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# Dynamic task selection: Effects of feedback and learner control on efficiency and motivation

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## Abstract

Structural features of learning tasks are relevant for problem solving but not salient for novice learners. Feedback in the form of Knowledge of Correct Response (KCR) during practice is expected to help learners recognize the structural features and to profit from learner control over the selection of learning tasks. A 2 x 2 factorial experiment (N = 118) was conducted to study the effects of the KCR feedback (present, absent) and control over the selection of learning tasks (learner control, program control). The presence of the KCR feedback yielded higher efficiency on a near transfer test as well as higher learner motivation. An interaction between feedback and control, indicating extra beneficial effects of feedback when learners control the selection of learning tasks, was not found. Theoretical and practical implications are discussed.


*Keywords:* Feedback; Learner control; Structural features; Transfer efficiency.

## 1. Introduction

Recent instructional theories advocate on-demand methods of education which give learners freedom to choose their own learning path (Williams, 1996). Optimal learner control allows learners to make selections according to their current knowledge, interests, and preferences (Merrill, 1980; van Merriënboer, Schuurman, de Croock, & Paas, 2002). This is believed to positively influence learning and motivation (Flowerday & Schraw, 2000; Schnackenberg & Sullivan, 2000). Studies report both positive and negative effects of learner control on learning (Katz & Assor, 2007; Williams, 1996). It seems that the effectiveness of learner control depends on what (e.g., which elements of instruction, such as pace, display or task features) is controlled by whom (e.g., novice or more experienced learners) and, moreover, is only realized if learners recognize the control that is given to them (Scheiter & Gerjets, 2007).

This study investigated how learner control over the selection of learning tasks with different structural features (i.e., what) can be optimized for novice learners (i.e., whom). More specifically, the study aimed at determining if feedback helps learners to recognize structural task features and thus enables them to select personally relevant tasks with beneficial effects on learning and motivation. In what follows we describe what structural task features are, how providing feedback on structural task features may facilitate learning and motivation, and how feedback might interact with different types of control over task selection.

### *1.1. Structural task features*

Structural task features refer to task aspects that are necessary to reach a solution for a particular problem (e.g., solution steps in inheritance tasks or the underlying mathematical procedure in statistical problems; Chen & Mo, 2004; Vosniadou & Ortony, 1989). These task features are generally not salient for, especially, novice learners in a domain. Therefore, novice learners are not able to spontaneously distinguish between tasks that differ in structural features (Cummins, 1992; Quilici & Mayer, 1996, 2002) and are also not able to strategically select learning tasks that differ from each other in their structural features. In this study, we define structural task features as the solution steps learners must complete in order to solve inheritance tasks. In such cases, for example, it is difficult for novices to distinguish tasks for which the solution step they must solve is to "determine the genotype of a parent" from tasks for which the solution step they must solve is to "determine the phenotype of a parent". Obviously, the lack of saliency of structural features may cause problems to learners if they are required to select their own learning tasks: they might unknowingly select equivalent tasks over and over again and not select structurally different tasks that also need to be practiced.

If learners do not recognize non-salient structural task features this may have negative effects on both learning and motivation. With regard to learning, learners may not develop motives for choosing between tasks that differ in their structural features and thus be unable to distinguish between tasks that are necessary for learning and tasks that could just as well be omitted (Ross & Morrison, 1989). This negatively influences the learning process (Kopcha & Sullivan, 2008; Tennyson & Buttery, 1980; Williams, 1996) and even enlarges individual differences between low and high ability learners (Merrill, 2002; Snow, 1980). With regard to motivation, learners who are not aware of structural differences between tasks will probably not see the reason for choosing between these tasks. For them, all tasks look the same, and this presumably negatively influences their motivation. Furthermore, these learners will not be able to choose personally relevant tasks. Personally relevant instruction facilitates learners to connect new information to their prior knowledge (Hanaffin, 1984; Ross & Morrison, 1989; Wouters, Tabbers, & Paas, 2007), with positive effects on transfer of learning (van Merriënboer, Kirschner, & Kester, 2003). Personally relevant instruction is also prerequisite for enhancing and maintaining learners' motivation (Katz & Assor, 2007).

*1.2. Feedback and structural task features*

In the present study, feedback during practice was used as a means to counteract the negative effects of the lack of saliency of structural task features. The form of feedback used is Knowledge of Correct Response (KCR). The KCR feedback provides learners with worked-out correct solution steps, regardless of the correctness of the solution steps generated by the learner. Studies comparing different types of feedback have yielded inconsistent results. The KCR feedback usually leads to better learning than feedback that only states whether a response is correct or incorrect (Ross & Morrison, 1993). In addition, some studies have shown positive effects of more elaborate feedback (which usually combines the KCR feedback with additional information), whereas many other studies on the contrary support simpler forms of feedback because they contain sufficient information and considerable less distracting information, thus minimizing the associated cognitive load to process the information (for a review see Mory, 2003). When elaborate feedback also contains KCR, learners may focus on KCR only and ignore the elaborate feedback elements, or, in contrast, be cognitively overloaded (Narciss & Huth, 2006). In a meta-analysis of the effects of feedback in computer-based instruction, Azevedo and Bernard (1995) concluded that feedback to be effective should stimulate the cognitive processes necessary to gain deep understanding, for example, by means of techniques that invite learners to evaluate their own actions before submitting their answers. Inviting learners to evaluate their own actions seems more effective than frame-by-frame immediate feedback (Moreno & Valdez, 2005).

The KCR feedback emphasizes structural features in the form of correct solution steps, and thus enables learners to focus their attention on those features and better recognize necessary solution steps for future tasks (Cummins, 1992; Mory, 2003; Quilici & Mayer, 1996). Structural task features that are recognized as shared aspects throughout a series of tasks promote generalization and abstraction of a common relational structure that can be stored in cognitive schemas (Loewenstein, Thompson, & Gentner, 1999). Hence, if a major difficulty in reaching transfer is recognizing structural commonalities between problems (Bassok, 1990), inducing these comparisons by making structural features more explicit during training will promote transfer. In addition, since feedback informs learners about their achievement, it gives them the opportunity to adjust and improve their cognitive strategies and to rectify misconceptions while progressing through the training (Azevedo & Bernard, 1995). Being aware of aspects of one's own knowledge is prerequisite for such forms of self-regulated learning (Mory, 2003).

### *1.3. Feedback and motivation*

Furthermore, many authors have recognized the motivational effects of feedback (Azevedo & Bernard, 1995; Chai, 2003; Hyland, 2001; Keller, 1983b; Mory, 2003; Ross & Morrison, 1993; Vollmeyer & Rheinberg, 2005). Since feedback in the form of KCR helps learners to focus on structural task features or solution steps, it will eventually promote the perceived relevance of the learning material because it enables learners to see the connection between what they need to learn and the learning opportunities presented to them (Keller, 1983b, 1987; Margueratt, 2007). In line with this assumption, Spinath and Spinath (2005) argue that only learners who are given the opportunity to evaluate their abilities realistically (for instance, based on accurate feedback) will be able to perceive their own learning progress and to choose adequate tasks. This will in turn not only enhance their abilities but also their positive self-evaluation. Accordingly, learner's feeling of achievement is enhanced when there is feedback attesting his or her success (Keller, 1983b). In addition, the cognitive effects of motivation result primarily from the relevance of what is being learned since relevance increases the use of cognitive strategies which will eventually improve learning (Means, Jonassen, & Dwyer, 1997). That is, transfer will be enhanced not so much by what is being taught, but by what learners are motivated to learn themselves (Berge & Collins, 1995).–To sum up, the provision of the KCR feedback emphasizing structural task features fosters learning and motivation because it enables learners to recognize the structural features in future tasks and to relate those tasks to what they already know.

### *1.4. Learner control and feedback*

It has been argued that the effectiveness of learner control depends in part on whether learners recognize the control given to them. In this study, learners are given control over the selection of tasks that differ in their structural features, that is, in the solution steps learners must complete. However, since these task features are generally not salient for, especially, novice learners in a domain, learner control over the structural task features may even hamper learning and motivation if learners are not aware of reasons for choosing between tasks that differ in these features, and are thus not able to strategically select learning tasks. If learners do not recognize the relevant aspects of a task and misclassify it (e.g., as easy while it is actually too difficult for them), this will affect both learners' self-assessment and their strategies to close the gap between actual and desired performance (Butler & Winne, 1995). Since the KCR feedback helps learners to recognize the structural task features, it makes these features more salient to the learners and, thus**,** helps them to profit from learner control over the selection of learning tasks. To sum up, if learners who have control over the selection of tasks with different structural features are also given the KCR feedback on structural aspects, then they will be better able to perceive the importance of the control given to them, and thus to choose personally relevant tasks. Consequently, the beneficial effects of providing the KCR feedback on learning and motivation may be higher in combination with learner-controlled selection of learning tasks than with program-controlled selection of learning tasks.

### *1.5. Cognitive load*

Learning outcomes are commonly measured in terms of test performance. Cognitive load theorists (Paas, Tuovinen, Tabbers, & van Gerven, 2003; Sweller, van Merriënboer, & Paas, 1998; van Gog, Paas, & van Merriënboer, 2008) have proposed that performance measures alone say very little about the quality of the learning outcomes, and that the imposed cognitive load to attain this performance should be considered as well. Cognitive load is commonly measured as the mental effort invested in task performance. Invested mental effort thus refers to the cognitive capacity that is allocated by the learners to the task in order to accommodate the demands imposed by the task. Self-ratings of invested mental effort which are given after task performance have been widely used and quickly accepted amongst cognitive load researchers because they are unobtrusive, reliable, relatively easy to use and analyze, and provide a good indication of the overall cognitive load a task imposed (Paas & van Merriënboer, 1993).

However, whereas mental effort only indicates how much mental effort is invested, the combination of performance and mental effort provides a more subtle indicator of the quality of the learning outcomes and, hence, it also provides a better indication of the effectiveness of different types of instruction (van Gog & Paas, 2008). The combination of performance and mental effort has been proposed by Paas and van Merriënboer (1993) as a reliable estimate of the relative efficiency of instructional conditions. According to this approach, efficiency is high if performance is higher than might be expected on the basis of the invested mental effort to perform the task. Conversely, efficiency is low if performance is lower than might be expected on the basis of the invested mental effort to perform the task. Whereas many studies report efficiency measures (for an overview, see Paas et al., 2003), there seems to be only one study (Halabi, 2006) which applied efficiency measures with instructional conditions that included feedback.

*1.6. The present study*

The present study investigated the effects of the KCR feedback on efficiency and motivation in the case of learners working on a series of learning tasks with different structural features (i.e., to-be-completed solution steps). The KCR feedback helps the learners to recognize the structural features of the tasks and to build generalized and abstract cognitive schemas that facilitate cognitive processing and decrease cognitive load (Sweller et al., 1998). Therefore, it was hypothesized that learners who are provided with the KCR feedback will show higher efficiency, namely higher performance on transfer test combined with less mental effort to reach it (Hypothesis 1). Also, learners who are provided with the KCR feedback will report higher motivation because they are better able to see the connection between what they personally need to know and the presented tasks (Hypothesis 2). In addition, if feedback makes the structural task features more salient for learners and helps them to select personally relevant learning tasks, the beneficial effects of providing the KCR feedback on learning and motivation may be higher in combination with learner-controlled selection of learning tasks than with program-controlled selection of learning tasks (Hypothesis 3).

## 2. Method

*2.1. Design – Participants*

A 2 x 2 factorial design was used to study the effects of control over the selection of learning tasks on the basis of their structural features (program control, learner control) and feedback in the form of KCR (present, absent).

First-year students (N = 118; 93 females and 25 males; mean age = 18.73 years; **SD** = 4.67) enrolled in the Health Science Program of a Dutch school for secondary vocational education participated in this study. Students were randomly assigned to one of the four experimental groups: program-control/KCR (n = 30); program-control/no-KCR (n = 29); learner-control/KCR (n = 30), and learner-control/no-KCR (n = 29). The number of male and female participants was evenly distributed over the conditions, $\chi^2(3, N = 118) = .84$, $p = .84$. To make participation attractive, they took part in a lottery making them eligible to win one of 20 cinema tickets.

### *2.2. Materials*

#### *2.2.1. Electronic learning environment*

The learning environment especially developed for this study was a web application written in the web scripting language Hypertext Preprocessor (PHP). A database[1] connected to the learning environment contained a basic introduction to the domain of genetics, a factual knowledge test, the learning tasks, a transfer test, mental effort measures, a perceived relevance item, and a motivational questionnaire.

#### *2.2.2. Basic introduction*

The basic introduction contained the main concepts in the domain of genetics included in the training (i.e., dominant and recessive genes, homozygous and heterozygous gene pairs, genotype and phenotype) and a worked-out example containing the five solution steps of an inheritance task reproducing the same solution steps identified in the learning tasks.

#### *2.2.3. Factual Knowledge test*

This test contained eight multiple-choice questions and assessed participants' prior factual knowledge about the domain of inheritance. The maximum test score was 8 points.

[1] For more information visit the URL http://www.mysql.com/

*2.2.4. Learning tasks*

The learning environment was connected to a database which contained 54 completion tasks in the genetics domain, dealing with the inheritance of particular features (e.g., inheritance of the color of hair, fur, or leaves). Completion tasks are learning tasks that present a given state, a goal state, and a partial solution (i.e., a number of solution steps) that learners have to complete by adding the missing steps (van Merriënboer, 1997; van Merriënboer & Kirschner, 2007). Each learning task could be solved following the same basic structure that comprised five solution steps, in order to: (a) determine the genotype of the male parent based on the given information, that is, whether it is a homozygous or a heterozygous organism; (b) determine the genotype of the female parent based on the given probabilities in her generation; (c) draw a punnett's square (i.e., a diagram that is used to predict all possible gene combinations in a cross of parents) by combining the genotypes of the two parents; (d) determine the genotype (i.e., a particular set of genes) of the offspring and calculate the proportion; and (e) determine the phenotype (i.e., the actually observed properties of an organism, such as the eye colour, type of skin, etc.) of the offspring and calculate the proportion. In each completion task, three solution steps were given by the program and the remaining two solution steps had to be completed by the learner. For instance, if solution Steps 2, 4, and 5 were given by the program, Steps 1 and 3 had to be completed by the learner. Each participant completed 12 learning tasks. Each correctly completed solution step scored 1 point, leading to a maximum score of 2 points per learning task and 24 points for the whole training phase. The reliability of the learning tasks was Cronbach's alpha = .85.

Participants in the learner-control conditions were given three tasks, which were pre-selected by the program, to choose from. This limited amount of control avoids overloading learners as a result of a (too) great amount of choice (Corbalan, Kester, & van Merriënboer, 2006, in press; Iyengar & Lepper, 2000; Scheiter & Gerjets, 2007; Schwartz, 2004; Tennyson & Buttery, 1980). The first learning task in the program-control conditions, as well as the first set of three tasks in the learner-control conditions, was randomly selected by the program. In the program-control conditions, the program pre-selected three tasks containing 0, 1, or 2 solution steps not completed by the learner in the preceding task, and then randomly selected and presented one task from this subset to the learners. In the learner-control conditions, the program also pre-selected and presented three tasks containing 0, 1, or 2 solution-steps not completed by the learner in the preceding task. Each of the three tasks presented to the learners contained the question “Which steps would you like to solve yourself?” The learner made the final task selection. To illustrate a possible range of tasks to choose from in the learner-control conditions, take, for example, a learner who had previously performed a task in which the female genotype (Step 2) and the punnett square (Step 3) were completed by the learner. This learner could be given a choice of three tasks with as steps to be completed: (a) Steps 2 and 3; (b) Steps 3 and 5; and (c) Steps 1 and 4.

In the no-KCR conditions no KCR feedback was provided after participants completed each task. Subsequently, the program presented the next task or set of tasks. In the KCR conditions, the correct solution of the steps completed by the learner was presented together with the given responses by the program immediately after the learning task was finished (i.e., after the last step was completed either by the learner or by the program).

Figure 1 illustrates the five solution steps of an inheritance task performed by all the participants plus the KCR feedback provided in the KCR conditions. The solution steps represent the structural features of the task because each step is crucial to reach the solution to the task. In all the experimental conditions, the description of each step appeared in the first column, while the computer’s and the participant’s answers to each step appeared in the second column. In our example, Steps 1 and 4 were completed by the learner, whereas Steps 2, 3, and 5 were completed by the program. After reading the givens of the task, the learner first filled in the solution of Step 1 (the first step to be completed). Second, the program presented Step 2 together with its correct solution followed by Step 3 and its corresponding solution. Next, the learner filled in the solution of Step 4 (the second step to be completed). Finally, Step 5 together with its correct solution was presented by the program. Once all the steps were completed either by the learner or by the program, participants' answers to the two to be completed solution steps (in our example, Steps 1 and 4) were placed to a third column labelled "your answer", and the second column then showed the "correct answer" to that solution step which was given by the program. Participants were then prompted to compare their own answers with the correct answers given. In this way, the KCR feedback further supported participants to focus their attention on the solution steps (i.e., the structural task features) they completed in order to compare both answers and detect possible differences. If there was a mismatch, participants were advised to restudy the basic information, which also contained a worked-out example showing how the solution steps should be applied.

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Insert Figure 1 about here

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*2.2.5. Transfer test*

The transfer test consisted of ten transfer tasks, divided in four near-transfer tasks and six far-transfer tasks. The near-transfer tasks were structurally similar to the learning tasks but contained different surface feature, for example**,** other members within the species (**e.g.,** fruit flies) and other traits (**e.g.,** position of the wings). They determined if participants were able to apply the learned procedures in the same way as in the learning tasks. The far-transfer tasks required participants to flexibly apply the learned solution procedures to structurally different tasks. More specifically, the following far-transfer tasks were used: (a) determine if the baby of two parents with the same disease will also have this disease; (b) infer the genotype and phenotype of the offspring of two parents from information given of one parent and about the father of the other parent; (c) infer the genotype of several family members based on the information given in a family tree; (d) determine the genotype and phenotype of the offspring of two individuals with co-dominant genes, that is, genes that are equally strong and both expressed; (e) use the information of the phenotype of the offspring (i.e., bottom-up) and of one of the parents to find out the genotype of the other parent and of the offspring, and (f) determine the genotype and phenotype of the offspring of two individuals in a dihybrid crossing task which requires the separate treatment of two different traits. The maximum score was 4 points for the near-transfer test and 6 points for the far-transfer test. The reliability was Cronbach's alpha = .90 and .80, for the near-transfer test and for the far-transfer test, respectively.

### *2.2.6. Mental effort*

Mental effort reflects the amount of cognitive capacity allocated to problem solving and was used as an index for cognitive load. Mental effort was measured as the "effort required to solve the task" (Paas et al., 2003) after each learning task and after each transfer task with a one-item 7-point Likert-type scale ranging from 1 (very low effort) to 7 (very high effort). Reliability of the reported mental effort measures was Cronbach's alpha = .96 and .94, for the near-transfer test and for the far-transfer test, respectively.

### *2.2.7. Efficiency*

Participants’ transfer test performance and associated mental effort were combined using the procedure of Paas and van Merriënboer (1993) to calculate instructional efficiency (E). Performance and mental effort scores are first standardized, and then the *z*-scores are entered into the formula:

$$E = \frac{z_{\text{performance}} - z_{\text{mental effort}}}{\sqrt{2}}$$

In a two-dimensional space defined by the standardized test performance and mental effort scores, efficiency is computed for each condition as the perpendicular distance between a point representing the condition (i.e., the *z*-score for transfer test performance and the *z*-score for mental effort) and the diagonal, E = 0, where performance and mental effort are proportionally related to each other. When performance is higher than might be expected on the basis of perceived mental effort, the instructional condition is relatively more efficient. Conversely, when performance is lower than might be expected on the basis of perceived mental effort, the instructional condition is relatively less efficient.

### *2.2.8. Instructional Materials Motivation Survey*

The Instructional Materials Motivation Survey (IMMS; Keller, 1983a; see also Margueratt, 2007) assesses the motivational effects of instructional situations. Specifically, it asks students to rate 36 statements tapping attention (i.e., need for stimulation and variety), relevance (i.e., desire to satisfy basic motives), confidence (i.e., desire to feel competent and in control), and satisfaction (i.e., desire to feel good about oneself), about the learning materials according to the ARCS model (Keller, 1983a) with four respective subscales, namely Attention (e.g., “There was something interesting at the beginning of each task that got my attention”), Relevance (e.g., “It was clear to me how the content of the tasks was related to things I already know”), Confidence (e.g., “As I worked on the tasks, I was confident that I could learn the content”), and Satisfaction (e.g., “Completing the tasks gave me a satisfying feeling of accomplishment”). The scales contained, in order, twelve, nine, nine, and six items and were measured with a 5-point rating scale ranging from 1 (completely not true) to 5 (completely true). Reliabilities of the measures were Cronbach’s alpha = .86, .71, .91, and .89 for the attention, relevance, confidence, and satisfaction subscales, respectively. The ARCS model has been successfully tested for its validity and reliability in numerous contexts (see for a review Gabrielle, 2003).

To examine the underlying factor structure in our sample, a factor analysis with Varimax rotation conducted on each scale showed that the subscales confidence and satisfaction were uni-dimensional. Attention and relevance showed three factors, accounting for 65.19% and 69.32% of the variance, respectively, and possessing eigenvalues of 1.0 or more). Keller (1992) identified different elements within each subscale. These elements are used to explain the multidimensionality of the subscales attention and relevance. With regard to attention, Factor 3 regarded perceptual arousal. Factors 1 and 2 were more difficult to interpret since both factors contained items regarding variability and perceptual arousal. With regard to relevance, Factor 1 contained four items regarding goal orientation, Factor 2 contained three items regarding familiarity, and Factor 3 contained two items about the examples provided.

*2.2.9. Perceived relevance measure*

In addition to the measure of the relevance of the learning material included in the ARCS model, the perceived relevance of each of the three choices provided in the two learner control conditions was measured with a 5-point Likert-type scale (i.e., “The three inheritance tasks I could choose from were relevant to my interests”). Answers ranged from 1 (not true) to 5 (completely true). Reliability of the measure was Cronbach’s alpha = .95.

### *2.2.10. Time logging*

The learning environment kept track of the time (in seconds) participants needed to complete the learning tasks and the transfer tasks.

## 2.3. Procedure

In the pre-training phase, participants received the basic introduction and completed the prior factual knowledge test. Subsequently, participants started the training phase. Participants were not informed on how the tasks were selected or pre-selected (for the program-control and learner-control conditions, respectively). While working on a learning task, participants could press a “continue” button after each step, so that the next given or to-be-completed step would appear on the computer screen. After each learning task, mental effort and perceived relevance were measured. Participants could always access the basic information by pressing a button that was at all times visible on the left-hand side of the screen. It was emphasized that they were not allowed to skip solution steps during training or self-rating questions: the program would prompt them to provide an answer before they were allowed to continue. After the training phase was completed, participants completed the IMMS questionnaire and subsequently started the transfer phase. During the transfer phase, the “basic information” button disappeared from the screen and participants were not provided with the KCR feedback. After each transfer task, mental effort was measured with the 7-point rating scale. Participants were allowed to work at their own pace. The times spent during the training phase and transfer phase were logged automatically.

# **3. Results**

Table 1 presents the means and standard deviations of the Factual Knowledge test, the time spent on the learning tasks, and the dependent variables measured during the training phase and the transfer phase.

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Insert Table 1 about here

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An ANOVA on the Factual Knowledge test filled out by the participants prior to the training revealed no differences between conditions, $F(1, 114) < 1$, ns. A significant main effect of control (computer vs. learner) was found on time on the learning tasks, $F(1, 114) = 4.05$, $p < .05$, partial $\eta^2 = .03$, although very weak[2]. Specifically, participants in the program-control conditions needed more time to perform the learning tasks ($M = 1819.07$, $SD = 521.04$) than participants in the learner-control conditions ($M = 1624.78$, $SD = 517.54$). No effects on time on the learning tasks were found for the KCR feedback and the interaction between control and the KCR feedback. Following the above findings, the transfer-task scores (time, performance, and mental effort) and the training scores (performance and mental effort) were analyzed with ANCOVAs with control (program control, learner control) and the KCR feedback (present, absent) as between-subjects factors and covariate the time on learning tasks. For all statistical tests a significance level of .05 was maintained.

### *3.1. Training phase*

[2] Effect size was measured via partial eta-squared (a measure of the portion of variance attributable to a factor), in which small, medium, and large effects were operationalized as .01, .06, and .14, respectively.

*3.1.1. Training performance*

The ANCOVA revealed no main effect of control on training performance, $F(1, 113) < 1$, ns, nor of the KCR feedback, $F(1, 113) < 1$, ns; also, there was no interaction effect, $F(1, 113) < 1$, ns.

*3.1.2. Mental effort*

The ANCOVA revealed a significant main effect of the KCR feedback on mental effort during training, $F(1, 113) = 5.69$, $p < .05$, partial $\eta^2 = .05$. Participants in the KCR conditions reported lower mental effort during training ($M = 2.71$, $SD = 1.37$) than participants in the no-KCR conditions ($M = 3.24$, $SD = 1.68$). There was no main effect of control on mental effort during training, $F(1, 113) < 1$, ns; also, there was no interaction effect, $F(1, 113) = .164$, ns.

*3.2. Transfer phase*

*3.2.1. Transfer time*

The ANCOVA revealed no main effect of control on test time, $F(1, 113) < 1$, ns, nor of the KCR feedback, $F(1, 113) < 1$, ns; also, there was no interaction effect, $F(1, 113) < 1$, ns.

*3.2.2. Efficiency*

The ANCOVA showed a significant main effect of the KCR feedback on the efficiency score in the near-transfer tasks, $F(1, 113) = 4.70$, $p < .05$, partial $\eta^2 = .04$. Efficiency in the near-transfer tasks was higher in the KCR conditions ($M = .20$, $SD = 1.20$) than in the no-KCR conditions ($M = -.20$, $SD = 1.31$). No main effect of control on efficiency in the near-transfer tasks was found, $F(1, 113) = 1.93$, ns; also, there was no interaction effect of the KCR feedback and control, $F(1, 113) = 1.24$, ns.

Similarly, no main effect of control on the efficiency score in the far-transfer tasks was found, $F(1, 113) = 1.12$, ns, nor of the KCR feedback, $F(1, 113) = 2.42$, ns; also, there was no interaction effect, $F(1, 113) < 1$, ns.

### *3.3. Motivation*

Table 2 provides an overview of the mean scores and standard deviations for the perceived relevance item and the four IMMS subscales.

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Insert Table 2 about here

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#### *3.3.1. The IMMS subscales*

A series of ANOVAs showed significant main effect of the KCR feedback on attention, $F(1, 114) = 12.31$, $p < .001$, partial $\eta^2 = .10$, on relevance, $F(1, 114) = 4.51$, $p < .05$, partial $\eta^2 = .04$, on confidence, $F(1, 114) = 4.72$, $p < .05$, partial $\eta^2 = .04$, and on satisfaction, $F(1, 114) = 9.65$, $p < .01$, partial $\eta^2 = .08$. Participants in the KCR conditions reported higher attention ($M = 3.29$, $SD = .73$), higher relevance ($M = 3.54$, $SD = .60$), higher confidence ($M = 3.73$, $SD = .97$), and higher satisfaction ($M = 3.27$, $SD = .94$) than participants in the no-KCR conditions ($M = 2.83$, $SD = .68$; $M = 3.28$, $SD = .60$; $M = 3.33$, $SD = .99$, and $M = 2.77$, $SD = .83$ for attention, relevance, confidence, and satisfaction, respectively).

Post hoc tests using Tukey's HSD revealed that participants in the learner-control/KCR condition reported significantly higher attention ($M = 3.42$, $SD = .59$) than participants in both the program-control/no-KCR condition ($M = 2.89$, $SD = .66$, $p < .05$) and the learner-control/no-

KCR condition ($M = 2.78$, $SD = .71$, $p < .01$). In addition, participants in the learner-control/KCR condition reported significantly higher satisfaction ($M = 3.45$, $SD = .82$) than participants in both the program-control/no-KCR condition ($M = 2.72$, $SD = .89$, $p < .05$) and the learner-control/no-KCR condition ($M = 2.82$, $SD = .78$, $p < .05$).

### *3.3.2. Perceived relevance*

A t-test showed a significant difference between participants' perceived relevance of the three choices provided in the two learner-control conditions, $t(57) = -2.95$, $p < .01$, Cohen's $d = .77$, indicating a medium to large effect size[3]. Perceived relevance was significantly higher in the learner-control/KCR condition ($n = 29$; $M = 3.16$, $SD = .66$) than in the learner-control/no-KCR condition ($n = 30$; $M = 2.61$, $SD = .77$).

## **4. Discussion**

This study investigated the effects of feedback in the form of KCR, which emphasizes structural features of learning tasks (i.e., to-be-completed solution steps), on efficiency and motivation. Moreover, it examined if potential beneficial effects of providing the KCR feedback are higher in combination with learner-controlled selection of learning tasks, which gives learners the opportunity to select personally relevant learning tasks, than with program-controlled selection of learning tasks.

We had hypothesized (Hypothesis 1 and 2) that providing learners with the KCR feedback would lead to higher efficiency and motivation. These hypotheses were largely supported by the findings of the present study. Learners provided with the KCR feedback showed higher efficiency on near-transfer tasks, indicating that the near-transfer performance of participants provided with the KCR feedback was higher than could be expected on the basis of

[3] Cohen's d is provided as an estimate of effect size, with $d = .20$ corresponding to a small effect, $d = .50$ to a medium, and $d = .80$ to a large effect (Cohen, 1988).

their invested mental effort. In addition, participants provided with the KCR feedback scored significantly higher on all four subscales of the IMMS questionnaire (attention, relevance, confidence, and satisfaction) than participants who were not provided with the KCR feedback. This seems to indicate that the KCR feedback helps learners to recognize structural features, which enables them to connect what is presented to them (i.e., learning tasks) to what they already know. In addition, results support Keller's (1983a, 1983b) theory of motivation, which argues that the motivation of a learner can be manipulated by the instructional design of the materials. They are also in line with Bassok (1990), who stated that it is possible to foster transfer of learning by increasing the relative weight of structural aspects, for example, by giving learners information about the relevance of structural features.

In contrast to the results on efficiency in the near-transfer tasks, no differences between the experimental conditions were found on efficiency in the far-transfer tasks. This may have been caused by the fact that the KCR feedback was focused where the error exactly was and what the learner could do to solve that problem (i.e., consult the basic information). This yielded "restricted" cognitive schemas that allowed learners to perform the steps of the near-transfer tasks as "routines", as indicated by their higher efficiency for near-transfer tasks (van Merriënboer, 1997). However, far transfer does not require learners to merely apply a routine; deep understanding of the rationale behind the solution steps is also crucial. Providing learners not only with the correct solution steps, but also with the rationale behind and/or the aim of the solution steps could have enabled them to more flexibly use those steps which is essential for far transfer (van Gog, Paas, & van Merriënboer, 2004, 2006, 2008).

Second, we studied if the beneficial effects of providing the KCR feedback would be higher in combination with learner control than in combination with program control, because the given feedback has the potential to make the structural task features more salient for learners, and enabling them to select personally relevant tasks that further enhances learning and motivation (Hypothesis 3). The findings of the present study do not support the superiority of combining the KCR feedback with learner control for efficiency, but the effects on motivation were in the expected direction. Participants in the learner-control/KCR condition reported higher attention and satisfaction than participants in the learner-control/no-KCR condition. Moreover, participants in the learner-control/KCR condition reported perceiving the choices provided as more relevant than participants in the learner-control/no-KCR condition.

Nevertheless, with regard to efficiency the learner-control conditions did not profit more from the KCR feedback than the program-control conditions. To make effective task selections learners must be capable to accurately self-assess their performance. However, most students are not very accurate self-assessors (Bjork, 1999). Apparently, the KCR feedback did not sufficiently support learners in self-assessing their own performance which seems to be a prerequisite for making more effective task selections. This seems to support the idea that less experienced learners are not able to make effective selections regarding structural features and must thus be explicitly guided in how to achieve learning objectives (Butler & Winne, 1995). More powerful feedback strategies, for instance, in the form of advice on task selection might better help learners to engage in appropriate actions (i.e., self-selecting optimal learning tasks) to close the gap between actual and desired performance (Butler & Winne, 1995). Alternatively, the small number of tasks to choose from (only three) and the small variety between the three tasks to choose from may also have limited the learners' opportunities to select a range of personally relevant tasks with a genuine effect on learning, although it positively influenced motivation.

A final unexpected result that needs to be discussed is that participants in the learner-control conditions invested less time in performing the learning tasks than participants in the program-control conditions. The descriptives revealed that in the learner-control/no-KCR condition, the time invested was lower (M = 1541, SD = 553.34) than in the learner-control/KCR condition (M = 1711, SD = 471.71). This lower time invested in the learner-control/no-KCR condition seems to account for the largest part of the lower time invested in both learner-control conditions together compared with the program-control conditions. Participants in the learner-control/no-KCR condition were not supported in recognizing the structural features, perceived the choices provided as being significantly less relevant, and scored relatively low on all motivational measures. Their lack of motivation may well explain the lower time invested in training.

The findings of the present study yielded some important implications for future research. First, more sophisticated process-tracking methods, such as eye-tracking or thinking-aloud protocols, may uncover whether learners who are provided with feedback indeed focus their attention to more relevant task aspects than learners who are not provided with feedback. Second, the issue of near and far transfer should be addressed in forthcoming studies. Possibly, richer types of feedback than the KCR feedback yield not only effects on efficiency in the near-transfer tasks, but also in the far-transfer tasks. Similarly, the effects on efficiency in the transfer tasks should be examined over a more extended period of time because transfer may not be apparent immediately after practice, but may only be present at a later time if the same or additional transfer tasks are repeated (Gick & Holyoak, 1987). Likewise, a measure of students' motivation after the transfer test may reveal other motivational effects than a measure right after the training phase only. Third, Bell and Kozlowski (2002) found that adaptive guidance which provided learners with diagnostic and interpretive information (i.e., a sort of guidance), supported learners in making more effective learning decisions. Future studies may examine the effects of adaptive feedback on learners' selection of learning tasks on the basis of their structural features.

To conclude, this study clearly shows the beneficial effects of the KCR feedback on efficiency in the near-transfer tasks, as well as its added value for motivating learners when they are given the freedom to select tasks that differ with regard to their structural features. These results are particularly important because more and more educational approaches stress the importance of providing learners with control over the learning tasks they perform. This could easily hamper learners' motivation if they are brought into a position in which they cannot see valid motives for choosing between different tasks.

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## References


Azevedo, R., & Bernard, R. M. (1995). A meta-analysis of the effects of feedback in computer-based instruction. Journal of Educational Computing Research, 13, 111-127.

Bassok, M. (1990). Transfer of domain-specific problem-solving procedures. Journal of Experimental Psychology: Learning, Memory, and Cognition, 16, 522-533.

Bell, B. S., & Kozlowski, A. W. J. (2002). Adaptive guidance: Enhancing self-regulation, knowledge, and performance in technology-based training. Personnel Psychology, 55, 267-304.

Berge, Z. L., & Collins, M. P. (1995). Computer mediated communication and the online classroom. Cresskill, NJ: Hampton.

Bjork, R. A. (1999). Assessing our own competence: Heuristics and illusions. In D. Gopher & A. Koriat (Eds.), Attention and performance XVII. Cognitive regulation of performance: Interaction of theory and application (pp. 435-459). Cambridge, MA: MIT Press.

Butler, D. L., & Winne, P. H. (1995). Feedback and self-regulated learning: A theoretical synthesis. Review of Educational Research, 65, 245-281.

Chai, L. (2003). To have or have not: An examination of feedback, learner control and knowledge type in online learning. In R. H. Sprague (Ed.), Proceedings of the 36th Hawaii International Conference on System Sciences (CD-Rom, p. 10). Hawaii, Big Island: IEEE Computer Society.

Chen, Z., & Mo, L. (2004). Schema induction in problem solving: A multidimensional analysis. Journal of Experimental Psychology: Learning, Memory, and Cognition, 30, 583-600.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Hillsdale, NJ: Erlbaum.

Conover, W. J. (1999). Practical nonparametric statistics (3rd Ed.). New York: Wiley.

Corbalan, G., Kester, L., & van Merriënboer, J. J. G. (2006). Towards a personalized task selection model with shared instructional control. Instructional Science, 34, 399-422.

Corbalan, G., Kester, L., & van Merriënboer, J. J. G. (in press). Selecting learning tasks: Effects of adaptation and shared control on learning efficiency and task involvement. Contemporary Educational Psychology. DOI: 10.1016/j.cedpsych.2008.02.003.

Cummins, D. D. (1992). The role of analogical reasoning in the induction of problem categories. Journal of Experimental Psychology: Learning, Memory, and Cognition, 18, 1103-1124.

Flowerday, T., & Schraw, G. (2000). Teachers' beliefs about instructional choice: A phenomenological study. Journal of Educational Psychology, 92, 634-645.

Gabrielle, D. M. (2003). The effects of technology-mediated instructional strategies on motivation, performance, and self-directed learning. Unpublished master's thesis, Florida State University, USA.

Gick, M., & Holyoak, J. (1987). The cognitive basis for knowledge transfer. In S. Cormier & J. Hagman (Eds.), Transfer of learning: Contemporary research and applications (pp. 9-46). San Diego, CA: Academic.

Halabi, A. K. (2006). Applying an instructional learning efficiency model to determine the most efficient feedback for teaching introductory accounting. Global Perspective on Accounting Education, 3, 93-113.

Hyland, F. (2001). Providing effective support: Investigating feedback to distance language learners. Open Learning, 16, 233-247.

Iyengar, S. S., & Lepper, M. (2000). When choice is demotivating: Can one desire too much of a good thing? Journal of Personality and Social Psychology, 79, 995-1006.

Katz, I., & Assor, A. (2007). When choice motivates and when it does not. Educational Research Review, 19, 429-442.

Keller, J. M. (1983a). Development and use of the ARCS model of motivational design. Enschede, The Netherlands: Toegepaste Onderwijskunde, Technische Hogeschool Twente.

Keller, J. M. (1983b). Motivational design of instruction. In C. M. Reigeluth (Ed.), Instructional theories and models: An overview of their current status (pp. 383-434). Hillsdale, NJ: Erlbaum.

Keller, J. M. (1987). Development and use of the ARCS model of motivational design. Journal of Instructional Development, 10(3), 2-10.

Keller, J. M. (1992). Enhancing the motivation to learn: Origins and applications of the ARCS model (Reports from the Institute of Education Vol. 11, pp. 45-62). Sendai, Japan: Tohoku Gakuin University.

Kopcha, T. J., & Sullivan, H. (2008). Learner preferences and prior knowledge in learner-controlled computer-based instruction. Educational Technology, Research and Development, 56, 265-286.

Loewenstein, J., Thompson, L., & Gentner, D. (1999). Analogical encoding facilitates knowledge transfer in negotiation. Psychonomic Bulletin and Review, 6, 586-597.

Margueratt, D. (2007). Improving learners' motivation through enhanced instructional design. Unpublished master's thesis, Athabasca University, Canada.

Means, T. B., Jonassen, D. H., & Dwyer, F. M. (1997). Enhancing relevance: Embedded ARCS strategies vs. purpose. Educational Technology Research and Development, 45(1), 5-17.

Merrill, M. D. (1980). Learner control in computer based learning. Computers and Education, 4, 77-95.

Merrill, M. D. (2002). Instructional strategies and learning styles: Which takes precedence? In R. A. Reiser & J. V. Dempsey (Eds.), Trends and issues in instructional technology (pp. 99-106). Upper Saddle River, NJ: Merrill Prentice Hall.

Moreno, R., & Valdez, A. (2005). Cognitive load and learning effects of having students organize pictures and words in multimedia environments: The role of student interactivity and feedback. Educational Technology, Research and Development, 53, 35-45.

Mory, E. H. (2003). Feedback research revisited. In D. H. Jonassen (Ed.), Handbook of research on educational communications and technology (pp. 745-783). Mahwah, NJ: Erlbaum.

Narciss, S., & Huth, K. (2006). Fostering achievement and motivation with bug-related tutoring feedback in a computer-based training for written subtraction. Learning and Instruction, 16, 310-322.

Paas, F., Tuovinen, J., Tabbers, H., & van Gerven, P. W. M. (2003). Cognitive load measurement as a means to advance cognitive load theory. Educational Psychologist, 38, 63-71.

Paas, F., & van Merriënboer, J. J. G. (1993). The efficiency of instructional conditions: An approach to combine mental-effort and performance measures. Human Factors, 35, 737-743.

Quilici, J. L., & Mayer, R. E. (1996). Role of examples in how students learn to categorize statistics word problems. Journal of Educational Psychology, 88, 144-161.

Quilici, J. L., & Mayer, R. E. (2002). Teaching students to recognize structural similarities between statistics word problems. Applied Cognitive Psychology, 16, 325-342.

Ross, S. M., & Morrison, G. R. (1989). In search of a happy medium in instructional technology research: Issues concerning external validity, media replication, and learner control. Educational Technology, Research and Development, 37, 19-33.

Ross, S. M., & Morrison, G. R. (1993). Using feedback to adapt instruction for individuals. In J. Dempsey & G. Sales (Eds.), Interactive instruction and feedback **(pp. 177-195)**. Englewood Cliffs, NJ: Educational Technology Publications.

Scheiter, K., & Gerjets, P. (2007). Learner control in hypermedia environments. Educational Psychology Review, 19, 285-307.

Schnackenberg, H. L., & Sullivan, H. J. (2000). Learner control over full and lean computer-based instruction under differing ability levels. Educational Technology, Research and Development, 48, 19-35.

Schwartz, B. (2004). The paradox of choice: Why more is less. New York: Ecco.

Snow, R. E. (1980). Aptitude, learner control, and adaptive instruction. Educational Psychologist, 15, 151-158.

Spinath, B., & Spinath, F. M. (2005). Longitudinal analysis of the link between learning motivation and competence beliefs among elementary school children. Learning and Instruction, 15, 87-102.

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (1998). Cognitive architecture and instructional design. Educational Psychology Review, 10, 251-296.

Tennyson, R. D., & Buttery, T. (1980). Advisement and management strategies as design variables in computer-assisted instruction. Educational Communication and Technology Journal, 28, 169-176.

Van Gog, T., & Paas, F. (2008). Instructional efficiency: Revisiting the original construct in educational research. Educational Psychologist, 43, 1-11.

Van Gog, T., Paas, F., & van Merriënboer, J. J. G. (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. G. (2006). Effects of process-oriented worked examples on troubleshooting transfer performance. Learning and Instruction, 16, 154-164.

Van Gog, T., Paas, F., & van Merriënboer, J. J. G. (2008). Effects of studying sequences of process-oriented and product-oriented worked examples on troubleshooting transfer efficiency. Learning and Instruction, 18(3), 211-222.

Van Merriënboer, J. J. G. (1997). Training complex cognitive skills. Englewood Cliffs, NJ: Educational Technology Publications.

Van Merriënboer, J. J. G., & Kirschner, P. A. (2007). Ten steps to complex learning: A systematic approach to four-component instructional design. Mahwah, NJ: Erlbaum.

Van Merriënboer, J. J. G., Kirschner, P. A., & Kester, L. (2003). Taking the load off a learner's mind: Instructional design for complex learning. Educational Psychologist, 38, 5-13.

Van Merriënboer, J. J. G., Schuurman, J. G., de Croock, M. B. M., & Paas, F. (2002). Redirecting learners' attention during training: Effects on cognitive load, transfer test performance and training efficiency. Learning and Instruction, 12, 11-37.

Vollmeyer, R., & Rheinberg, F. (2005). A surprising effect of feedback on learning. Learning and Instruction, 15, 589-602.

Vosniadou, S., & Ortony, A. (1989). Similarity and analogical reasoning: A synthesis. In S. Vosniadou & A. Ortony (Eds.), Similarity and analogical reasoning (pp. 1-17). Cambridge, England: Cambridge University Press.

Williams, M. D. (1996). Learner-control and instructional technologies. In D. H. Jonassen (Ed.), Handbook of research on educational communications and technology (pp. 957-982). New York: Simon & Schuster Macmillan.

Wouters, P., Tabbers, H. K., & Paas, F. (2007). Interactivity in video-based models. Educational Psychology Review, 19, 327-342.

Table 1 Overview of the results from the Factual Knowledge test, the training phase, and the transfer phase

| | Program-control conditions | | | | Learner-control conditions | | | |
|---|---|---|---|---|---|---|---|---|
| | No-KCR | | KCR | | No-KCR | | KCR | |
| | M | SE / SD | M | SE / SD | M | SE / SD | M | SE / SD |
| Factual Knowledge test | 4.23 | 1.77 | 4.51 | 1.88 | 4.83 | 1.82 | 4.62 | 1.86 |
| Training phase | | | | | | | | |
| Time on training (s) | 1823 | 585.19 | 1815 | 455.68 | 1541 | 553.34 | 1711 | 471.71 |
| Performance | 16.16 | .94 | 16.95 | .95 | 16.52 | .95 | 17.41 | .95 |
| Mental effort | 3.19 | .26 | 2.77 | .27 | 3.40 | .26 | 2.56 | .26 |
| Transfer phase | | | | | | | | |
| Test time (s) | 2141 | 114.98 | 2217 | 116.83 | 2234 | 116.21 | 2223 | 116.37 |
| Performance on near-transfer tasks | 2.57 | .22 | 2.89 | .22 | 2.03 | .22 | 2.61 | .22 |
| Performance on far-transfer tasks | 3.37 | .29 | 3.72 | .29 | 2.97 | .29 | 3.45 | .29 |
| Mental effort on near-transfer tasks | 3.66 | .30 | 3.53 | .31 | 4.25 | .30 | 3.30 | .30 |
| Mental effort on far-transfer tasks | 4.28 | .30 | 4.12 | .30 | 4.74 | .30 | 4.11 | .30 |
| Efficiency on near-transfer tasks | .04 | .22 | .27 | .22 | -.51 | .22 | .21 | .22 |
| Efficiency on far-transfer tasks | .02 | .22 | .23 | .22 | -.35 | .22 | .12 | .22 |

Estimated marginal means and Standard Errors (SE) are presented with total training time as covariate (except for the Factual Knowledge test and Time on Training, for which means and standard deviations (SD) are presented).

Table 2 Overview of the results from the Perceived Relevance item and the Instructional Materials Motivation Survey (IMMS)

| | Program-control conditions | | | | Learner-control conditions | | | |
|---|---|---|---|---|---|---|---|---|
| | No-KCR | | KCR | | No-KCR | | KCR | |
| | M | SD | M | SD | M | SD | M | SD |
| IMMS subscales | | | | | | | | |
| Attention | 2.89 | .66 | 3.16 | .83 | 2.78 | .71 | 3.42 | .59 |
| Relevance | 3.30 | .63 | 3.38 | .77 | 3.28 | .59 | 3.70 | .56 |
| Confidence | 3.28 | 1.03 | 3.52 | 1.09 | 3.39 | .96 | 3.93 | .80 |
| Satisfaction | 2.72 | .89 | 3.10 | 1.03 | 2.82 | .78 | 3.45 | .82 |
| Perceived relevance | -- | -- | -- | -- | 2.61 | .77 | 3.16 | .66 |

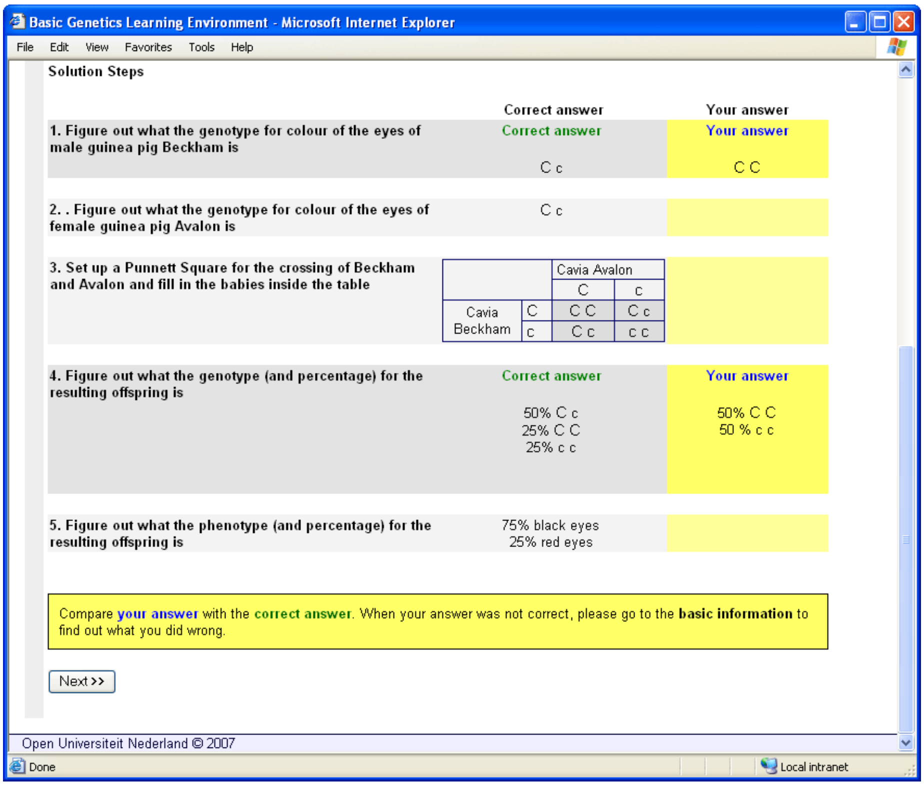


Fig. 1. Partial screendump illustrating the completed solution steps of a training task in the KCR conditions.