

Using Cognitive Load Theory to Tailor Instruction to Levels of Accounting Students' Expertise

Paul Blayney^{1*}, Slava Kalyuga² and John Sweller²

¹School of Business, University of Sydney, Australia // ²School of Education, University of New South Wales, Australia // paul.blayney@sydney.edu.au // s.kalyuga@unsw.edu.au // j.sweller@unsw.edu.au

*Corresponding author

ABSTRACT

Tailoring of instructional methods to learner levels of expertise may reduce extraneous cognitive load and improve learning. Contemporary technology-based learning environments have the potential to substantially enable learner-adapted instruction. This paper investigates the effects of adaptive instruction based on using the isolated-interactive elements effect that occurs when learners who are initially presented with elements of information in an isolated, non-interactive form (followed by a fully interactive form) outperform those who are presented with the same information only in a fully interactive form. Cognitive load theory explains the effect for novice learners by their potential cognitive overload when dealing with a fully interactive form of instruction from the beginning. However, according to the expertise reversal effect in cognitive load theory, the effect may reverse for relatively more knowledgeable learners. Experiment 1 found that more knowledgeable accounting students performed better with interactive rather than isolated presentations. For less knowledgeable learners, there was no statistically significant performance difference between the presentation formats. Thus, there was a significant interaction between the instructional procedures and levels of learner prior knowledge as an indicator of an expertise reversal effect. In one of the two conditions used in Experiment 2, information was adaptively presented in isolated form to less knowledgeable learners but in interactive form to more knowledgeable learners (based on the pre-tests of learner prior knowledge). In another (control) group, students were randomly allocated to isolated and interactive instructional formats irrespective of levels of their prior knowledge. As expected, the adaptive instruction group was superior to the non-adaptive group. The paper concludes with implications for the technology enabled design of learner-tailored instructional presentations.

Keywords

Adaptive instruction, Cognitive load theory, Isolated-interacting elements effect, Expertise reversal effect, Accounting training

Introduction

Cognitive load theory has been extensively used to investigate the implications of human cognitive architecture for instruction and learning in different domains (Sweller, Ayres, & Kalyuga, 2011). This instructional theory draws on various characteristics of the major components of human cognitive architecture, primarily working memory as a conscious information processor and long-term memory as our knowledge base, to advance teaching and learning techniques. The theory recognises the limited capacity of working memory (Miller, 1956; Baddeley, 1992) when dealing with novel information as well as the critical role of available knowledge structures in long-term memory for learning and performance (De Groot, 1965; Chase & Simon, 1973). Together, these two factors determine the magnitude of working memory load which is essentially cognitive load.

Tailoring the design of instructional procedures and formats to levels of learner prior knowledge is one of the essential recommendations of this theory based on research on the expertise reversal effect (Kalyuga, 2007). This research has demonstrated that different instructional methods are suitable for learners with different levels of expertise in a task domain. Therefore, the cognitive load consequences of using various instructional methods can be optimized if these methods are intentionally tailored to individual learners' levels of expertise (learner-tailored or adaptive instruction). Any type of effective practical implementation of individualized, adaptive, learner-tailored instruction today requires the use of modern technology. Without the use of technology, adaptive instruction methods have usually been limited to individual or small group face to face teaching. The experiments in this study rely on the most widely used technology in the accounting profession – the Excel spreadsheet. This study's adaptive alteration of instructional methods on a large scale basis is substantially enabled by spreadsheet technology-based learning environments.

The expertise reversal effect

The expertise reversal effect (Kalyuga, Ayres, Chandler, & Sweller, 2003; Kalyuga, 2007) recognises the differential effectiveness of instructional methods and techniques according to the level of a person's expertise or prior knowledge. This effect provides a theoretical basis for suggesting that less knowledgeable learners (e.g., novices) should be provided with a high degree of instructional support for their learning activities. On the other hand, relatively more knowledgeable learners (e.g., experts) should be provided with a lower level of assistance thus allowing them to use their previously developed schemas for guiding problem solving activities. Most versions of the effect occur when less knowledgeable learners perform better after instruction with more guidance while more knowledgeable learners perform better following instruction that includes less guidance.

The main instructional implication of the expertise reversal effect within a cognitive load framework is the need to adapt instructional methods to varying levels of learner expertise (e.g., Kalyuga & Sweller 2005; Kalyuga 2007). Kalyuga and Sweller (2004; 2005) investigated adaptive instruction through the use of a rapid test of expertise that allowed their instructional materials to be dynamically altered as learners' expertise changed during the experimental session. This research provided strong evidence in support of adaptive instruction with the learner-adapted instruction group significantly outperforming the randomly assigned instruction group. Rapid evaluations of learner expertise were made throughout the learning session with instructional methods changed as deemed appropriate by the underlying expertise reversal effect.

The need for learner-tailored instruction was discussed in earlier studies by Tobias (1989). The effects of different methods of adaptive learning task selection in computer-based training for air traffic control were also investigated by Camp, Paas, Rikers, and van Merriënboer (2001). In three experimental conditions, learning tasks were selected using reported mental effort, performance scores, or a mental efficiency indicator that combined these two variables while in the control group, learning tasks were provided in a fixed predetermined simple-to-complex task sequence. Results indicated that the learner-tailored task selection generated better results than non-tailored task selection, with no significant advantages of any of the task selection methods over the other two methods. Similar results were obtained by Kalyuga (2006) in a study based on the expertise reversal effect.

Isolated - interacting elements effect

The instructional material's element interactivity is one of the key concepts in cognitive load theory (Sweller, 1994, 2010; Sweller & Chandler, 1994). Levels of element interactivity are determined by the extent to which learning elements can be assimilated individually or only in combination with other elements. When elements interact with other elements, they all must be learned simultaneously resulting in a heavy working memory load. Alternatively, if an element can be learned in isolation from other elements because it does not interact with them, then element interactivity is low. It needs to be emphasised that levels of element interactivity are not just dependent on the characteristics of the information being processed but also depend on the knowledge base of a learner. High element interactivity for a novice in an area may constitute low element interactivity for a more expert learner. Recent work by Johnson and Slayter (2012) with introductory accounting students illustrated the applicability of this concept in an accounting context. The appropriate instructional design was achieved by reducing the complexity of the learning task by initially restricting the scope of accounting transaction types.

Acquiring organised knowledge structures in long-term memory allows multiple interacting elements to be treated as a single higher-level element thus reducing cognitive load. The expertise reversal effect occurs because novice learners tend to have their working memory overloaded by highly interactive learning material that has not as yet been chunked into fewer elements. Novice learners will therefore usually benefit from well-guided instructional materials (Kirschner, Sweller, & Clark 2006) that introduce new elements of information gradually. More knowledgeable learners, on the other hand, may have their working memory overloaded as they are required to process instructional guidance that is unnecessary for them because their partially developed schemas already provide the required guidance.

The segmenting or breaking down of a complex task to facilitate learning for novice learners is an instructional method applicable to all but the most basic physical or mental activities. However such isolated elements instruction requires an additional step in the learning process, being the subsequent integration of the learning task's various

basic elements to achieve the ultimate learning goal. Thus, the presentation of information as isolated elements should be followed by the presentation of the same elements in an interactive form. Initially, for novice learners, isolated elements instruction may be a necessity as their working memory could be overloaded if they attempt to deal with the learning task in its entirety, with all the interacting elements involved (Pollock, Chandler, & Sweller, 2002). In contrast, for more prepared learners, the same step-by-step instruction that is beneficial to novices may impose a greater cognitive load than presenting all the interacting elements simultaneously. This increased cognitive load forms the basis of the redundancy effect according to which requiring a learner to cognitively process information that they already possess imposes an additional, extraneous cognitive load as the learner must reconcile the redundant information with what they already know. Learning could be inhibited by the need to process the redundant information when understanding is already ensured by the existing knowledge structures in long-term memory, while the learner is nevertheless provided with the same information in another form. Therefore, any forms of instructional guidance and learning activities that are essential for novices may have negative consequences for more experienced learners, especially if these learners cannot ignore or otherwise avoid such redundant information or activities.

For example, Clarke, Ayres and Sweller (2005) obtained an expertise reversal effect with instruction using spreadsheets to teach mathematics concepts. The study showed that students with low-level experience and knowledge of spreadsheets learned more effectively if they were provided with spreadsheet instruction separately before being presented with the mathematics material. However, this instructional format resulted in a redundancy effect and reduced learning efficiency for more experienced spreadsheet users.

The current study

The study reported in this paper was designed to investigate the expertise reversal effect based on the isolated-interactive elements instructional procedure in the domain of accountancy to provide more evidence for the relevance of cognitive load theory to accounting and other similar “rule-based” domains such as engineering, particularly in relation to the opportunities for its application that are currently provided by means of contemporary technology. As mentioned by Mostyn (2012), there has not been widespread application of cognitive load theory to the discipline of accounting. Halabi (2004) and Halabi et al. (2005) examined the use of worked examples in accounting education focusing on measuring the efficiency of instruction for students with differing levels of prior knowledge. They found that students who had not previously studied accounting achieved higher learning efficiency with the use of worked examples compared to problem solving exercises. Further work by Halabi (2006) with introductory accounting students showed that prior knowledge impacted on the efficiency of feedback type with rich feedback significantly more efficient for novice students.

Blayney et al. (2010) found an expertise reversal effect with accounting students that was driven primarily by the learning benefits for novices from receiving isolated elements instruction during the initial phase of learning. In accordance with the general logic of prior expertise reversal research, this paper reports the results of two studies in the domain of accounting instruction. The first experiment investigated if an expertise reversal effect could be confirmed in this domain. It extends previous research by Blayney et al. (2010) with introductory accounting students that provided evidence in support of the expertise reversal effect. Those previous results showed a significant disordinal interaction between the isolated and interactive elements learning conditions and levels of learner expertise. Isolated elements instruction eliminates explicit connections between various elements in order to reduce working memory load. Interacting elements instruction includes the connections between elements. Less prepared or lower expertise students learned more from the isolated elements instructional method, while students with greater expertise performed better with the interacting elements format.

A detailed analysis of those earlier results revealed that the effect had been driven primarily by novice learners benefiting from isolated elements instruction with no statistical differences between relatively more experienced students. A possible reason for this non-significant result for more experienced learners is that their level of expertise was not sufficiently high to render a reversal in the relative effectiveness of the isolated and interacting elements instructional methods; i.e., even the most expert learners lacked sufficient schemas to fully benefit from interacting elements instruction.

In a similar manner to this previous research, the current Experiment 1 investigated the learning effect of using intermediary solution formulas to solve complex (i.e., high element interactivity) accounting problems for learners with different levels of domain expertise. However, this experiment used students who, in contrast to participants in the Blayney et al. (2010) study, had previously been exposed to the computer laboratory environment on two occasions. Not having to learn how to function in a new learning environment may have freed working memory resources that consequently could be deployed to learn the accounting content (Clarke et al., 2005). Using these learners who generally were relatively experienced in a computer-based environment was expected to demonstrate an expertise reversal effect with a statistically significant reversal in the effectiveness of isolated and interacting instructional methods for expert learners.

The second experiment reported in this paper investigated the instructional effectiveness of tailoring instruction to levels of learner expertise based on the established expertise reversal effect. In contrast to previous studies within a cognitive load framework (e.g., Kalyuga & Sweller, 2004; 2005), Experiment 2 attempted to establish the benefits of adaptive instruction with the use of a simpler, non-dynamic assessment method. Learners' expertise levels were evaluated once only at the beginning of the instructional session with the assigned instructional method based on levels of expertise maintained throughout the session. This approach is similar to the pre-task adaptation model suggested by Tennyson (1975) that assigned students to specific instructional treatments based on pre-task measures of prior achievement in a given domain taken before the learning session.

Experiment 1

According to the expertise reversal effect in cognitive load theory, an interaction was hypothesised with experts performing better using interactive over isolated element instructions and novices performing better using isolated over interactive element instructions. The participants in this study were relatively more experienced in general compared to participants in the study by Blayney et al. (2010), as indicated by a comparison of scores on the pre-session tests in both experiments. The results from the pre-session test showed participants in Experiment 1 performed at a significantly higher level (average of 2.56 out of 5, $SD = 1.70$) than participants in the previous study (average of 1.60 out of 5, $SD = 1.40$), $F(1, 455) = 42.03$, $MSe = 96.87$, $p \leq .01$, partial $\eta^2 = 0.085$ (the same pre-test questions were used in both studies).

Method

Participants

Experiment 1 was conducted with 171 students enrolled in a first year university accounting course comprised of 63 (37%) males and 108 (63%) females. All students had successfully completed a prerequisite introductory accounting course and were studying to earn a Bachelor of Commerce degree (68.4%), Bachelor of Economics degree (7.6%) or a combined Commerce degree such as Bachelor of Commerce and Laws (4.1%), Bachelor of Commerce and Arts (8.2%), Bachelor of Engineering and Commerce (4.1%) and some other degrees.

Only students who felt that they needed the additional tutorial sessions were expected to attend. Participant numbers were further reduced by attending students who did not agree to participate in the study and by those who failed to attempt both the pre-test and post-test questions. As a result only 171 students (out of the total class enrolment of 429 students) actually participated in the study. Participants' relative levels of expertise were determined from the scores achieved on five pre-test questions administered at the beginning of the tutorial session. It needs to be reiterated that in this study (as in research on the expertise reversal effect in general), expertise is considered on a continuum rather than as a dichotomy: the participants are not actual "experts" but rather relatively less or more knowledgeable learners in a specific task domain.

Materials and procedures

Students were presented with learning materials using a highly customized Excel computer spreadsheet designed to largely eliminate the need for specific spreadsheet skill and previous spreadsheet experience. The research

instrument used in this study incorporated the use of automated system-controlled procedures to allocate each student's laboratory session time (i.e., 50 minutes) to the various tasks. Students' time on task for the pre-test and post-test questions was strictly limited to 5 minutes and 10 minutes respectively. The structure of the laboratory session included the following stages:

- (1) Log on to computer and open spreadsheet model - 5 min
- (2) Pre-session knowledge test (five questions) - 5 min
- (3) Main learning activity—phase 1 - 15 min
- (4) Main learning activity—phase 2 - 15 min
- (5) Post-session knowledge test (ten questions) - 10 min

The main learning activities of the lab sessions (stages 3 and 4 above) comprised 30 minutes (i.e., 60%) of the 50-minute session. Prior to this activities, students were instructed that Phase 1 would provide five problems and a bonus question (if they still had some time left), and Phase 2 repeated similar problems with different data. Students were also provided with a worked example prior to receiving each problem (to be used if they were uncertain about solving that type of problem). The participants were reminded that they had about 3 min for each of the five problems to complete the tasks in the 15 min time limit, and that for each problem, they would be given further help after three incorrect attempts. After three incorrect attempts students were provided with a dialogue box describing the solution process together with a solution formula (e.g., +D6-D8-D12).

The key feature of the automated spreadsheet was the provision of learning materials in one of two formats; isolated elements or interacting elements. Interacting elements instruction required students to provide their answers to the various accounting problems in a single spreadsheet cell. Intermediary entries (rough workings) in other spreadsheet cells were not permitted for this experimental group. Therefore, the interacting elements group participants were restricted to a single, final answer cell. In contrast, isolated elements instruction required completion of one or more "working entries" (isolated elements) before finalising a solution to the accounting problem with a formula incorporating the working entry calculations (interactive elements). For both experimental groups, comprehensive worked examples were available to assist participants in learning. Students could access these examples as desired at any time during phases 1 and 2. These worked examples could not be used during the final stage - post-question performance test.

Learning was assisted for students in both experimental groups with the provision of the three clickable buttons shown in Figure 1. In addition to the ability to display a worked example students could also self-assess their work at any time or be shown the correct numerical answer for the problem. The "Show correct answer" button did not however provide the formula required to achieve the required result. Entering of this correct answer value to the shaded entry cell yielded a "Sorry, not right yet" feedback. All entry cells required the input of a proper spreadsheet formula to be assessed as being correct.

PHASE #1 Budgeting (the Master Budget)			
QUESTION DATA			
	January	February	March
Sales forecast (number of units)	100	120	135
Ending inventory desired (% of next month's sales)	20%	20%	20%
Beginning inventory (number of units)	20	???	???
Direct labour required for production (hours per unit)	5.0	5.0	5.0
Direct material required for production (kgs. per unit)	50	50	50
Ending direct material inventory (number of kilograms)	160	180	195

PROBLEM #1
Use the single cell below to calculate the number of units to be produced in January.

Enter your "final answer" formula to the shaded cell.

Buttons: Display worked example, Show correct answer, Assess my work

Figure 1. Problem displaying learning assistance features available with all Phase 1 & 2 problems

Figure 2 illustrates an accounting problem provided to the isolated elements experimental group with its provision of (and requirement for) three intermediary or working entries. In this illustration the student has already made an attempt for each of the three working entries to cells F26, F29 and F32. Intermediary formula #1 is comprised of the entry $(E7 * F6) - (D7 * E6)$ which provided the value of 3 in cell F26 for the isolated elements format. Intermediary formula #2 should then have used this result plus the February sales forecast in cell E6 to determine the production volume required for the month of 123 units. In the same manner intermediary formula #3 could incorporate this value multiplied by the direct material requirement of 50 (cell E12) to derive the kilograms of direct material needed for February production (i.e., 6150 in cell F32).

The complexity of the problem in Figure 2 is derived from the multiple concepts that must be understood before the arithmetical calculations are undertaken to determine the February direct material purchase requirement. Interactive elements instruction students had to recognise that firstly, they needed to calculate a production volume amount for February before any direct material values could be determined. In contrast, students in the isolated elements group were provided with a template for calculation of the production volume amount (intermediary formulas #1 & #2). Students then needed to recognise the need to convert the production volume amount into a direct material quantity. While the isolated elements group was provided with intermediary formula #3 in Figure 2, participants in the interactive elements group simply needed to know how to include this calculation in their overall formula. Both experimental groups were then required to convert the February direct material production requirement (i.e., 6150 kg) to the February purchase volume by accounting for the change in the direct material volume from the beginning to the end of the month.

PHASE #1 Budgeting (the Master Budget)			
QUESTION DATA			
	January	February	March
Sales forecast (number of units)	100	120	135
Ending inventory desired (% of next month's sales)	20%	20%	20%
Beginning inventory (number of units)	20	???	???
Direct labour required for production (hours per unit)	5.0	5.0	5.0
Direct material required for production (kgs. per unit)	50	50	50
Ending direct material inventory (number of kilograms)	160	180	195

PROBLEM #4	
The goal here is to determine the number of kilograms of direct material to be purchased in February. Some preliminary workings will help us here.	
Enter your "final answer" formula to the shaded cell.	
Intermediary formula #1 Let's first calculate the desired change in the finished goods inventory level from the beginning to the end of February.	3
Intermediary formula #2 And now let's use the change in inventory plus the budgeted sales volume to get production for February.	123
Intermediary formula #3 We can now calculate the total kilograms of direct material required for production in February.	6,150

Figure 2. Problem presented in isolated elements format

With the interacting elements format, the students were not allowed to use intermediary formulas. The complete answer formula (e.g., $=(((E7 * F6) - (D7 * E6) + E6) * E12) + E13 - D13$) had to be entered in a single spreadsheet cell, cell F23 for the Figure 2 example. Rows 25-32 containing the intermediary formulas in Figure 2 were not provided to the interacting elements instructional group. The procedure required students in this experimental group to solve the accounting problems without completing the intermediary formula working entries. All other aspects of the learning model were unchanged between the two experimental groups. Figure 3 below demonstrates the "single cell" format of the interacting elements method.

PHASE #1 Budgeting (the Master Budget)			
QUESTION DATA			
	January	February	March
Sales forecast (number of units)	100	120	135
Ending inventory desired (% of next month's sales)	20%	20%	20%
Beginning inventory (number of units)	20	???	???
Direct labour required for production (hours per unit)	5.0	5.0	5.0
Direct material required for production (kgs. per unit)	50	50	50
Ending direct material inventory (number of kilograms)	160	180	195

PROBLEM #1
Determine the number of kilograms of direct material to be purchased in February.

Enter your "final answer" formula to the shaded cell.

Display worked example

Assess my work

Figure 3. Problem presented in the interacting elements format

Experimental design and procedure

A 2 (instructional conditions) x 2 (levels of expertise) experimental design was implemented in this study. Prior to the lab session exactly one half of the class was randomly allocated to receive isolated elements instruction and the other half was instructed using interactive elements. The random non-participation of students in the experimental tutorial session resulted in some deviation of the actual numbers of participants in the two experimental learning conditions from exactly 50% (see bottom three rows of Table 1).

Testing for expertise equivalence by learning condition for the novice and expert subgroups was conducted. For novices there was no significant difference between learning conditions on the pre-session test scores, $F < 1$ ($M = 1.46$, $SD = 1.31$ for the interacting elements group and $M = 1.66$, $SD = 1.28$ for the isolated elements group), indicating equivalence between the two instructional groups. Similarly for the expert subgroup there was no significant difference between learning conditions on the pre-session test scores, $F < 1$ ($M = 4.40$, $SD = 0.50$ for the interacting elements group and $M = 4.28$, $SD = 0.45$ for the isolated elements group).

A set of five pre-test questions (e.g., pre-test question #1: calculate the number of units of product that need to be produced in January) provided to participants at the beginning of their laboratory session was used to gauge level of expertise in the accounting topic area to be learned. A cut-off score was subsequently used to designate students as relative novices or experts. Three or more correctly answered pre-test questions were required to classify a learner as a relative expert in this task domain.

Table 1 also displays the disparity in the learning condition / expertise cells caused by the relatively higher proportion of novices (according to the above criteria). Still, the totally random nature of student non-participation and preparation for learning should eliminate any possibility of bias in the results of the current study. The dependent variable was the post-test performance score based on student responses to a set of ten questions administered at the conclusion of the tutorial session. Correctly solved questions were assigned a score of 1 giving a maximum post-session test score of 10. Non-answered questions were treated as incorrect responses, as their exclusion would upwardly bias these scores. Both the pre-test and post-test questions were developed by the senior staff of the academic teaching team for the introductory accounting course in which they were administered. Evaluation of the test questions was performed by various team members. Cronbach alpha scores of 0.79 and 0.68 respectively indicated a sufficiently high degree of internal reliability for the experiment's post-test and an acceptable level for the pre-test.

Results and discussion

Table 1 indicates post-test means and standard deviations. A 2 (instructional condition: isolated vs. interacting elements) x 2 (levels of expertise: novice vs. expert) ANOVA indicated no overall effect of instructional condition, F

(1, 167) = 0.261, $MSE = 1.879$, $p = .610$, partial $\eta^2 = .002$; a significant effect of expertise, $F(1, 167) = 24.522$, $MSE = 176.413$, $p < .001$, partial $\eta^2 = .128$; and a significant interaction effect, $F(1, 167) = 5.880$, $MSE = 42.298$, $p < .05$, partial $\eta^2 = .034$. Figure 4 demonstrates the disordinal interaction between expertise and learning condition.

Table 1. Post-question results by expertise and instructional condition in Experiment 1

Expertise	Instructional condition	Mean	SD	N
Novice	Interacting elements	5.15	2.836	46
	Isolated elements	5.98	2.925	64
	Total	5.64	2.904	110
Expert	Interacting elements	8.36	1.655	25
	Isolated elements	7.08	2.590	36
	Total	7.61	2.326	61
Total	Interacting elements	6.28	2.914	71
	Isolated elements	6.38	2.845	100
	Total	6.34	2.866	171

Following the significant interaction, tests for simple effects revealed a significant difference between instructional conditions favouring the interacting elements condition for the expert learners $F(1, 61) = 4.721$, $MSE = 24.047$, $p < .05$, partial $\eta^2 = .074$, but no significant difference between instructional conditions for novice learners, $F(1, 108) = 2.222$, $MSE = 18.535$, $p = .139$, partial $\eta^2 = .020$.

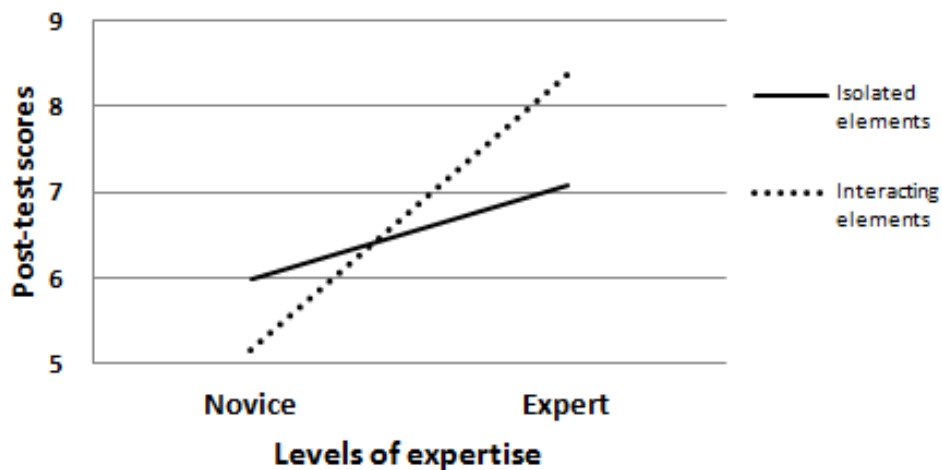


Figure 4. Interaction between levels of learner expertise and isolated-interacting learning conditions

The primary hypothesis for this experiment was that students would learn more when they receive an appropriate method of instruction according to their levels of expertise. Blayney et al. (2010) provided strong evidence for this hypothesis for novice learners but much weaker evidence for more expert learners. Experiment 1 was carried out to see if an advantage could also be obtained for relatively more knowledgeable students learning from interactive elements instruction by using generally more experienced learners than previously.

The results confirm that for experts, presenting instruction in an interacting element format was beneficial. These learners were sufficiently knowledgeable to be able to benefit from interacting elements instruction by employing their partially developed schemas. When using an isolated elements instructional format, knowledge acquisition by these learners was presumably inhibited by the inclusion of redundant learning material that did not emphasize the relations between elements that these more knowledgeable learners required.

On the other hand, in contrast to Blayney et al. (2010), for novices, while the means were in the expected direction with the isolated elements condition resulting in higher test scores than the interacting elements condition, the difference was not statistically significant. Since the participants in Experiment 1 were generally more experienced than learners in the previous study, the levels of expertise of the novice participants may have been higher than that

required to demonstrate a benefit of using isolated over interacting elements format. Together, the results of this experiment and those of Blayney et al. (2010) imply the need to tailor instructional formats to levels of learner expertise in this specific instructional domain.

Experiment 2

In accordance with the expertise reversal effect and the results of Experiment 1, less knowledgeable students should learn better when instruction is presented in an isolated elements form while more knowledgeable students should learn better when instruction is presented in an interactive elements form. The main hypothesis of Experiment 2 is that for a group of students that includes learners at different levels of expertise, learning will be facilitated if students are provided with instruction that is tailored to their level of expertise (i.e., adaptive instruction). Experiment 2 used the above adaptation principle based on the expertise reversal effect for the allocation of participants to the two alternative instructional formats in the study's adaptive condition group. The allocation of the non-adaptive group's participants between instructional formats was done on a random basis irrespective of their levels of expertise.

The random allocation of instructional format (i.e., isolated or interacting elements) to participants in the non-adaptive group was expected to cause relatively lower learning outcomes for participants who did not receive the optimal instructional format according to the expertise reversal effect. In contrast to the non-adaptive group, participants in the adaptive group received the optimal instructional format according to their level of expertise. Accordingly, the overall expectation was that students in the adaptive group would perform better on the post-test questions at the end of their laboratory session than their counterparts in the non-adaptive group. Thus, this experiment tested the effectiveness of the adaptation methodology based on the previously established expertise reversal effect in this specific domain.

Method

Participants

Experiment 2 was conducted with 94 students enrolled in a first year university accounting course comprised of 39 (41%) males and 55 (59%) females. As in Experiment 1, all students had successfully completed a prerequisite introductory accounting course and were studying to earn a Bachelor of Commerce degree (76.6%), Bachelor of Economics degree (3.2%) or a combined Commerce degree such as Bachelor of Commerce and Laws (8.5%), Bachelor of Commerce and Arts (3.2%), Bachelor of Engineering and Commerce (2.1%) and some other degrees. Only students who felt that they needed to attend the additional tutorial sessions were expected to participate. As a result, in conjunction with non-agreement to participate in the study and failure to attempt both the pre-test and post-test questions, only these 94 students (out of the total class enrolment of 299 students) actually participated in the study.

The attending student group was further reduced by nine (to 85) by eliminating those participants who took less than 120 seconds to complete the five pre-questions administered at the beginning of their tutorial laboratory session. Given that it took a domain expert more than two minutes to complete the five pre-questions it was considered that these participants had not given an honest effort to this task thus making it impossible to judge their level of expertise. Since the level of prior knowledge was used as the basis for allocation of participants to learning condition sub-groups, the data for these nine participants was removed from the analysis.

Materials and procedures

Students were presented with learning materials using a customised, largely automated Excel computer spreadsheet similar to that used in Experiment 1. The automated spreadsheet provided the learning materials in one of two formats: isolated elements (multiple spreadsheet cells) or interacting elements (single spreadsheet cell). Students were assigned to one of these learning formats based on their levels of prior knowledge in the adaptive condition or

randomly in the non-adaptive condition. The same automated system-controlled procedures as those used in Experiment 1 determined and equalised students' time on task in Experiment 2.

Experimental design and procedure

The 85 participants were randomly assigned to either an experimental adaptive instruction group (46 participants) in which less knowledgeable learners were presented isolated elements instruction and more knowledgeable learners were presented interactive elements instructions or a non-adaptive control group (39 participants) in which learners were allocated to isolated or interactive instructional formats on a random basis. An unequal split between the groups resulted from students' random non-attendance to the tutorial sessions. There was no significant difference between the adaptive and non-adaptive groups on the pre-session test scores, $F < 1$ ($M = 1.91$, $SD = 1.41$ for the adaptive group and $M = 1.79$, $SD = 1.58$ for the non-adaptive group), indicating equivalence between the two instructional groups.

Participants in this study completed pre-session and post-session knowledge tests identical to those used in Experiment 1. The learning condition allocation scheme was programmed into the computer spreadsheet tutorial with the novice /expert cut-off designation based on the participant's performance on the pre-test questions administered at the beginning of their laboratory session. Three or more correct pre-test questions were required for a participant to be deemed a relative expert (more knowledgeable student). Participants achieving less than three correct pre-test questions were deemed novices.

Results and discussion

The dependent variable was the post-test performance score based on student responses to a set of ten questions administered at the conclusion of the tutorial session, while the independent variable was the instructional condition (adaptive vs. non-adaptive). An ANOVA for the two instructional groups revealed higher performance for the adaptive group ($M = 7.17$, $SD = 2.48$) compared to the non-adaptive group ($M = 5.97$, $SD = 2.71$), $F(1, 84) = 4.54$, $MSE = 30.37$, $p < 0.05$, partial $\eta^2 = .020$.

This study's main hypothesis was that students in the adaptive instruction condition who received the appropriate method of instruction according to their level of expertise would perform at a higher level than students in the non-adaptive instruction condition who were randomly assigned to an instructional method. The results supported this expectation by indicating that adaptive instruction that took the learner's expertise into account was beneficial.

This study demonstrated that learning could be improved through the adaptation of instructional techniques according to the expertise of the individual even with a very simple adaptation approach based on using only pre-test results for assigning students to instructional techniques. Less knowledgeable learners need to be compensated for their lack of relevant schemas in long-term memory through the provision of an isolated elements learning environment, while more knowledgeable learners may be able to successfully deal with fully interactive instructional materials.

General discussion

The major finding of Experiment 1 concerns the interaction between the isolated-interacting elements effect and levels of learner expertise. Previous studies have indicated that for novices, presenting very high element interactivity information in isolated rather than in its more natural, interactive form during the initial phase of instruction is beneficial. According to cognitive load theory, novices may have difficulty processing very complex information in the initial stages of instruction and so should benefit from having the information initially divided into isolated elements. That result was obtained in previous studies, including Blayney et al. (2010) in accounting instruction and Pollock et al. (2002) in engineering instruction. In those studies, it also was hypothesised that providing more knowledgeable learners with interactive rather than isolated information should be beneficial. More knowledgeable learners may have already acquired the knowledge associated with individual elements. Providing that knowledge during instruction may be redundant with all of the negative consequences associated with the

redundancy effect. Rather than learning about individual elements of information, more expert learners may need to learn how various elements of information interact. Presenting information in interactive form is more likely to demonstrate to students how elements interact than if those elements are presented in isolated form. Previously, that result was not obtained but the current study fills that particular gap. Experiment 1 demonstrated that for more knowledgeable learners, presenting information in interactive form was superior to presenting it in isolated form, a result that was not obtained for novices.

The distinction between the results of Blayney et al. (2010) and the results of Experiment 1 of the current study can be ascribed to different levels of expertise between the two relevant populations. The generally relatively more knowledgeable learners in Experiment 1 of the current study might have had sufficient working memory capacity to easily process isolated elements and rather, required information on the manner in which the elements interact. That information could be obtained more readily by these learners from the interactive elements condition than the isolated elements condition. In contrast, the less knowledgeable learners of Blayney et al. (2010) required information presented in isolated elements form. Overall, these results are in line with other studies on the expertise reversal effect (Kalyuga, 2007; Sweller et al., 2011).

An implication of this result is that better, more finely-grained methods of evaluation of learner prior experience are required for optimal tailoring of instructional methods to levels of learner expertise. However, even a simple, static pre-session allocation of learners to corresponding instructional methods (the pre-task adaptation model according to Tennyson, 1975) in Experiment 2 was sufficient to demonstrate the significant benefits of learner-tailored instruction. From a practical, instructional perspective, the current results in conjunction with previous findings indicate the importance of the isolated-interacting elements effect. When providing novices with information that is very complex, it is likely to be desirable to decompose that information into isolated elements in the first instance. While isolated elements may only result in a partial understanding of the information, that negative consequence can be rectified by following the partially understood information with fully interactive materials allowing full understanding. Nevertheless, as the current work demonstrates, if isolated elements instruction is provided to learners who have already assimilated those elements, the consequences will be negative rather than positive. More knowledgeable learners should be presented with fully interactive information at the beginning of instruction. Based on these conclusions, the need to use instruction that is adaptive to levels of expertise is critical.

It should be noted that, even though the simple pre-task form of adaptation used in Experiment 2 improved learning in comparison with non-adapted instruction, this form of adaptation may not work with relatively more complex or multi-task tutoring sessions that require multiple, real-time adaptations based on the assessment of learner progress during the tutorial. Various specific techniques have been proposed and developed to implement the concept of adaptive instruction. Renkl and Atkinson (2003) suggested a faded worked example approach for transitioning from fully worked-out examples to conventional problems. Kalyuga and Sweller (2004; 2005) proposed the use of rapid diagnostic tests for monitoring learner's progress and altering the instructional techniques in real time. Such adaptive learning environments that dynamically tailor instructional formats to changing levels of learner expertise need to be investigated in future studies using the potential of contemporary technological means. Future research may also be enhanced through the establishment of internal validity by measuring and analysing indicators of participants' cognitive load during the learning and testing phases and possibly using such indicators for refining adaptation procedures.

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