The Expertise Reversal Effect is a Variant of the More General Element Interactivity Effect

Abstract

Within the framework of cognitive load theory, the element interactivity and the expertise reversal effects usually are not treated as closely related effects. We argue that the two effects may be intertwined with the expertise reversal effect constituting a particular example of the element interactivity effect. Specifically, the element interactivity effect relies on changes in element interactivity due to changes in the type of material being learned while the expertise reversal effect also relies on changes in relative levels of element interactivity but in this case, due to changes in relative levels of expertise. If so, both effects rely on equivalent changes in element interactivity with the changes induced by different factors. Empirical evidence is used to support this contention.

Keywords: cognitive load theory, element interactivity, expertise, worked example effect, generation effect

Within cognitive load theory, the element interactivity and expertise reversal effects are regarded as distinct cognitive load effects. However, empirical evidence obtained recently (Chen, Kalyuga, & Sweller, 2015), along with previous evidence (Blayney, Kalyuga, & Sweller, 2010; Kalyuga, Chandler, & Sweller, 2001; Leahy & Sweller, 2005), can be interpreted as indicating that the expertise reversal effect may be a variant of the more general element interactivity effect. In this paper, we review the two effects and suggest possible relations between them.

The Expertise Reversal Effect

The expertise reversal effect focuses on the interaction between levels of learners' expertise and the instructional procedures used. Consider two instructional procedures, one of which results in superior test performance compared to the other when instructing novices. Under the expertise reversal effect, with increases in levels of expertise, the difference between the two procedures first decreases, then is eliminated, and may finally reverse (Kalyuga, 2007; Kalyuga & Renkl, 2010). Based on these changes in the relative effectiveness of instruction, two formats of this effect can be categorized: An ordinal interaction in which one of two instructional procedures is effective for novices, but is less effective or has no effects when testing more experienced learners, and a dis-ordinal interaction where one instructional procedure is effective for novices with the relative effectiveness reversed for more experienced learners (Nievelstein, Van Gog, Van Dijck, & Boshuizen, 2013). Which form occurs depends on the relative levels of expertise of the learners. If the differences in expertise are small, test performance may not include a cross-over point resulting in an ordinal interaction. Larger differences in expertise are more likely to include a cross-over point resulting in a dis-ordinal interaction.

Evidence for the Expertise Reversal Effect. The expertise reversal effect was initially investigated in a series of longitudinal studies by intensively training groups of technical apprentices from novices to experts in the domain of engineering (Kalyuga, Chandler, & Sweller, 1998, 2000, 2001). In one set of experiments (Kalyuga et al., 1998), text integrated with diagrams was compared with a diagrams alone condition, testing for the redundancy effect. Results indicated that the diagrams and text condition was superior to the diagrams alone condition for novices, but after a period of training, the effectiveness of the diagrams and text condition deceased compared to the increasing effectiveness of the diagrams alone condition. Subjective ratings of cognitive load further supported the hypothesis that diagrams alone were more easily processed by more knowledgeable learners, whereas, the diagrams and text condition was more suitable for novices who needed additional textual instructions to understand the presented diagrams. With an increase in learner's expertise, textual information that had been beneficial for novices became redundant for more knowledgeable learners.

Subsequent experiments by Kalyuga et al. (2000, 2001) and Kalyuga, Chandler, Tuovinen, and Sweller (2001) provided more data concerning the expertise reversal effect. Kalyuga et al. (2000), using mechanical engineering materials, found novices benefited more if narrated explanations used to explain how to use specific diagrams were presented together with relevant animated diagrams, as opposed to a diagram only condition. However, integrating narrated explanations with animated diagrams interfered with learning after novices had received a series of intensive training sessions which developed their expertise in the relevant domain. For these more knowledgeable students, diagrams alone were superior to the diagrams with narrations format. Kalyuga et al. (2001) obtained a full expertise reversal effect when they compared worked examples with instructions to explore in writing switching equations for relay circuits. The results demonstrated that worked examples initially were superior to instructions to explore, but after additional training, the advantage was reversed. For more knowledgeable learners, instructions to explore resulted in superior learning than studying worked examples.

In mathematics curriculum areas, Kalyuga and Sweller (2004) investigated the expertise reversal effect in studying coordinate geometry. Participants were assigned to a worked example group or a problem-solving group. A post-test indicated an interaction of instructional formats and learner expertise. Less knowledgeable learners benefited more from the worked example format with the opposite result found for more knowledgeable learners. In other mathematics areas, similar results were found. Brunstein, Betts, and Anderson (2009) observed an expertise reversal effect in algebra learning. They found that for students given considerable practice, a low level of guidance was superior to explicit guidance, whereas, for novices who had less practice, high guidance led to better test results than minimal guidance. Similarly, in the domain of statistics, Leppink, Broers, Imbos, van der Vleuten, and Berger (2012) assigned students with different levels of expertise to four groups: reading only;

answering open-ended questions; answering open-ended questions in which the answer had to include supporting arguments; and studying worked examples that included the type of arguments that students in the previous group were required to generate. Results again confirmed the expertise reversal effect. Specifically, students with low expertise learned more from worked examples, whereas, high-expertise students learnt more from answering open-ended questions with supporting arguments. Rey and Buchwald (2011) also observed an expertise reversal effect when asking students to learn the gradient descent (a mathematical optimization algorithm). Students whose expertise was increased by practice during the experiment had higher test scores if they did not receive additional text explaining a relevant animation, whereas, students with a low level of knowledge benefited more from the provision of additional text.

An expertise reversal effect has also been demonstrated in the area of English literature. Oksa, Kalyuga, and Chandler (2010) compared two instructional formats used in studying Shakespearean plays. One group received material that combined modern English explanations with Shakespeare's original old English line by line, while another group had the modern English explanatory materials presented as footnotes. Participants, who were less knowledgeable about Shakespearean plays, demonstrated better performance with an integrated format, whereas, for the participants who were Shakespearean experts, the separated format was better.

Nückles, Hübner, Dümer, and Renkl (2010) found the expertise reversal effect in learning journal writing skills. Students were divided into a group with prompts and a group without prompts in writing journal entries. During the first semester, students with prompts provided more writing strategies and outperformed students without prompts, but at the end of the semester, as the levels of learner expertise increased, the advantage reversed in line with the expertise reversal effect.

Van Gog, Paas, and van Merriënboer (2008) demonstrated an expertise reversal effect by comparing product-oriented worked examples and process-oriented worked examples. The first type of worked example only indicates the procedure to solve a problem, whereas, the latter includes not only the procedure but also the reasons for each step (Van Gog, Paas, & Van Merriënboer, 2004). Students were divided into product-product, product-process, process-product and process-process conditions. Results indicated no initial differences between the conditions, but after two sessions of practice, the process-product group was superior to the process-process group because with an increase of expertise, explanations became redundant resulting in an expertise reversal effect.

The expertise reversal effect also has been found in a computer-based learning environment. Rey and Fischer (2013) tested the effect with a computer program teaching statistical data analysis and induced expertise experimentally by providing some extra examples and illustrations in addition to textual explanations during the experiment. Students were randomly assigned to four groups: experts with textual explanations, experts without textual explanations, novices with textual explanations and novices without textual explanations. Results replicated the expertise reversal effect. Students with a low level of expertise benefited more from the provision of textual explanations compared to the more expert students who performed better without additional textual explanations.

Johnson, Ozogul, and Reisslein (2015) investigated the effects of both visual signaling and of the visual presence of an animated pedagogical agent by comparing the performance of four groups: visual signaling with the animated pedagogical agent present; visual signaling without the animated pedagogical agent present; no visual signaling with the animated pedagogical agent present; and no visual signaling without the animated pedagogical agent present. Students were divided into low or high levels of prior knowledge. The results indicated that students with a high level of knowledge performed better without the animated pedagogical agent present, whereas, the opposite result was observed for students with a low level of knowledge.

In summary, work on the expertise reversal effect indicates that in a large variety of curriculum areas, novice students benefit from the presentation of additional information and guidance. With increasing levels of expertise, additional information becomes redundant resulting in a reduction or reversal of the advantage. None of these studies explicitly linked the expertise reversal effect with element interactivity.

Element Interactivity

Element interactivity is a basic concept of cognitive load theory. It can be used to determine categories of cognitive load as well as constituting an effect in its own right. Interactive elements are defined as elements that must be processed simultaneously in working memory as they are logically related (Sweller, Ayres, & Kalyuga, 2011). An element can be a symbol, a concept, or a procedure that must be learned.

Considered from a broad perspective, the concept of element interactivity provides a practically usable approximation for describing the complexity of information involved in learning, especially when the acquisition of domain-specific knowledge in long-term memory is the goal of instruction. As is the case for any theoretical abstraction, ideally this description should include details of relevant processes and operations, as well as the timescale on which they occur. Of course, some of these details may be difficult to precisely describe and quantify. For example, processes such as making inferences to construct mental representations, integrating them with prior knowledge, or blocking irrelevant information are likely to consume working memory resources but may be difficult to describe in terms of clearly defined interacting elements of information (Kalyuga, 2015). However, the elements associated with most cognitive processes can be described and the concept of element interactivity is effective in assessing levels of cognitive load imposed by specific learning tasks on specific categories of learners. Element interactivity levels can be determined by estimating the number of interacting elements in learning materials (Sweller, 1994; Sweller & Chandler, 1994; Tindall-Ford, Chandler, & Sweller, 1997). That number will depend on both the nature of the material being processed and the levels of expertise of the learner as discussed in the next section.

Element Interactivity and Intrinsic Cognitive Load. Intrinsic load is determined by levels of element connectedness that determine the nature of information, and by learners' knowledge (Van Merriënboer, Kester, & Paas, 2006). With respect to element connectedness, instructional materials can be divided into high or low element interactivity materials. For example, students learning the symbols of the periodic table in Chemistry can study each symbol individually with no reference to other symbols. Students learning the symbol for hydrogen, *H*, can do so independently of learning the symbol for copper, *Cu,* without considering any relations between them. Such material has a low degree of element interactivity and a low intrinsic cognitive load.

In contrast, a simple algebra equation such as, $x-3=2$, solve for x, is relatively high in element interactivity. In order to understand and solve this problem, students must consider not only the individual symbols, but also the relations among them. All must be processed simultaneously in working memory. If they are considered in isolation, the problem cannot be understood and solved. Therefore, relatively more interactive elements will need to be processed simultaneously in working memory increasing intrinsic cognitive load compared to low element interactivity material that allows fewer elements to be processed simultaneously.

As well of the structure of information, the expertise of learners also affects intrinsic load. Experienced learners who have acquired relevant schemas for the above problem can treat the entire equation and the problem solution as a single element in working memory, thus reducing the intrinsic load. Element interactivity is a combination of the characteristics of the material to be learned and the knowledge base of the learner. It cannot be determined merely by reference to the characteristics of the information alone. When estimating the level of element interactivity, elements that have been combined into a single, higher order element by relatively more knowledgeable learners enable them to reduce working memory load and so need to be taken into account.

Element interactivity is not equivalent to task difficulty because as indicated above, not all elements interact. A task that requires many elements to be learned will be difficult but because not all of the elements may interact, element interactivity may be low. Learning the chemical symbols of the periodic table or the vocabulary of a second language may be very difficult tasks because there are many elements that need to be learned but element interactivity is low. Each element can be learned independently of every other element. The task is difficult but working memory load and intrinsic cognitive load is low due to low element interactivity.

Element Interactivity and Understanding. Element interactivity also can be used to define **“**understanding**”.** Information will be fully understood if all interactive elements can be processed in working memory simultaneously (Sweller et al., 2011). Nevertheless, the term “understanding” tends not be used when dealing with low element interactive information. If someone deals with information low in element interactivity, such as “Cu” stands for “copper”, we would not refer to them understanding or failing to understand the relation. If we fail to recall this relation, we will attribute the failure to forgetting or having no prior knowledge rather than failing to understand. Therefore, “understanding” is only used for materials high in element interactivity.

The distinction between learning by understanding and learning by rote is also related to element interactivity. Learning by understanding increases the number of interactive elements that must be processed in working memory simultaneously. However, if a large number of interactive elements cannot be handled simultaneously, learning by rote reduces the number of interacting elements albeit at the expense of understanding. Of course, learning by understanding is the ultimate goal of instruction.

Element Interactivity and Extraneous Cognitive Load. Extraneous cognitive load is imposed by inappropriate instructional procedures. It must be reduced or eliminated (Kalyuga, 2011) to provide more working memory resources to deal with intrinsic load, which enhances learning. Extraneous load also is determined by element interactivity (Sweller, 2010). It occurs under conditions where element interactivity can be reduced without altering what is learned. For example, if instructional procedures require learners to study worked examples, they will need to process fewer elements simultaneously in working memory than if instruction requires learners to solve the equivalent problems.

The Element Interactivity Effect. This effect indicates that any cognitive load effects, such as the worked example effect, may not be obtained if the intrinsic load is very low (Sweller et al., 2011). The addition of intrinsic and extraneous load determines the total load imposed on working memory. If the intrinsic load is low, a high extraneous load may not matter as the total cognitive load may still be within the capacity of working memory. However, if intrinsic load is high with a high extraneous load imposed by suboptimal instruction, working memory may be overloaded. Total cognitive load needs to be reduced by reducing extraneous load. Under these circumstances, cognitive load effects can be obtained by reducing extraneous load.

A body of evidence has demonstrated the element interactivity effect. Sweller and Chandler (1994) and Chandler and Sweller (1996) tested for the split-attention and redundancy effects using computers and computer manuals with students learning computer applications. They found both effects using high element interactivity material but the effects disappeared using low element interactivity material. Rey (2011) also found that the split-attention effect was eliminated for low element interactivity information. Similarly, Tindall-Ford et al. (1997) obtained the modality effect according to which learners who were presented instructions on how to read wiring diagrams and tables in spoken form performed better than students presented the same information in written form, using high but not low element interactivity materials. Leahy and Sweller (2005) tested students learning to read a bus timetable and obtained an imagination effect that occurs when learners asked to imagine procedures learn more than learners asked to study the same procedures. The effect only was obtained using high rather than low element interactivity material.

Marcus, Cooper, and Sweller (1996) investigated the relation between levels of element interactivity and understanding by comparing identical textual and diagrammatic information when students learned the effects of connecting resistors in series or in parallel. Textual information required learners to process multiple, interacting elements while diagrammatic information allowed students to use previously acquired knowledge to treat the multiple elements as a single, schematic element. The results revealed that information presented in diagrammatic form reduced element interactivity and cognitive load.

Expertise and the element interactivity effect. Because levels of element interactivity not only depend on the nature of the information being processed but also on the expertise of the learner, so learner expertise will also affect the element interactivity effect. For given information, higher levels of expertise reduce the level of element interactivity, whereas lower levels of expertise increase the level of element interactivity. Since levels of element interactivity are affected by levels of expertise, we can expect that the occurrence of the element interactivity effect also will be affected by levels of expertise. As is the case with all cognitive load effects, high element interactivity is a necessary condition. The element interactivity effect itself requires high element interactivity. If element interactivity is low due to high levels of expertise, the effect will not be obtained.

The suggestion that expertise alters element interactivity and provides the machinery underlying the expertise reversal effect is the central thesis of this paper. There is considerable empirical evidence for the suggested effects of expertise on element interactivity leading to the expertise reversal effect. That evidence is discussed below in the sub-section entitled "Empirical Evidence for the Hypothesis".

Human Cognitive Architecture and the Reciprocity of Complexity and Expertise

The reason for the equivalent effects of decreases in complexity and increases in expertise can be found in the cognitive architecture that underlies cognitive load theory. Human cognitive architecture (Sweller et al., 2011) can be used to indicate how novel information is acquired, and the differences in the manner in which familiar and unfamiliar information is processed (Sweller, 2015).

Human Cognitive Architecture

The Borrowing and Reorganizing Principle. Almost all of the knowledge we acquire is borrowed from other people via listening, reading and imitating before being reorganized when combined with previously acquired information.

Randomness as Genesis Principle. Borrowed information initially must be created. It is created by a random generation and test process during problem solving.

Narrow Limits of Change Principle. Novel information is initially processed by a limited capacity, limited duration working memory.

The Information Store Principle. Long-term memory has a large, effectively unlimited capacity to store information transferred from working memory.

Environmental Organizing and Linking Principle. Information in long-term memory does not become active until it has been triggered by cues from the environment that induce working memory to choose which knowledge set to use. The specific knowledge set held in long-term memory can be used to govern complex behavior that is suitable for that environment. Unlimited amounts of information can be transferred from long-term to working memory.

Reciprocity between Levels of Element Interactivity and Expertise

This cognitive architecture explains the reciprocity between levels of element interactivity and expertise. Based on the environmental organizing and linking principle, knowledge held in long-term memory leads to learners' expertise and determines how they perceive and organize information. Novices do not have relevant knowledge stored in their long-term memory (the information store principle). They are likely to perceive novel information as a collection of discrete, interacting elements that can easily overwhelm limited working memory resources. They have not developed knowledge structures used to integrate individual elements, so a task that is presented may contain high levels of element interactivity leading to a high intrinsic load. In addition, if external guidance is not provided, novices may have to randomly generate solutions (randomness as genesis principle) to solve problems, which will cause a high extraneous load, leaving few resources available for learning (narrow limits of change principle).

More knowledgeable learners use their knowledge to integrate individual elements presented by the same task into fewer elements, reducing the levels of element interactivity. When that knowledge is transferred by experts to working memory using the environmental organizing and linking principle, there may be little pressure on working memory resources. Novices who lack relevant knowledge cannot effect such an action. In this manner, levels of expertise have a reciprocal influence on the levels of element interactivity. For given information, low levels of expertise with respect to that information increase the level of element interactivity, whereas high levels of expertise decrease the level of element interactivity. In turn, these changes in element interactivity have instructional consequences.

Relations between the Element Interactivity and the Expertise Reversal Effects

As discussed above, the element interactivity effect suggests that every cognitive load effect relies on materials that are high in element interactivity. The expertise reversal effect suggests that instruction that is suitable for novices may not be suitable for more knowledgeable learners. If high levels of expertise reduce the levels of element interactivity rendering most cognitive load effects unobtainable, whereas, low levels of expertise increase the level of element interactivity, facilitating cognitive load effects, then the expertise reversal effect may be regarded as an example of the more general element interactivity effect.

A specific example can be used to clarify the relation. Consider the expertise reversal affect as it applies to the worked example effect. We know, based on the worked example effect, that novices are more likely to benefit from studying worked examples rather than solving problems. We also know that with increasing expertise, the worked example effect decreases in magnitude, then disappears and finally reverses with problem solving being superior to studying worked examples.

Consider this expertise reversal effect from an element interactivity perspective. For novices, searching for suitable problem moves using the randomness as genesis principle, determining whether a particular move is suitable with respect to the problem goal, remembering which moves have been previously chosen, both possibly successful moves for later use and unsuccessful moves to ensure they are not chosen again, requires the processing of a large number of interacting elements. Working memory tends to be overwhelmed and learning may be inhibited. Far fewer interacting elements need to be processed when studying worked examples by using the borrowing and reorganizing principle. Learning is facilitated resulting in the worked example effect when compared to problem solving.

Now consider more expert learners presented either problems to be solved or worked examples to study. When solving problems, the learner already is likely to have acquired knowledge indicating which moves need to be made for that particular problem. Practicing those moves may be needed but determining which moves to make is relatively straightforward and can be accomplished merely by referring to information held in long-term memory via the environmental organizing and linking principle. Moves are generated by knowledge rather than the random generate and test process of novices. There may be only a single element (or schema) that needs to be retrieved from long-term memory to generate the problem solution. In contrast, if studying a worked example, more expert learners must compare their known problem solution with the redundant solution presented. The consequence is an increase in element interactivity due to redundancy rather than the decrease we find with novices resulting in a reverse worked example effect with problem solving being superior to studying worked examples. That reverse worked example effect is an example of the redundancy effect.

Based on the above argument, comparing problem solving with studying worked examples causes a reverse result depending on whether novices or more expert learners are used. That result is the basis of the expertise reversal effect but on the current analysis, leads to the conclusion that the expertise reversal effect is caused entirely by changes in element interactivity. In other words, the expertise reversal effect may merely be an example or variant of the element interactivity effect.

Empirical Evidence for the Hypothesis

There are a number of research studies that were designed to simultaneously investigate the expertise reversal and the element interactivity effects within a cognitive load theory framework. These studies may be used to reveal the hypothesized relation between the two effects.

Kalyuga, Chandler, and Sweller (2001) looked at the worked example effect. For high element interactivity material they found when testing novices that studying worked examples was superior to problem solving but that with increased expertise, problem solving was superior to worked examples, providing an example of an expertise reversal effect. In contrast, no significant differences were found with materials that were low in element interactivity. In other words, the worked example effect was obtained with high but not low element interactivity material. That worked example effect could be eliminated not only by using different information that was low in element interactivity, it also could be eliminated by increased expertise that had a similar effect to decreased complexity.

Leahy and Sweller (2005) looked at the imagination effect that occurs when learners asked to imagine procedures or concepts learn more than learners who study the information instead. They found the effect using more but not less knowledgeable students. The less knowledgeable students were not able to imagine the procedures and so needed to study the information. This expertise reversal effect only was obtained using high, not low element interactivity material. Again, element interactivity could be altered either by altering the information or altering the expertise of the learners. The level of element interactivity was influenced by the level of expertise.

Blayney et al. (2010) studied the isolated elements effect and its interaction with levels of expertise. The isolated elements effect occurs when learners presented with very complex information that normally requires them to process more interacting elements than can be handled by working memory, learn more if the information first is presented in isolated form such that relations between interacting elements are omitted. In a subsequent phase, the information is presented in integrated form emphasizing the interactions between elements. The effect occurs when isolated followed by interacting elements phases results in better performance than multiple presentations of the interacting form only. Students first can learn the isolated elements followed by the interactions between the previously learned elements, without overloading working memory in either phase. In contrast, if the full interacting set of elements is presented initially, working memory is likely to be overloaded resulting in decreased learning..

Blayney et al. (2010) found that in accountancy training, less knowledgeable learners benefited more when presented isolated elements of information, in accord with the isolated elements effect but more knowledgeable learners benefited more from interactive elements of information. For less knowledgeable learners who demonstrated a standard, isolated elements effect, we can assume that they required the presentation of isolated elements first in order to be able to process excessive amounts of information in working memory, as indicated above. In the case of more knowledgeable learners, element interactivity and intrinsic cognitive load is reduced due to the environmental organizing and linking principle. Since element interactivity is low for these students, reducing it further by unnecessarily presenting isolated elements, will inhibit rather than facilitate further learning. In this manner, the expertise reversal effect that was obtained is really a variant of the element interactivity effect.

The failure to find an isolated elements effect using more knowledgeable learners is no different to the failure to find any other cognitive load effect using low element interactivity information (e.g., Sweller & Chandler, 1994; Tindall, Chandler & Sweller, 1997). High element interactivity information is essential for any cognitive load effect to manifest itself. Increases in expertise reduce element interactivity and low element interactivity eliminates cognitive load effects. If so, it is the reduction in element interactivity with increases in expertise that underlies the expertise reversal effect.

Blayney et al. (2010) manipulated element interactivity by altering the manner in which the same information was presented to more and less knowledgeable learners. Chen et al. (2015) rather than altering the way in which the same information was presented to learners with different levels of expertise, altered what students at different levels of expertise had to learn. Some of the information was low in element interactivity while other information was high. In addition, rather than investigating the isolated elements effect, Chen et al. (2015) investigated the worked example and generation effects.

The worked example and generation effects are interesting because they ostensibly appear to be contradictory. As indicated above, the worked example effect occurs when learners provided with high levels of guidance in the form of worked examples perform better on subsequent test problems than learners presented with the same material as problems to be solved (Cooper & Sweller, 1987; Paas, 1992; Paas & Van Merriënboer, 1994; Renkl, 2014; Sweller & Cooper, 1985). Requiring learners to solve a problem provides much lower levels of guidance than studying worked examples.

In contrast to the worked example effect, the generation effect occurs when learners are asked to generate responses rather than being provided with the correct responses. This effect has been investigated by various research studies using different types of testing materials. The most commonly used format is paired associates, such as *hot – c_* (opposite) (Slamecka & Graf, 1978). Other research studies used single word fragments (Glisky & Rabinowitz, 1985) in which learners had to generate missing letters to complete word fragments, such as ALC-H-L as the fragments for ALCOHOL; incomplete sentences as contexts (Anderson, Goldberg, & Hidde, 1971) requiring learners to generate the last word of an incomplete sentence such as "The doctor looked at the time on his (*watch*)"; and algebra materials (McNamara, 1995), such as 2 x 4 = 8, in which students needed to generate the answer 8 or read the whole formula. Contrary to the worked example effect according to which explicitly providing problem solutions (providing high guidance) benefits learners more than asking them to solve problems (a low guidance condition), the generation effect demonstrates that generating answers in order to memorize information (a low guidance condition) is more effective than providing answers explicitly (high guidance).

Chen et al. (2015) designed experiments to directly investigate the relations between levels of guidance and element interactivity. They hypothesized that the worked example effect required high element interactivity information while the generation effect required low element interactivity information. Two experiments were conducted in the domain of geometry. Learning simple, low element interactivity geometry formulae were used to test for the generation effect. In contrast, learning to solve geometry problems using those formulae, a high element interactivity task, was used to test for the worked example effect. Participants in Experiment 1 were novices while those in Experiment 2 were more knowledgeable learners. The same topic areas were used in both experiments.

The results indicated that when novices were tested in Experiment 1, the worked example effect was obtained for the high element interactivity information whereas the generation effect was obtained for the low element interactivity information. In Experiment 2 using more knowledgeable learners, a generation effect for learning formulae or reversed worked example effect for learning problem solutions, was obtained for both sets of information. Generating answers or solution procedures rather than studying provided answers or procedures, was superior irrespective whether learners were learning the formulae or learning to use the formulae in problems.

These results support the suggestion that the expertise reversal effect depends on changes in levels of element interactivity. In the first experiment, the worked example effect was obtained using high element interactivity information while the generation effect, was obtained using low element interactivity information. In the second experiment, increased expertise rendered all of the information low in element interactivity and a reversed worked example effect and a generation effect were obtained for all information. It also might be noted that using the high element interactivity problem solving information across both experiments yielded an expertise reversal effect. A worked example effect was obtained using low expertise learners in Experiment 1 while a reverse worked example effects was obtained using higher expertise learners in Experiment 2, with the same content material being taught in both experiments. These results provide evidence that the expertise reversal effect is caused by changing levels of element interactivity due to changes in expertise.

Conclusions

In this paper we have suggested that there are both theoretical and empirical reasons for assuming that the expertise reversal effect is a variant of the element interactivity effect. From a theoretical perspective, it was pointed out that increases in expertise have long been assumed to result in decreases in element interactivity. Element interactivity associated with intrinsic cognitive load only can be varied by changing the task or changing levels of expertise. Based on human cognitive architecture, a primary manifestation of expertise is the ability to treat multiple elements as a single element in working memory thus transforming our ability to function in a variety of environments. With increasing expertise, high element interactivity information is transformed into low element interactivity information, leading directly to the expertise reversal effect. Instructional procedures designed to reduce working memory load for novices under a high element interactivity environment no longer can reduce working memory load in the already low element interactivity environment of more expert learners. The result is the elimination or reversal of usual cognitive load effects. Empirical evidence for this suggestion comes from data indicating that changes in expertise result in changes in element interactivity, ultimately generating the expertise reversal effect.

It should be noted that a similar argument was presented by Wulf and Shea (2002) in the area of motor learning. They suggested that results obtained from simple motor tasks may not generalize to complex tasks. They also suggested that results using simple and complex tasks may be more similar from data obtained after more practice on complex tasks due to increases in expertise. These suggestions from motor learning bear a considerable similarity to the current suggestions based on cognition.

Cognitive load theory and cognitive load effects are intended to have direct instructional implications and the current work is no exception. Element interactivity is a central concept of cognitive load theory and all cognitive load effects rely on differences in element interactivity between instructional conditions (Sweller, 2010). By analyzing element interactivity between instructional conditions, we can predict which instructional procedures are likely to be effective. That analysis simultaneously must take into consideration both the nature of the information learners are processing and the knowledge levels of the learners. Such an analysis of element interactivity leads to the expertise reversal effect and can provide us with guidelines for effective instructional design.

References

Anderson, R. C., Goldberg, S. R., & Hidde, J. L. (1971). Meaningful processing of sentences. *Journal of Educational Psychology, 62*, 395-399.

Blayney, P., Kalyuga, S., & Sweller, J. (2010). Interactions between the isolated–interactive elements effect and levels of learner expertise: Experimental evidence from an accountancy class. *Instructional Science, 38*, 277-287.

Brunstein, A., Betts, S., & Anderson, J. R. (2009). Practice enables successful learning under minimal guidance. *Journal of Educational Psychology, 101*, 790-802.

Chandler, P., & Sweller, J. (1996). Cognitive load while learning to use a computer program. *Applied Cognitive Psychology, 10*, 151-170.

Chen, O., Kalyuga, S., & Sweller, J. (2015). The worked example effect, the generation effect, and element interactivity. *Journal of Educational Psychology*, 107, 689-704.

Cooper, G., & Sweller, J. (1987). Effects of schema acquisition and rule automation on mathematical problem-solving transfer. *Journal of Educational Psychology, 79*, 347-362.

Glisky, E. L., & Rabinowitz, J. C. (1985). Enhancing the generation effect through repetition of operations. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 11*, 193-205.

Johnson, A., Ozogul, G., & Reisslein, M. (2015). Supporting multimedia learning with visual signalling and animated pedagogical agent: moderating effects of prior knowledge. *Journal of Computer Assisted Learning, 31*, 97-115.

Kalyuga, S. (2007). Expertise reversal effect and its implications for learner-tailored instruction. *Educational Psychology Review, 19*, 509-539.

Kalyuga, S. (2011). Cognitive load theory: How many types of load does it really need? *Educational Psychology Review, 23*, 1-19.

Kalyuga S. (2015). *Instructional guidance: A cognitive load perspective*. Charlotte, NC: Information Age Publishing.

Kalyuga, S., Chandler, P., Tuovinen, J., & Sweller, J. (2001). When problem solving is superior to studying worked examples. *Journal of Educational Psychology, 93*, 579-588.

Kalyuga, S., Chandler, P., & Sweller, J. (1998). Levels of expertise and instructional design. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 40*, 1-17.

Kalyuga, S., Chandler, P., & Sweller, J. (2000). Incorporating learner experience into the design of multimedia instruction. *Journal of Educational Psychology, 92*, 126-136.

Kalyuga, S., Chandler, P., & Sweller, J. (2001). Learner experience and efficiency of instructional guidance. *Educational Psychology, 21*, 5-23.

Kalyuga, S., & Renkl, A. (2010). Expertise reversal effect and its instructional implications: Introduction to the special issue. *Instructional Science, 38*, 209-215.

Kalyuga, S., & Sweller, J. (2004). Measuring knowledge to optimize cognitive load factors during instruction. *Journal of Educational Psychology, 96*, 558-568.

Leahy, W., & Sweller, J. (2005). Interactions among the imagination, expertise reversal, and element interactivity effects. *Journal of Experimental Psychology: Applied, 11*, 266-276.

Leppink, J., Broers, N. J., Imbos, T., van der Vleuten, C. P., & Berger, M. P. (2012). Self-explanation in the domain of statistics: an expertise reversal effect. *Higher Education, 63*, 771-785.

Marcus, N., Cooper, M., & Sweller, J. (1996). Understanding instructions. *Journal of Educational Psychology, 88*, 49-63.

McNamara, D. S. (1995). Effects of prior knowledge on the generation advantage: Calculators versus calculation to learn simple multiplication. *Journal of Educational Psychology, 87*, 307-318.

Nievelstein, F., Van Gog, T., Van Dijck, G., & Boshuizen, H. P. (2013). The worked example and expertise reversal effect in less structured tasks: Learning to reason about legal cases. *Contemporary Educational Psychology, 38*, 118-125.

Nückles, M., Hübner, S., Dümer, S., & Renkl, A. (2010). Expertise reversal effects in writing-to-learn. *Instructional Science, 38*, 237-258.

Oksa, A., Kalyuga, S., & Chandler, P. (2010). Expertise reversal effect in using explanatory notes for readers of Shakespearean text. *Instructional Science, 38*, 217-236.

Paas, F. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive-load approach. *Journal of Educational Psychology, 84*, 429-434.

Paas, F., & Van Merriënboer, J. J. (1994). Variability of worked examples and transfer of geometrical problem-solving skills: A cognitive-load approach. *Journal of Educational Psychology, 86*, 122-133.

Renkl, A. (2014). Toward an instructionally oriented theory of example-based learning. *Cognitive Science, 38*, 1-37.

Rey, G. D. (2011). Interactive elements for dynamically linked multiple representations in computer simulations. *Applied Cognitive Psychology, 25*, 12-19.

Rey, G. D., & Buchwald, F. (2011). The expertise reversal effect: cognitive load and motivational explanations. *Journal of Experimental Psychology: Applied, 17*, 33-48.

Rey, G. D., & Fischer, A. (2013). The expertise reversal effect concerning instructional explanations. *Instructional Science, 41*, 407-429.

Slamecka, N. J., & Graf, P. (1978). The generation effect: Delineation of a phenomenon. *Journal of Experimental Psychology: Human Learning and Memory, 4*, 592-602.

Sweller, J. (1994). Cognitive load theory, learning difficulty, and instructional design. *Learning and Instruction, 4*, 295-312.

Sweller, J. (2010). Element interactivity and intrinsic, extraneous, and germane cognitive load. *Educational Psychology Review, 22*, 123-138.

Sweller, J. (2015). In academe, what is learned, and how is it learned? *Current*

Directions in Psychological Science, 24, 190-194.

Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive Load Theory.* New York: Springer.

Sweller, J., & Chandler, P. (1994). Why some material is difficult to learn. *Cognition and Instruction, 12*, 185-233.

Sweller, J., & Cooper, G. A. (1985). The use of worked examples as a substitute for problem solving in learning algebra. *Cognition and Instruction, 2*, 59-89.

Tindall-Ford, S., Chandler, P., & Sweller, J. (1997). When two sensory modes are better than one. *Journal of Experimental Psychology: Applied, 3*, 257-287.

Van Gog, T., Paas, F., & Van Merriënboer, J. J. (2004). Process-oriented worked examples: Improving transfer performance through enhanced understanding. *Instructional Science, 32*, 83-98.

Van Gog, T., Paas, F., & van Merriënboer, J. J. (2008). Effects of studying sequences of process-oriented and product-oriented worked examples on troubleshooting transfer efficiency. *Learning and Instruction, 18*, 211-222.

Van Merriënboer, J. J., Kester, L., & Paas, F. (2006). Teaching complex rather than simple tasks: Balancing intrinsic and germane load to enhance transfer of learning. *Applied Cognitive Psychology, 20*, 343-352.

Wulf, G., & Shea, C. H. (2002). Principles derived from the study of simple skills do not generalize to complex skill learning. *Psychonomic Bulletin and Review, 9*, 185-211.