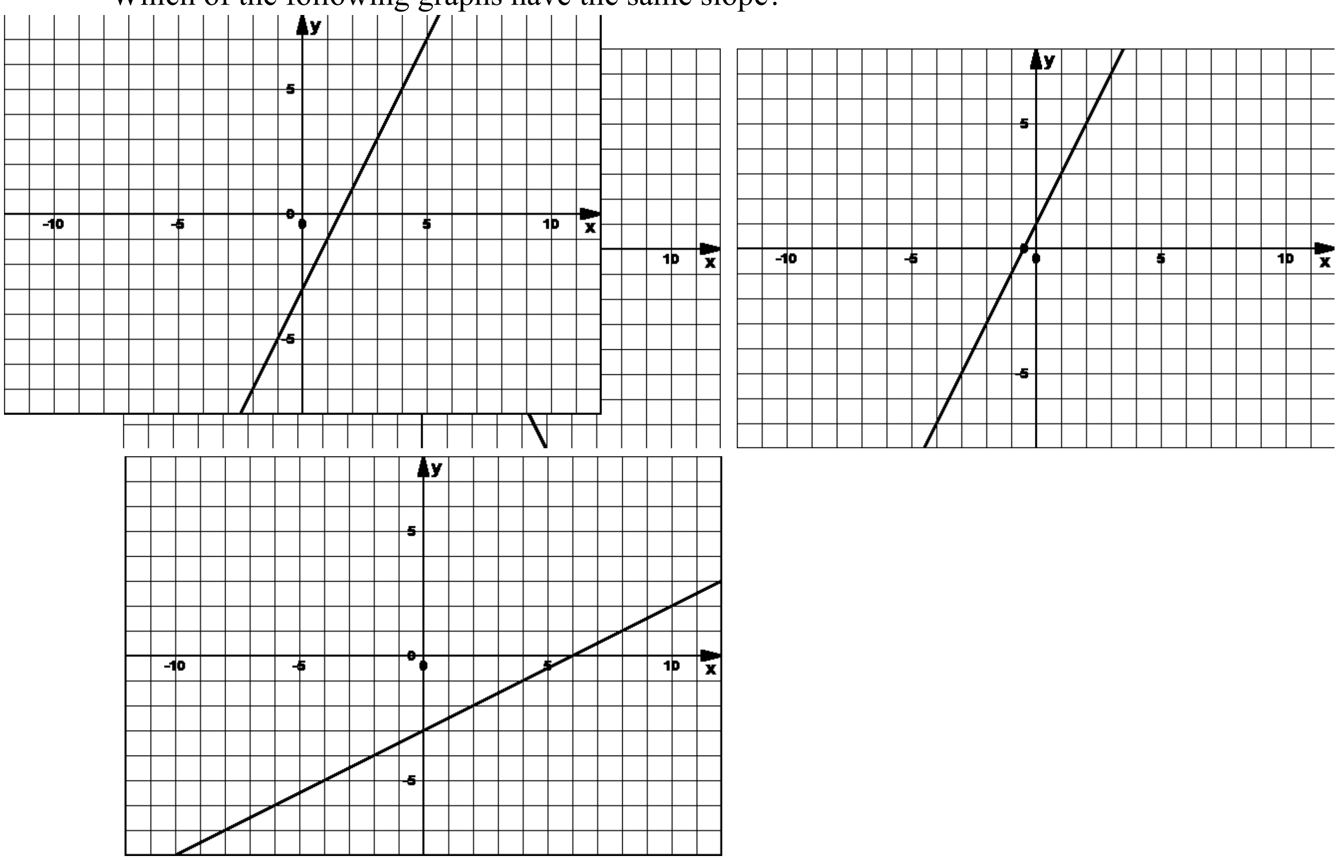
What is sign of slope of the following graph?



Which of the following graph has x=1 and y=3?

Which of the following graph with positive slope?

Which of the following graphs have the same slope?



Appendix C

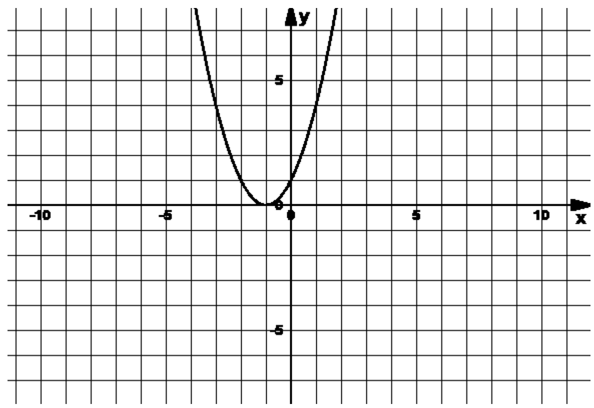
Sample questions in the posttest.

Remembering

Using the following graph y=f(x) to answer

What are the values of roots of an equation f(x)=0?

What is the sign of the discriminant of an equation f(x)=0?



Understanding

Which of the following graph is $y=ax^2+bx+c$ if $ax^2+bx+c=0$ has no real roots?

Which of the following graph is $y=ax^2+bx+c$ if when $a>0$?

Analyzing

Consider the quadratic equation $ax^2+bx+c=0$ and the graph $y=ax^2+bx+c$, where a, b, c are real numbers, and x and y are unknowns in a domain of real numbers. (a is not equal to 0) Rate the following pairs of statements or expressions. (1 – related or true, 2 – not related or false)

Statement or expression 1	Statement or expression 2
$\Delta=b^2-4ac$	Determines number of y-intercepts
value of a	Determines shape of the function $y=ax^2+bx+c$.
x-intercepts are 2 and 3	Determines (x-2)(x-3)=0