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Reanalyzing the expertise reversal effect

Wolfgang Schnotz

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Finding the best match between learners' expertise and instruction is a central issue in educational psychology. The idea that different learners might need different instruction gave rise to the concept of aptitude-treatment interaction (ATI) launched by Cronbach and Snow (1977). The expertise reversal effect is a variant of an ATI effect. It occurs, when an instructional format that is beneficial for novices compared to other formats looses its advantage with increasing expertise of the learners and finally becomes disadvantageous for individuals with higher expertise (Kalyuga et al. 2003).

Expertise reversal effects have been found for example by Kalyuga et al. (1998, 2000, 2001a, b, 2003), Leahy et al. (2003). The contributions of this special issue further elaborate these findings. Oksa, Kalyuga, and Chandler (this issue) demonstrate that the expertise reversal effect can be found not only in well-structured, but also in ill-structured domains such as the interpretation of literacy. Nückles, Hübner, Dümer, and Renkl (this issue) show that the expertise reversal effect has also motivational aspects and applies to the use of strategies. The article of Homer and Plass (this issue) indicates that the effect is not only related to domain-specific prior knowledge, but also to the general developmental level of learners. The findings of Blayney, Kalyuga, and Sweller (this issue) argue for the importance of adapting learning environments to the changing levels of learner expertise in the use of spreadsheets. Finally, Salden, Aleven, Schwonke, and Renkl (this issue) address the question of balance between providing sufficient instructional assistance on the one hand and self-regulated generative learning on the other hand in the case of worked examples, and they demonstrate that adaptive fading of instructional assistance is crucial for effective learning.

There are some fundamental assumptions that can be found throughout the contributions of this special issue and in other papers on cognitive load theory. One assumption is that cognitive load is contingent to the limited capacity and duration of working memory. Another assumption refers to the concept of redundancy. It implies that information that is necessary for novices may become redundant for more advanced learners and may overload working memory. The following comments will analyze these assumptions more

W. Schnotz (✉)
University of Koblenz-Landau, Thomas-Nast-Str. 44, 76829 Landau, Germany
e-mail: schnotz@uni-landau.de

closely. It will be pointed out that some "silent" changes have taken place in cognitive load theory that are directly related to the expertise reversal effect.

Conceptual shifts in cognitive load theory

The expertise reversal effect is analyzed in this special issue according to the framework of cognitive load theory that has been developed by John Sweller and his colleagues (cf. Paas et al. 2003, 2004; Paas and Van Gog 2006; Sweller 1999, 2003, 2005; Sweller and Chandler 1994; Sweller et al. 1998). Cognitive load theory tries to integrate knowledge about the structure and functioning of the human cognitive system with principles of instructional design. More specifically, the theory argues that many traditional instructional techniques do not adequately take into account the limitations of the human cognitive architecture as they unnecessarily overload the learner's working memory, the central "bottleneck" of his/her cognitive system.

Within cognitive load theory, a distinction is made between intrinsic load, extraneous load, and germane load. Whereas intrinsic load is caused by the task-intrinsic aspects of learning, extraneous load is caused entirely by the format of the instruction (Sweller 2005). More specifically, extraneous load is an unnecessary load that requires an extra effort caused by the design and organization of the learning material (Kalyuga et al. 1998). Germane load is caused by effortful learning: It corresponds to the working memory capacity required for processes of schema abstraction and schema automation (Sweller et al. 1998).

Why do expertise reversal effects occur? The answer given by cognitive load theory is that an instruction appropriate for learners with lower expertise can become inappropriate for learners with higher expertise because the instruction would cause an unnecessarily high extraneous cognitive load on working memory for the latter group of learners. Although this explanation seems to be plausible at first sight, a closer look reveals that it is inherently inconsistent with the traditional version of cognitive load theory. Let us assume that some instruction is the optimal one for learners with low expertise, which implies that no extraneous load was involved for these learners. Learning increases expertise through the construction of new schemata and through automation. According to cognitive load theory, new schemata and more automated schemata reduce cognitive load for the learner. It follows that the cognitive load on working memory should be higher for learners with low expertise and lower for learners with high expertise. Insofar, it is questionable why an instruction that did not overload low expertise learners' working memory should overload high expertise learners' working memory because a simplification decreases cognitive load rather than increases it (cf. Oksa, Kalyuga, and Chandler this issue). More specifically, this explanation is inappropriate as long as according to the traditional view of cognitive load theory, cognitive load is defined in terms of required working memory capacity. Remember that in the original version of the theory, cognitive load was derived from the number of cognitive elements that have to be held simultaneously in working memory (the so-called element interactivity), not from the number of elements that have to be processed in total (Sweller and Chandler 1994). For example, if an individual has to learn long lists of vocabulary, a huge number of elements must be assimilated. Nevertheless, cognitive load is low because the elements do not have to be held simultaneously in working memory (Sweller et al. 1998).

The definition of extraneous cognitive load has undergone a conceptual shift in cognitive load theory during the last years (Schnotz and Kürschner 2007). Originally, the concept of extraneous load was derived from the limited capacity or the limited duration of working memory. Regarding the limited capacity of working memory, an instruction imposes extraneous load on the learner, if it draws on his/her working memory capacity to an unnecessarily high degree. For example, if the instruction presents relevant information as well as irrelevant information that is hard to ignore, the irrelevant information causes superfluous element interactivity that draws on working memory capacity (cf. Kalyuga 2000; Kalyuga et al. 2000). Regarding the limited duration of working memory, an instruction imposes extraneous load on the learner if it unnecessarily requires extra effort to compensate for the limited temporal duration of information in working memory. For example, if an instruction requires split of attention between different sources of information and if these sources are presented in a segregated rather than in integrated format, the learner has to invest additional effort to keep information in working memory while his/her attention is shifting from one source to another source of information. In the latter case, extraneous load is due to the need of maintaining cognitive elements in working memory rather than too high element interactivity.

Since recently, however, the concept of extraneous load is not only related to the capacity or duration of working memory, but also to the amount of cognitive processing. Accordingly, an instruction imposes extraneous load on the learner if it requires irrelevant cognitive activities, which do not result in learning (Sweller 2005). For example, if an advanced learner studies a diagram that is perfectly intelligible for him/her without further explanation and if afterwards he/she reads an accompanying text that explains the diagram, then reading this text means processing unnecessary information with no added value for learning. The text reading does not necessarily require high element interactivity in working memory. This becomes most obvious when it turns out that novices would benefit from the combination of the diagram with the text, which demonstrates that the novices are able to integrate successfully pictorial and the verbal information. It therefore implies that reading the text does not exceed their working memory capacity. There is no way to assume that element interactivity would be higher for advanced learners than for novices because learning results in new schemata and reduces cognitive load rather than increases it. Accordingly, if irrelevant cognitive processing is considered as extraneous load, this load is simply due to a waste of time and effort of the learner (Kalyuga et al. 1998).

If irrelevant cognitive activities are also assumed to impose extraneous load on the learner, the concept of extraneous cognitive load is fundamentally changed compared to its original version. Whereas extraneous load was originally considered as resulting from high element interactivity (so-called ‘cognitive overload’) or the need of maintaining cognitive elements in working memory, the new concept of extraneous load includes also other forms of unnecessary usage of resources, namely resources such as time and effort.

Learning is a process that takes time. Learning can only take place if the individual uses his/her cognitive resources for a sufficiently long time in order to understand a message, elaborate it, integrate it into his/her prior knowledge, and draw further conclusions from the message. Insofar time is an essential resource for learning. Cognitive processing also needs effort and it is more or less exhausting. It is the amount of cognitive processing that seems to be critical here because more cognitive processing is more exhausting than less processing. Even vocabulary learning, which has traditionally been considered as a task of low intrinsic load by cognitive load theory, needs mental effort and can be exhausting.

Accordingly, there are different kinds of resources, which are limited but relevant for learning, and which are prerequisites for the efficient use of another limited resource, the use of time. The traditional resource considered by cognitive load theory is working memory with its limitations in capacity and duration. However, another resource relevant for learning is the mental energy, from which an individual draws the effort that he/she invests into cognitive processing. This mental energy can be exhausted during the process of learning and then needs to be recharged in order to continue learning. This is a fundamental conceptual shift in cognitive load theory because in the latter case, it is the total amount of processing rather than the amount of information to be kept simultaneously in working memory that causes cognitive load. It also makes another relation more obvious, which has so far often been hidden in cognitive load theory: the relation between cognitive load and motivation (cf. Schnotz et al. 2009).

Cognitive and motivational resources

There are striking similarities between research on cognitive load and research on motivation with regard to theoretical constructs and the corresponding measurement procedures. Among the various ways to measure cognitive load (Brünken et al. 2003), the most frequently used method is using self-reports. For example, Paas et al. (1994) asked students to judge the amount of effort they have invested in learning or in solving specific tasks on a nine-point scale ranging from “very, very low mental effort” (1) to “very, very high mental effort” (9). Whereas this measurement procedure is meant to grasp cognitive load, another very similar measurement procedure is meant to grasp motivation. An example is given by Rheinberg et al. (2001) who developed the questionnaire of actual motivation (QAM), which includes nearly the same kind of questions.

Research on learning and motivation has investigated motivationally relevant dispositions such as goal orientations, academic self-concept or the achievement motive. Among these dispositions goal orientations play a prominent role. Researchers distinguish between learning goal orientation (mastery orientation) and a performance goal orientation (e.g., Dweck and Leggett 1988). Goal orientations describe preferences for different types of goals. Individuals preferring learning goals are focused on experiencing an increase in knowledge or abilities. Individuals preferring performance goals are satisfied whenever they outperform others. In many studies, the relation of goal orientations and strategic learning was analyzed. Results show positive relations of learning goal orientations and strategic learning (Entwistle and Ramsden 1983; Renninger et al. 1992).

Higher motivation leads to higher persistence in learning. In other words, the higher the motivation of an individual, the more effort he/she will invest into a learning task, and the more time he/she will be willing to deal with the learning task. Finally, the higher persistence will in turn result in better learning (Vollmeyer and Rheinberg 2000). In other words, highly motivated learners will invest more energy into the process of learning, and they will spend more time until they feel exhausted by the learning task. In other words, the extraneous load due to a waste of time and effort resulting from irrelevant cognitive processing is essentially a load on a motivational resource rather than a cognitive resource.

Metacognition and cognitive economy

It is frequently argued that the expertise reversal effect can to some extent be explained by the need for higher knowledge learners to integrate and cross-reference redundant instructional guidance with available knowledge structures. Integrating and cross-referencing redundant information is assumed to consume additional cognitive resources and therefore to impose cognitive load on working memory. I am not sure whether such a need of integrating and cross-referencing redundant information really exists. Research on metacognition in learning suggests that individuals not only evaluate the value of incoming information in terms of relevance for their goals and interests (Dunlosky et al. 2005; Tiede et al. 2003). They also evaluate the expected costs in terms of time and energy as well as the benefits of additional cognitive processing for learning from the perspective of cognitive economy. Learners can make two kinds of errors in this respect: One error is to process irrelevant information, which does not improve learning, and the other error is to ignore relevant information, which would improve learning (cf. Schnotz and Heiß 2009). Because learners have to avoid both kinds of errors, one can expect learners to continuously check incoming information with regard to its efficiency for learning. Information that does not contribute to more learning because it is redundant with regard to previously processed information will not rate high in terms of its relevance for learning. Instead of the assumption that incoming redundant information will be integrated and cross-referenced it seems more plausibly to hypothesize that the information will be evaluated with regard to its relevance for learning. The so-called redundant information will not get high relevance ratings and, accordingly, will not be further processed intensively. Nevertheless, the screening and evaluation of information takes some time and energy, which also draws on motivational sources.

Problems with redundancy

The extraneous load caused by irrelevant cognitive processing, which is essentially a waste of time and effort, is also an inherent part of the redundancy effect. This effect occurs, when two sources of information are intelligible in isolation but are presented in an integrated format. When the second source of information merely reiterates the information of the first source in a different form, it is considered as redundant. If learners process information from the second source, this processing has no additional benefit for learning. In this case, removing the redundant information is beneficial for learning. The beneficial effect of removing redundancy is referred to as the redundancy effect (Sweller and Chandler 1994). The redundancy effect occurs when students who were not presented with redundant information perform better after learning than students who were presented with redundant information.

How do we know whether information is redundant or not? As mentioned above, if a second source reiterates the information from a first source, it is considered as redundant according to cognitive load theory. However, only if the information from the first source has been fully understood, then processing the information from the second source is really superfluous. When the learner did not fully understand the information from the first source, the information from the second source might still be helpful for learning. Thus, it depends on the learner's state of comprehension, whether the second source is really redundant and should be removed in order to enhance learning.

This suggests that redundancy should not only refer to the relation between two sources of information, but should also refer to the individual's state of comprehension and learning. In this case, information can be considered as redundant for the learner if it is not new for him/her and therefore does not result in further learning. Although it seems plausible at first sight to define redundancy in this way, a closer look reveals that it makes then no sense to use the redundancy effect as an explanation for better learning: If learning requires new information to be processed, redundant information (i.e., information that is not new for the learner) cannot stimulate learning. In other words, information is considered as redundant if it does not result in further learning. Whereas it is possible to define redundancy in this way, the concept cannot be used in this case to explain why no learning occurs because the lack of learning is already included in the definition of the concept. Accordingly, there is an inherent danger of circularity in the concept of redundancy.

Instructional efficiency and the expertise reversal effect

It is widely accepted in educational psychology that instruction should take place within what Vygotski (1963) called the zone of proximal development (ZPD). The ZPD has been defined by Vygotski (1963) as the difference between an upper limit of task difficulty that the learner can accomplish without help and an upper limit of task difficulty that the learner can accomplish with help. The lower limit of the ZPD is defined as the most difficult task the learner can perform successfully without help. The upper limit of the ZPD is defined as the most difficult task that the learner can perform successfully with the best possible help available for this task. If learners receive easy tasks that are beneath the lower limit of the ZPD, there is no challenge for the individual and no (or very little) learning takes place. If learners receive difficult tasks that are beyond the upper limit of the ZPD, the individual is overwhelmed and no (or very little) learning takes place too. Learning can take place if the presented tasks are within the ZPD.

The concept of the ZPD can also be mapped on the concept of instructional efficiency, that is, the amount of learning resulting from an instruction. If a learner has too low expertise to deal successfully with a specific instruction (i.e., the presented learning tasks are too difficult) he/she will not be able to benefit from this instruction. If a learner has too high expertise with regard to a specific instruction (because the instruction aims at lower level learners) he/she will not be able to benefit from this instruction. The instruction will only be effective for a 'medium' level of expertise. Accordingly, the efficiency of a specific instruction for learners at different levels of expertise follows a u-inverse function as shown in Fig. 1. At a too low level of expertise, learners are not able to profit from the instruction because they lack the necessary learning requirements. At some higher level of expertise, instructional efficiency increases to a maximum and then decreases again. Finally, at a too high level learners are not able to profit from the instruction because there is nothing to learn from the instruction for these learners.

Let us assume that two kinds of instructions A and B are being compared, one instruction (A) is tailored to learners with lower expertise and the other (B) is tailored to learners with higher expertise. Accordingly, there are two somewhat shifted u-inverse curves—one for instruction A and the other for instruction B—as shown in the upper panel of Fig. 2. In this case, the result of comparing A and B will depend on the learners' level of expertise. The result of comparison to be expected will correspond to the difference

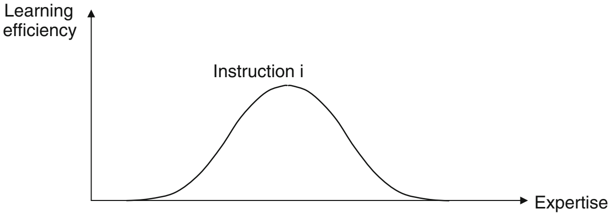
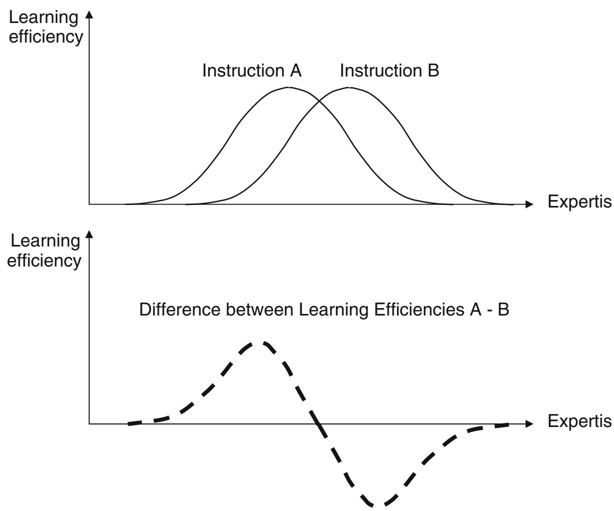


Fig. 1 The efficiency of a specific type of instruction for learners at different levels of expertise

Fig. 2 Comparison of two instructions tailored to learners with different levels of expertise



between the two curves of learning efficiency, which is shown in the lower panel of Fig. 2. At a too low level of expertise, the two instructions do not differ in terms of effectiveness because learners are unable to benefit from any of them. At a somewhat higher level of expertise, instruction A results in better learning than instruction B. At a still higher level of expertise, the situation reverses because instruction B results in better learning than instruction A. Finally, beyond some level of expertise, the two instructions do not differ in terms of effectiveness because at this level, individual can neither learn from instruction A nor from instruction B. In other words, the expertise reversal effect can be seen as a direct derivate of the shifts between u-inverse curves of efficiency for different instructions tailored to different levels of expertise (i.e., different zones of proximal development).

Conclusion

The contributions of this special issue extend our view on learning and instruction in various ways. They emphasize the generalizability of the expertise reversal phenomenon across different domains. They point out various facets of expertise besides prior domain specific knowledge such as cognitive strategies, metacognitive skills, and general cognitive skills. Most important, they underline the practical relevance of adaptivity of learning environments, namely, that instructional aids, prompts, strategy activators etc. have to be provided at the right time and have also to be faded out at the right time. The assistance dilemma that is inherent in every instructional design task (Koedinger and Aleven 2007) requires finding the right balance of providing instructional help at the one side and sufficient independence of learning at the other side at any time. Accordingly, successful teaching and learning means following instructional trajectories with the right balance found as far as possible.

The expertise reversal effect is not only related to the assistance dilemma, but also to Vygotski's (1963) ZPD mentioned above. From both concepts, one can derive that learners should neither be unchallenged nor overcharged. In other words, they should be given as much aids as needed and as little aids as possible in order to enhance their learning.

The expertise reversal effect and the ZPD are both powerful concepts for the analysis of teaching and learning. It might be fruitful for further research to analyze the relation between these two concepts in more detail and to embed them into a broader theoretical framework.

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