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Does Instructional Approach Matter? How Elaboration Plays a Crucial Role in Multimedia Learning

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This study compared the affordances of 4 multimedia learning environments for specific learning processes. The environments covered the same domain but used different instructional approaches: (a) hypermedia learning, (b) observational learning, (c) self-explanation-based learning, and (d) inquiry learning. Although they all promote an active attitude, they differ in the specific learning processes they intend to foster. In earlier research (Eysink et al., 2009), we found that learners involved in self-explanation-based or inquiry learning had the highest learning outcomes. In these approaches learners were required to generate (parts of) the subject matter, from which we concluded that they presumably stimulated learners to elaborate. Therefore, in the present study we expected that learners involved in self-explanation-based or inquiry learning would engage in more learning processes connected to elaboration than would learners involved in hypermedia or observational learning. Forty participants worked through the learning environments while thinking aloud; their protocols were coded using a generic learning processes scheme. Results showed that self-explanation-based learning and inquiry learning led to greater engagement in learning processes in general and more elaborative processes in particular. The results suggest that elaboration is indeed the key process explaining differences in learning across different instructional approaches within multimedia learning environments.

Whereas in the first part of the past century learning was seen as a process of knowledge transmission, learning nowadays is generally seen as a process of...
knowledge construction. Educational scientists to a large degree agree that in order for people to learn, relevant aspects of the presented material must be selected, organized into a coherent mental representation, and integrated with other information and prior knowledge (Mayer, 2001). This view is related to an increased emphasis on meaningful learning. *Meaningful learning*, in contrast to rote or superficial learning, refers to the idea that new information is solidly anchored in the learner’s knowledge base and is enriched with causal relations, abstractions, and elaborations (Bransford, Brown, & Cocking, 2000; Clark & Linn, 2003; Hmelo-Silver, Marathe, & Liu, 2007; Reif, 2008). In the past half-century, these ideas on learning led to the development of a range of instructional approaches. Most of these approaches, such as inquiry learning and problem-based learning, translated the idea of knowledge construction into more active cognitive engagement for the learner with the learning material. Examples of the most recent developments are cognitive engagement by invention activities and learner-generated representations and artifacts (e.g., Chase, Chin, Oppezzo, & Schwartz, 2009; de Jong et al., 2010).

In a recent study (Eysink et al., 2009), four instructional approaches representing modern views on learning were compared to one another in the domain of probability theory. The four approaches were (a) hypermedia learning, (b) observational learning, (c) self-explanation-based learning, and (d) inquiry learning. Each of the instructional approaches had the same goal, but they differed in the path taken to achieve that goal. The choice for these instructional approaches arose from joined research activities. Each partner committed to this collaboration had extensive expertise in designing, implementing in the classroom, and evaluating one of the four instructional approaches. This ensured that all resulting learning environments followed up-to-date design guidelines so that fair comparisons could be made between ecologically valid instructional approaches. The results of the comparative study showed that learners in the self-explanation-based and inquiry learning environments had significantly higher learning outcomes than those in the hypermedia and observational learning environments. They understood the subject matter better in terms of problem categories and relations between variables, and they were better able to transfer their knowledge to new problem situations. From these results, we concluded that a partition existed between, on the one hand, two effective approaches that could be characterized by the fact that the learners had to generate (parts of) the subject matter themselves (i.e., self-explanation-based learning and inquiry learning) and, on the other hand, two less effective approaches having in common that the subject matter was more or less directly presented to the learners (i.e., observational learning and hypermedia learning).

As the study by Eysink et al. (2009) merely assessed learning outcomes, we can only speculate about the explanations for the results found. Comparing the same approaches in terms of learning processes would give more insight in the learning
processes each approach affords. Hence, the current study was developed as a follow-up study in which the same four instructional approaches were compared with regard to the learning processes they elicit.

GAINING INSIGHT INTO LEARNING PROCESSES

It has been widely acknowledged that the same information can be processed at different levels (Craik & Lockhart, 1972; Cromley, Snyder-Hogan, & Luciw-Dubas, 2010) so that not all learning processes lead to the same quality or depth of knowledge (de Jong & Ferguson-Hessler, 1996). For example (see Fox, 2009), when one is studying a text, information can be processed superficially by merely reading it without any further processing (superficial learning), or it can be processed more deeply by, for example, relating concepts to one another or integrating new information with prior knowledge (meaningful learning). Although a certain amount of superficial processing is always necessary, meaningful learning is especially connected to elaborative activities. When elaborating, learners better understand the subject matter, have a more abstract view of it, and are consequently better able to transfer their knowledge to new situations or domains (Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Ferguson-Hessler & de Jong, 1990), which is an important aspect of problem-solving capability (Jacobson & Archodidou, 2000). As a consequence, instructional methods that elicit these elaborative learning processes are expected to be more successful in promoting meaningful learning than instructional methods that do not (Bransford et al., 2000; Merrill, 2002).

Regulation of learning activities is an important condition for all learning, whether by way of superficial or deep processing. Regulative processes comprise activities aiming at managing learning. Learners need to orient to the learning task at hand, they must make decisions about what they want to learn and how much time they want to spend on learning, they need to set learning goals and think of strategies, they need to monitor their learning activities and adjust them if necessary, and they need to reflect on how they learned and on their acquired knowledge (Azevedo, Cromley, & Seibert, 2004). Regulative processes do not directly yield knowledge but are considered to be necessary for learning.

INSTRUCTIONAL APPROACHES AND THEIR AFFORDANCES

In this section, we briefly describe the four chosen instructional approaches and their underlying assumptions. We also describe the learning processes each is hypothesized to elicit in an individual learning context. A table summarizing the assumptions, strengths, and risks of the four instructional approaches as well
as a table summarizing the learning processes assumed to be elicited by each instructional approach are given in Eysink et al. (2009).

Hypermedia Learning

Hypermedia learning environments are nonlinear computer environments in which learners have random, dynamic access to a wide range of information presented in different representational formats such as text, graphics, animation, audio, and video (Jacobson & Archodidou, 2000; Jonassen, 1996). Learners have the freedom to decide which information they select and observe and which they ignore. They can do this when they like, at their own pace, and following their own order. To gain access to the information, learners have to identify which knowledge they need (Lawless & Brown, 1997). They must relate the information already selected to their prior knowledge and integrate the two into a coherent mental representation (Schnotz & Heiß, 2009). As soon as they realize which knowledge is missing, they can make intentional information selections (Barab, Bowdish, Young, & Owen, 1996), a process that requires self-regulatory processes (Azevedo, 2005) such as orienting, planning, monitoring, and reflecting (Azevedo & Cromley, 2004). Once information has been selected, it must be observed and filtered, and, in the case of problem-solving, the solution steps must be checked. The network-like information structure of hypermedia learning environments gives learners the opportunity to acquire a good overview of the structure of the domain (de Jong & van der Hulst, 2002).

Hypermedia learning allows learners to retrieve information adapted to their needs and abilities and thereby enables active, flexible, and constructive learning (Spiro & Jehng, 1990). However, this flexibility can also have disadvantages. Learners may find it hard to decide which information they should select, observe, and integrate (Lawless & Brown, 1997; Rouet, Levonen, Dillon, & Spiro, 1996), and they can experience structural and semantic disorientation (Hill & Hannafin, 1997). These problems can be reduced by instructional solutions such as decreasing the level of learner control and giving support for representational and navigational choices (Burke, Etnier, & Sullivan, 1998).

Observational Learning

In an observational learning environment, a learner observes a pedagogical agent performing a task or solving a problem. Because any cognitive processes involved are not visible, they must be made explicit (Collins, 1991). This means that the pedagogical agent must explicate the decision processes and strategies underlying the problem-solving activities and that an explanation must be given of why and when particular strategies are useful. The learner observes the pedagogical agent solving the task, checks the solution steps, and reads or listens to the
agent’s explanation of why the problem is solved in that particular way. After each task, the learner is supposed to reflect on the learning experience by rehearsing the task mentally and integrating the newly received information into a mental representation (Wouters, Paas, & van Merriënboer, 2008).

Observational learning is thought to be effective for learning because of this combination of emphasis on the procedure itself as well as on the rationale behind the procedure (Collins, 1991; van Gog, Paas, & van Merriënboer, 2004). Furthermore, learners are expected to go over the task mentally and refine their initial representations accordingly (Bandura, 1976). The main disadvantage of observational learning is that learners may watch the expert passively without actively trying to encode the information received from the pedagogical agent and without building or refining their cognitive representation of the domain. Several ways to overcome this problem have been proposed. In the scaffolding whole-task practice approach, learners are given extensive support and guidance at the beginning of the learning activity that is faded as more expertise is acquired (van Merriënboer, Kirschner, & Kester, 2003; van Merriënboer & Sweller, 2005). Other suggested instructional variables concern pacing (Schwan & Riempp, 2004), visual grouping (Rieber, 1993), and segmentation of the animation (Schwan & Garsoffky, 2004; Zacks & Tversky, 2001).

**Self-Explanation-Based Learning**

Self-explanation-based learning combines the ideas of example-based learning and generating self-explanations. While studying worked-out examples, the learner reads, watches, and filters the information provided and checks the solution steps. Mentally following the solution steps offered is assumed to be effective because learners are freed from the need to find the solution on their own. Instead of searching for the correct solution, they can devote their cognitive resources to understanding the solution steps (cf. Paas, Renkl, & Sweller, 2003). This understanding can be reached by prompting the learners to self-explain the solution steps of the worked-out examples. The prompts to self-explain make the learners think about underlying concepts and the rationale behind the procedure, make them generate inferences to fill in missing information or repair faulty knowledge, and make them relate and integrate the offered information together with prior knowledge into a mental representation (Roy & Chi, 2005). Research has shown that learners who more actively explained worked-out examples to themselves learned more than learners who did not self-explain the examples (Chi et al., 1989; Renkl, 1997). Relevant instructional supports for self-explanation-based learning include making subgoals in examples salient (Atkinson & Derry, 2000) and supporting learners’ integration of different representations used in the worked-out example (Tarmizi & Sweller, 1988).
Inquiry Learning

In inquiry learning, learners have active experiences with the subject matter that can lead them to induce characteristics of the domain (de Jong, 2005; Swaak & de Jong, 2001). The learner must first become oriented to the environment and to prior knowledge related to the subject matter (de Jong & van Joolingen, 1998). Based on this information and supported by guidance in the learning environment, the learner develops hypotheses and tests them by performing one or more experiments (de Jong, 2006). Comparing and relating the collected data makes the underlying concepts and relations between variables salient to the learner. This knowledge can then be integrated into a mental representation; if it becomes clear after reflection that extra information is needed, new experiments can be performed (Klahr & Dunbar, 1988). Evidence is accumulating that inquiry learning has advantages over traditional, more expository forms of instruction (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011; Deslauriers & Wieman, 2011; Linn, Lee, Tinker, Husic, & Chiu, 2006; Minner, Levy, & Century, 2010).

However, studies also show that learners often do not succeed in this (de Jong & van Joolingen, 1998). They often have difficulties formulating hypotheses (Klayman & Ha, 1987; Njoo & de Jong, 1993) and they search only for evidence supporting their hypotheses, not for evidence disproving them (Quinn & Alessi, 1994), and they often draw conclusions that are not justified according to the data (Klahr & Dunbar, 1988). As a consequence, learners require support for their inquiry learning processes to make this an efficient and effective instructional approach (de Jong, 2005; de Jong & van Joolingen, 1998; Mayer, 2004). Examples of such effective support tools are proposition tables that make comparison and discussion of different hypotheses easier (Gijlers & de Jong, 2009), assignments in which short tasks are given so that learners receive subgoals while investigating the domain, and model progression that makes complex domains more manageable (Swaak, van Joolingen, & de Jong, 1998).

HYPOTHESES

In our earlier study comparing four instructional approaches on learning outcomes (Eysink et al., 2009), we found a distinction between self-explanation-based learning and inquiry learning, on the one hand, as more effective instructional approaches and observational learning and hypermedia learning, on the other hand, as less effective. Effectiveness concerned better understanding of the subject matter and the ability to transfer this knowledge to new problem situations. We inferred that the two more effective instructional approaches shared the characteristic that the learners had to generate (parts of) the subject matter. Learners in the self-explanation-based learning environment had to generate self-explanations; learners in the inquiry learning environment had to generate
DOES INSTRUCTIONAL APPROACH MATTER?

589

data by performing experiments. The two less effective approaches had in common that the subject matter was more or less directly presented to the learners. We assumed that the differences in effectiveness were caused by differences in the types of learning processes elicited. Therefore, in the present study we expected that learners working with the instructional approaches in which they had to generate (parts of) the subject matter themselves (i.e., self-explanation-based learning and inquiry learning) would engage more in learning processes associated with meaningful learning (i.e., elaborative processes) than would learners working with the approaches in which the learning material was more or less directly presented to them (i.e., hypermedia learning and observational learning). This assumption contrasts the view of Kirschner, Sweller, and Clark (2006), who instead have made a plea for instructivist approaches, arguing that approaches in which learners have to “search problem space,” as they call it, require them to use their limited cognitive resources for searching instead of for learning, which thus cannot lead to superior learning. In addition to our main hypothesis, we also expected differences (in terms of both quantity and distribution) between the instructional approaches in the other characteristic learning processes identified for each instructional approach in the preceding section.

METHOD

In this study, we compared the four instructional approaches on the learning processes elicited. In order to do this, we implemented the four instructional approaches in computer-based learning environments. The environments were designed using the latest insights into instructional design for each particular approach. All four computer environments focused on the domain of mathematics and shared the same content: probability theory. Learners were asked to think aloud as they worked individually through one of the four learning environments.

Participants

Participants were 40 Dutch students (17 boys, 23 girls) in Grade 10 (ages 15–16) of the highest level of secondary education (i.e., preparing for university). In contrast to the participants in our former study, the participants in the current study had prior knowledge of the presented content in the sense that the topic had been part of their curriculum 1 year before the current study. The participants completed the experiment during school time. They did not receive any compensation for their participation.
The Domain

The domain that we used was elementary probability theory. This domain concerns situations involving the determination of the probability of randomly selecting a particular configuration of elements out of a set of elements (e.g., What is the probability that someone else correctly guesses your PIN code in one try?).

There are several factors to be considered in order to calculate the probability of such a complex event: (a) the total number of elements from which selections will be made (i.e., the possible outcomes \( n \)), (b) the number of elements within the total set of elements that meet the selection criteria (i.e., the acceptable outcomes \( k \)), (c) the number of selections that are made (i.e., the number of individual events), (d) whether elements are replaced after selection, and (e) whether the order of selection of elements is relevant. Combining the two variables of replacement and order results in four categories of problems: (a) order important with replacement, (b) order not important with replacement, (c) order important without replacement, and (d) order not important without replacement.

There are two ways to calculate the probability: either by the individual events method or by the formula-based method. In the individual events method, the probability of the complex event can be calculated by multiplying together the probabilities of the individual events. In the formula-based method, a formula is used to determine the number of possible combinations \( A \), after which the probability can be calculated. In three of the learning environments, only the individual events method was used. In the observation-based learning environment both problem-solving procedures were used, as this learning environment mirrored expert problem-solving behavior and experts would use both procedures.

Figure 1 shows a typical example of a problem in elementary probability theory. In this example, the problem situation is set up in such a way that a question can be formulated for each of the four problem categories identified previously. The figure shows questions and the corresponding answers in order to clarify the differences between the four problem categories. The problem situation and questions were taken from the learning environments.

Learning Material

Introductory text. An introduction text was presented to activate learners’ prior knowledge. This text consisted of an introduction to the domain of probability theory, including the basic notion of random experiments, individual and complex events, the general rationale behind calculating the probability of outcomes (including the variables order and replacement), and a summary of the four problem categories.
Problem situation:

Together with a friend you take part in a two-day mountain bike course. Both days the instructor has 5 different-colored helmets: green, blue, orange, red, and silver. Each day the helmets are distributed at random. At the end of the day each participant returns the helmet to the instructor. Both days you are the first one to get a helmet and your friend is the second one.

<table>
<thead>
<tr>
<th>replacement?</th>
<th>order important?</th>
<th>yes</th>
<th>no</th>
</tr>
</thead>
<tbody>
<tr>
<td>yes</td>
<td>what is the chance that you get the red helmet on the first day and the green one on the second day?</td>
<td>what is the chance that during the two days you will get a red and a green helmet?</td>
<td>answer: 1/5 × 1/5 = 1/25</td>
</tr>
<tr>
<td>no</td>
<td>what is the chance that on the first day you get the red helmet and your friend gets the green one?</td>
<td>what is the chance that on the first day you and your friend get the red and green helmet?</td>
<td>answer: 1/5 × 1/4 = 1/20</td>
</tr>
</tbody>
</table>

FIGURE 1 A typical example of a problem situation and four questions and solution steps corresponding to the four problem categories.

Concrete problem situations. Research has shown that the use of examples assists in learning to solve mathematical problems (Catrambome, 1994; Cooper & Sweller, 1987; Zhu & Simon, 1987). Therefore, all of our learning environments were designed around a set of concrete examples or problem situations. Four problem situations were developed, one for each problem category. These situations concerned (a) guessing a PIN code: What is the probability of guessing the code correctly in one try? (b) a marketing campaign in which collectible objects are given away together with a pack of muesli: What is the probability of getting the three objects you want most? (c) predicting the first three finishers in a race: What is the probability of correctly predicting the persons in positions one, two, and three? and (d) checking mobile phones on an assembly line for manufacturing errors: What is the probability of correctly predicting which phones will
be checked? (see Figure 2 for an overview). Furthermore, a fifth description of a situation was developed (a 2-day mountain bike course in which helmets of different colors are handed out) that could be adapted to each of the four problem categories, resulting in four more problems (see Figure 1). These last four problems were consequently identical in terms of surface characteristics (hanging out helmets for a mountain bike course) but different in terms of underlying structure (the problem category; Quilicy & Mayer, 1996).

### Posttest

A posttest was administered to give the learners a goal while working in the environment. As the focus of this study was on learning processes and not on learning outcomes, this test was not used as a formal assessment, so the number of items on it could be small. The posttest was an abbreviated version of the posttest that was used in our earlier study (Eysink et al., 2009). The test consisted of a total of six items (two conceptual multiple choice items and four procedural open items) that

![Figure 2](image-url)  
**FIGURE 2** The eight problem situations used in the experiment, each representing one of the four problem categories.
were seen as examples of typical questions. Instead of giving a pretest, as in our former study, we gave the learners the opportunity to take a look at the posttest items before they started working in the learning environment. By having this opportunity, learners got an idea of what kind of knowledge they were expected to master. What is important to notice in this context is that in order to correctly answer these items, learners needed a coherent and abstract mental representation of the domain so that they could use their knowledge in different problem situations at different levels (conceptual as well as procedural). In other words, the specific answers to the items in the test literally could not be found in any of the learning environments, so previewing the posttest did not lead to the side effect of a goal-oriented search for specific information.

**Design and Learning Environments**

Learners were randomly assigned to one of four conditions, each offering a learning environment that used a specific instructional approach: (a) hypermedia learning, (b) observational learning, (c) self-explanation-based learning, or (d) inquiry learning. All learning environments were in Dutch.

The hypermedia learning environment used in the present study was based on the learning environments used by Gerjets, Scheiter, Opfermann, Hesse, and Eysink (2009), of which a screenshot is given in Figure 3. In this learning environment, learners were presented with the eight concrete problem situations. These concrete problem situations were given in the following order: mountain bike problem I, race problem, mountain bike problem II, PIN code problem, mountain bike problem III, mobile phones problem, mountain bike problem IV, and marketing campaign problem. In order to avoid structural and semantic disorientation (Hill & Hannafin, 1997), we used a low level of learner control in which learners had fewer representational and navigational choices (Burke et al., 1998). Learners were allowed to go back and forth between the problems by using the buttons “Back” and “Further.” For each problem situation, the problem was presented to the learners, followed by the solution steps to the correct solution. Calculation of the probability of a complex event was presented by explaining each individual event in succession. The solution steps for calculating the probability of a complex event were given as a formula or as a formula complemented with a textual description.

The observational learning environment used an animated dolphin as a pedagogical agent within eight animations representing the eight problem situations. The order in which the problem situations were given was the same as in the hypermedia learning environment. For each problem situation, an animation was presented to the learners in which the dolphin moved around, addressing the learner in a personalized style while giving explanations in written text. The dolphin first presented the problem and subsequently described the steps for solving
the problem and gave information about the underlying rationale for the solution steps. While doing this, the dolphin used signaling cues, such as pointing to, highlighting, or encircling, to indicate important information. See Figure 4 for an example screenshot in which the dolphin explains the possible outcomes of the second individual event in the race problem. Because this learning environment represents the way experts would solve the problems, both the individual events–based and the formula-based approaches of probability theory were used here. The problem-solving process was divided into a number of problem-solving steps. The animations in the learning environment were segmented in such a way that each segment represented a single solution step. The segments were defined in consultation with the mathematics teachers of the schools that participated in our former study. After each segment, the animation turned grey and paused. In addition, the animations were learner paced, so that learners could navigate between segments and pause within segments by using the buttons beneath each animation. More information on this learning environment can be found in Wouters, Paas, and van Merriënoer (2006).

In the self-explanation-based learning environment, learners received eight worked-out examples combined with self-explanation prompts. The order in which the eight examples were presented was the same as in the hypermedia and observational learning environments. In each worked-out example, learners successively received a series of questions concerning the variable of order and
its effect on the acceptable outcomes, the variable of replacement and its effect on the possible outcomes, and the final probability of acceptable and possible outcomes. In the first problem situation for each problem category (which was always a mountain bike problem), the answers were supported in the form of fill-in-the-blank self-explanations (e.g., “There are __ times __ branches. Thereby, all possible combinations are included.”). In the second problem situation for each problem category, this support was withheld, and the learners received six open prompts in which the same questions were posed. The solution steps were represented as a formula or as a combination of a formula and a tree diagram. Learners in the combined condition received help in integrating the formula and tree diagram by having the corresponding information from the two representations flashing simultaneously in the same color. An example screenshot is given in Figure 5, in which the formula and tree diagram of the first mountain bike problem are accompanied by fill-in-the-blank self-explanations concerning the importance of the order and the corresponding acceptable outcomes for each of the individual events. For more detailed information, see Berthold and Renkl (2009) and Berthold, Eysink, and Renkl (2009).
The inquiry learning environment consisted of five sections, one section for each of the four problem categories and one additional section in which the four problem categories were integrated (i.e., the mountain bike cover story). In all sections, simulations were provided in which the learners could vary different variables (e.g., the number of possible outcomes and the number of acceptable outcomes) and see the resulting changes in the solution steps and the effect on the calculated probability. In order to guide the learners in their discovery processes, assignments given were open ended as well as had multiple choice questions. In each section that treated only one problem category at a time, five assignments were given. These assignments concerned determining the correct problem category and corresponding structure, investigating the problem-solving steps and corresponding probability of the problem situation, calculating the probability with increased numbers of possible outcomes, investigating what happens to the probability if the number of possible or acceptable outcomes increases or decreases, and determining what happens to the probability if one of the two variables of replacement or order changes. An example screenshot is given in Figure 6, in which learners are asked to investigate what happens to the probability when the number of possible outcomes in the race problem decreases. They do this by using the simulation in which different values for the possible and acceptable outcomes...
can be inserted and the corresponding tree diagram, formula, and probability can be observed. In the section in which the four problem categories were integrated, seven assignments were given. Four of these assignments concerned investigating the meaning of different problem categories and the effect of the variables of order and replacement on the corresponding structures, solution steps, and probabilities. The remaining three assignments concerned examining whether certain statements were true or false and why. Learners were instructed to use the simulations to complete the assignments. More details about the inquiry learning environment can be obtained from Kolloffel, Eysink, de Jong, and Wilhelm (2009).

Procedure

The experiment took place in one session of 1 hr and 40 min. The participants were tested individually. The session started with a short introduction on the research context. Then the participants were told that they would have to think aloud and were given an explanation of the purpose of this procedure. They received think-aloud instruction consisting of a think-aloud example and think-aloud practice. The example showed a person thinking aloud while solving a matchstick problem in which two matchsticks had to be removed so that the remaining matches formed two squares. In the example, the learners saw the matchstick configuration and the actions the person performed on the matchsticks and heard the person thinking aloud. This example was considered to provide a high-quality model of thinking aloud. In the example, the person (a) reads the assignment, (b) repeats the assignment in his own words, (c) thinks about a possible solution but discovers and indicates that it is not the right solution, (d) tells what he thinks of the assignment, (e) thinks of an action plan for arriving
at the solution, (f) finds the correct solution, and (g) summarizes what he did to arrive at the right solution. After showing the example, the experimenter explicitly pointed out these parts in the think-aloud process to the learners.

After the think-aloud example, the learners had to practice and get used to thinking aloud. They had to solve a tangram (a Chinese dissection puzzle of seven pieces) while thinking aloud. When the learners fell silent, the experimenter prompted them to continue talking. Afterward, the experimenter indicated what went well and why and, if necessary, how the learners could improve the think-aloud process. Subsequently, the learners were given the introductory text on paper and were shortly thereafter presented with the posttest items. After this, they started working with the learning environment while thinking aloud. If participants fell silent for too long, they were prompted to continue talking. All utterances were recorded on minidisks. After the participants worked through the entire learning environment, or up to a maximum time of 1 hr and 30 min, they were given the posttest on paper.

Learning Processes Scheme

In our learning processes scheme, the difference in levels of processing is represented by a distinction between superficial processes and elaborative processes (cf. Ferguson-Hessler & de Jong, 1990). Superficial processes concern learning processes by which information in the learning environment is processed at a surface level, in such a way that no further information is deduced from or attached to this information. This type of processing includes processes such as reading texts, filtering information, and merely checking worked-out examples. Although this type of processing does not seem to be important, it is necessary in order to process information on a deeper, elaborative level (Mayer, 2002). Elaborative processes concern learning processes by which information in the learning environment is processed at a deeper level, in such a way that the information is related and connected to prior knowledge and new information is deduced. Elaborative activities include processes such as developing and testing hypotheses, relating and integrating, and giving (self-) explanations.

In addition to superficial processing activities and elaborative activities, which together are often referred to as transformative processes (e.g., de Jong & Njoo, 1992), we included regulative processes in our scheme. Regulation of learning activities, whether by way of superficial or deep processing, is an important condition for all learning. Regulative processes comprise activities aimed at managing learning. Within the regulative category, we followed Azevedo and Cromley’s (2004) classification of orienting, planning, monitoring, and reflecting. In our case, we decided to restrict reflection to purely regulative activities, which means that it does not directly yield knowledge. It concerns reflection on how learning proceeded (e.g., whether the strategy used was a good one), reflection on the
knowledge gained (e.g., whether the learner reached a certain goal), and reflection on the learning environment (e.g., whether the learner understands the workings of the learning environment). The deeper reflective processes come under the elaborative category. This gives us the opportunity to describe these deeper reflective processes more specifically.

The complete learning processes scheme is given in the Appendix. The scheme consists of mutually exclusive categories. The types of learning processes included in each category are indicated. Furthermore, examples of verbal utterances clarify what the specific learning processes mean. The scheme was first applied to data collected in a pilot study and successively adjusted into its final format. The scheme was constructed to have a generic character allowing the representation of all instructional approaches and applicability to problem-solving domains other than probability theory.

RESULTS

Protocol Coding

The think-aloud protocols were transcribed and coded by four coders. All protocols were segmented into utterances. An utterance was defined as a statement expressing one distinct learner activity. After segmenting, all utterances were coded into one of the learning processes categories. Each coder coded 10 different think-aloud protocols. A fifth coder coded 10% of the data of each coder independently from the other coders, which corresponded to a total of 580 utterances. The interrater reliability coefficients of coding utterances in terms of the three main categories (superficial processes, elaborative processes, and regulative processes) reached .85 (Cohen’s kappa). The interrater reliability coefficients of coding utterances in terms of subcategories reached .74 (Cohen’s kappa).

In addition to the quantitative analyses, a qualitative analysis was done for which all protocols were inspected by the fifth coder. The fifth coder used the underlying assumptions of each instructional approach together with the quantitative data as input for the qualitative analysis. This revealed aspects of learning that were prototypical for each particular instructional approach.

Average Number of Learning Processes

Table 1 gives the average number of identified instances of engagement in learning processes within different categories for each instructional approach. Figure 7 summarizes the data for the three main categories in a graphical representation. The data sets of the four instructional approaches concerning the total number of identified instances of engagement in learning processes were normally
**TABLE 1**

Mean (SD) Identified Instances of Engagement in Learning Processes for Each Instructional Approach

<table>
<thead>
<tr>
<th>Process</th>
<th>HL M</th>
<th>HL SD</th>
<th>OL M</th>
<th>OL SD</th>
<th>EL M</th>
<th>EL SD</th>
<th>IL M</th>
<th>IL SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Superficial processes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reading/watching and filtering</td>
<td>20.30</td>
<td>8.03</td>
<td>36.50</td>
<td>10.62</td>
<td>91.80</td>
<td>25.94</td>
<td>63.50</td>
<td>22.09</td>
</tr>
<tr>
<td>Checking solution steps</td>
<td>9.00</td>
<td>5.38</td>
<td>3.10</td>
<td>3.25</td>
<td>2.70</td>
<td>3.20</td>
<td>9.50</td>
<td>10.06</td>
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<tr>
<td>Total</td>
<td>29.30</td>
<td>10.98</td>
<td>39.60</td>
<td>12.45</td>
<td>94.50</td>
<td>23.98</td>
<td>73.00</td>
<td>27.44</td>
</tr>
<tr>
<td>Elaborative processes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Developing and testing hypotheses</td>
<td></td>
<td>16.10</td>
<td>3.57</td>
<td>14.80</td>
<td>4.83</td>
<td>80.60</td>
<td>30.02</td>
<td>70.50</td>
</tr>
<tr>
<td>Relating and integrating</td>
<td>7.50</td>
<td>5.34</td>
<td>4.90</td>
<td>5.63</td>
<td>28.70</td>
<td>9.55</td>
<td>24.70</td>
<td>14.33</td>
</tr>
<tr>
<td>Giving (self-) explanations</td>
<td>4.20</td>
<td>3.29</td>
<td>2.20</td>
<td>1.69</td>
<td>14.00</td>
<td>9.89</td>
<td>10.10</td>
<td>6.54</td>
</tr>
<tr>
<td>Total</td>
<td>27.80</td>
<td>7.90</td>
<td>21.90</td>
<td>7.31</td>
<td>123.30</td>
<td>37.71</td>
<td>105.30</td>
<td>35.04</td>
</tr>
<tr>
<td>Regulative processes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Orienting</td>
<td>0.90</td>
<td>0.88</td>
<td>4.80</td>
<td>4.10</td>
<td>6.30</td>
<td>4.37</td>
<td>8.50</td>
<td>6.79</td>
</tr>
<tr>
<td>Planning</td>
<td>1.70</td>
<td>2.67</td>
<td>2.00</td>
<td>2.67</td>
<td>2.60</td>
<td>2.17</td>
<td>9.90</td>
<td>8.58</td>
</tr>
<tr>
<td>Monitoring</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.20</td>
<td>0.42</td>
<td>0.20</td>
<td>0.42</td>
</tr>
<tr>
<td>Reflecting</td>
<td>3.70</td>
<td>3.20</td>
<td>9.00</td>
<td>5.72</td>
<td>11.00</td>
<td>10.97</td>
<td>9.10</td>
<td>8.08</td>
</tr>
<tr>
<td>Total</td>
<td>6.30</td>
<td>4.62</td>
<td>15.80</td>
<td>11.12</td>
<td>20.10</td>
<td>12.38</td>
<td>27.70</td>
<td>18.08</td>
</tr>
<tr>
<td>Total</td>
<td>63.40</td>
<td>16.64</td>
<td>77.30</td>
<td>23.85</td>
<td>237.90</td>
<td>47.78</td>
<td>206.00</td>
<td>64.09</td>
</tr>
</tbody>
</table>

*Note.* HL = hypermedia learning; OL = observational learning; EL = self-explanation-based learning; IL = inquiry learning.

distributed (Shapiro-Wilk W test: hypermedia: W = .94, \(p = .50\); observational: W = .94, \(p = .57\); self-explanation: W = .97, \(p = .90\); inquiry: W = .90, \(p = .20\)); not all data sets of the four instructional approaches were normally distributed concerning the three main categories and their subcategories, so analyses concerning these levels were performed with nonparametric tests. All post hoc analyses using the Bonferroni procedure used adjusted alpha levels of .008 per test (.05/6). A univariate analysis of variance showed a significant difference between the average number of total identified instances of engagement in learning processes in each instructional approach, \(F(3, 36) = 43.47, p < .001\), partial \(\eta^2 = .78\). Learners in the self-explanation-based learning environment and the inquiry learning environment had significantly more identified instances of engagement in learning processes than those in the hypermedia and observational learning environments (all \(ps < .001\)).

A Kruskal-Wallis test was conducted with the identified instances of engagement in learning processes in the three main categories (superficial processes, elaborative processes, and regulative processes) as dependent variables and
the instructional approach as the independent variable. Significant differences between instructional approaches were found on superficial processes, $\chi^2(3, 40) = 29.94, p < .001$; on elaborative processes, $\chi^2(3, 40) = 30.43, p < .001$; and on regulative processes, $\chi^2(3, 40) = 13.11, p < .01$. Pairwise comparisons using Mann-Whitney $U$ tests with Bonferroni corrections revealed that learners in the hypermedia learning environment engaged in significantly fewer instances of superficial, elaborative, and regulative processes than those in the self-explanation-based learning environment ($Z = -3.78, p < .001$; $Z = -3.78, p < .001$; and $Z = -2.80, p < .008$, respectively) and those in the inquiry learning environment ($Z = -3.78, p < .001$; $Z = -3.78, p < .001$; $Z = -2.80, p < .008$, respectively), and learners in the observational learning environment engaged in significantly fewer instances of superficial and elaborative processes than those in the self-explanation-based learning environment ($Z = -3.41, p \leq .001$; and $Z = -3.78, p < .001$, respectively) and the inquiry learning environment ($Z = -3.78, p < .001$; and $Z = -3.78, p < .001$, respectively).

In order to examine the superficial processes more closely, we conducted a Kruskal-Wallis test with the identified instances of engagement in the two superficial subcategories of learning processes as dependent variables and the
instructional approach as the independent variable. The analysis showed significant differences between instructional approaches on reading/watching and filtering, \( \chi^2(3, 40) = 31.88, p < .001 \); and on checking solution steps, \( \chi^2(3, 40) = 10.85, p < .05 \). Pairwise comparisons using Mann-Whitney \( U \) tests with Bonferroni corrections showed that learners in the self-explanation-based learning environment and learners in the inquiry learning environment read and filtered significantly more than those in the hypermedia learning environment (\( Z = -3.78, p < .001 \); and \( Z = -3.79, p < .001 \), respectively) and the observational learning environment (\( Z = -3.71, p < .001 \); and \( Z = -3.56, p < .001 \), respectively), and learners in the observational learning environment read and filtered significantly more than learners in the hypermedia learning environment (\( Z = -2.88, p < .008 \)). Furthermore, learners in the hypermedia learning environment checked significantly more solution steps than those in the self-explanation-based learning environment (\( Z = -3.80, p < .001 \); and \( Z = -3.80, p < .001 \), respectively).

To examine in more detail the elaborative processes, the category whose activities are supposed to lead to meaningful learning, we performed a Kruskal-Wallis test with the identified instances of engagement in the three elaborative subcategories of learning processes as dependent variables and the instructional approach as the independent variable. Significant differences between instructional approaches were found for developing and testing hypotheses, \( \chi^2(3, 40) = 29.99, p < .001 \); relating and integrating, \( \chi^2(3, 40) = 26.52, p < .001 \); and giving (self-) explanations, \( \chi^2(3, 40) = 19.66, p < .001 \). Pairwise comparisons using Mann-Whitney \( U \) tests with Bonferroni corrections revealed that learners in the self-explanation-based learning environment and learners in the inquiry learning environment developed and tested more hypotheses than those in the hypermedia learning environment (\( Z = -3.80, p < .001 \); and \( Z = -3.80, p < .001 \), respectively) and the observational learning environment (\( Z = -3.79, p < .001 \); and \( Z = -3.78, p < .001 \), respectively). The same pattern was found for relating and integrating: Learners in the self-explanation-based learning environment and learners in the inquiry learning environment related and integrated more than those in the hypermedia learning environment (\( Z = -3.60, p < .001 \); and \( Z = -3.26, p < .001 \), respectively) and the observational learning environment (\( Z = -3.71, p < .001 \); and \( Z = -3.48, p < .001 \), respectively). Furthermore, pairwise comparisons showed that learners in the self-explanation-based learning environment gave significantly more (self-) explanations than those in the observational learning (\( Z = -3.26, p < .001 \)) and the hypermedia learning environment (\( Z = -2.73, p < .008 \)), and learners in the inquiry learning environment gave significantly more (self-) explanations than those in the observational learning environment (\( Z = -3.63, p < .001 \)).

In order to have a closer look at the regulative processes, we performed a Kruskal-Wallis test with the identified instances of engagement in orienting, planning, monitoring, and reflecting as dependent variables and the instructional
Does Instructional Approach Matter?

Significant differences between instructional approaches were found for orienting, $\chi^2(3, 40) = 9.12, p < .05$; and planning, $\chi^2(3, 40) = 8.55, p < .05$; but no significant differences between instructional approaches for orienting and planning were revealed by pairwise comparisons using Mann-Whitney $U$ tests with Bonferroni corrections. Furthermore, no significant differences between instructional approaches were found for monitoring, $\chi^2(3, 40) = 4.33, p = .23$; or reflecting, $\chi^2(3, 40) = 5.32, p = .15$.

Percentages of Learning Processes

Table 2 gives the average percentage of identified instances of engagement in the different categories of learning processes for each instructional approach. In order to see whether there were differences between instructional approaches on the average percentage of observed learning processes in the three main categories, we conducted a Kruskal-Wallis test with the percentages of utterances coded as

<table>
<thead>
<tr>
<th>Process</th>
<th>Instructional Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$HL$</td>
</tr>
<tr>
<td></td>
<td>$M$</td>
</tr>
<tr>
<td>Superficial processes</td>
<td></td>
</tr>
<tr>
<td>Reading/watching and filtering</td>
<td>31.98</td>
</tr>
<tr>
<td>Checking solution steps</td>
<td>13.57</td>
</tr>
<tr>
<td>Total</td>
<td>45.55</td>
</tr>
<tr>
<td>Elaborative processes</td>
<td></td>
</tr>
<tr>
<td>Developing and testing hypotheses</td>
<td>26.89</td>
</tr>
<tr>
<td>Relating and integrating</td>
<td>11.98</td>
</tr>
<tr>
<td>Giving (self-) explanations</td>
<td>6.69</td>
</tr>
<tr>
<td>Total</td>
<td>45.57</td>
</tr>
<tr>
<td>Regulative processes</td>
<td></td>
</tr>
<tr>
<td>Orienting</td>
<td>1.48</td>
</tr>
<tr>
<td>Planning</td>
<td>2.34</td>
</tr>
<tr>
<td>Monitoring</td>
<td>0.00</td>
</tr>
<tr>
<td>Reflecting</td>
<td>5.07</td>
</tr>
<tr>
<td>Total</td>
<td>8.88</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
</tr>
</tbody>
</table>

Note. HL = hypermedia learning; OL = observational learning; EL = self-explanation-based learning; IL = inquiry learning.
falling within each of the three main categories (superficial processes, elaborative processes, and regulative processes) as dependent variables and the instructional approach as the independent variable. Significant differences between instructional approaches were found for percentage of superficial processes, $\chi^2(3,40) = 16.65, p \leq .001$; percentage of elaborative processes, $\chi^2(3, 40) = 20.15, p < .001$; and percentage of regulative processes, $\chi^2(3, 40) = 10.45, p < .05$. Pairwise comparisons using Mann-Whitney $U$ tests with Bonferroni corrections showed that learners in the observational learning environment spent a significantly higher percentage of their learning activities on superficial processing than those in the inquiry learning environment ($Z = -3.10, p < .008$) and those in the self-explanation-based learning environment ($Z = -2.87, p < .008$). Furthermore, learners in the observational learning environment devoted significantly fewer of their learning activities to elaborative processes than those in all three other environments ($Z = -3.78, p < .001$, for inquiry learning; $Z = -3.63, p < .001$, for self-explanation-based learning; and $Z = -2.80, p < .008$, for hypermedia learning). Finally, learners in the observational learning environment spent a significantly higher percentage of their learning activities on regulative processing than those in the hypermedia learning environment ($Z = -2.80, p < .008$) and those in the self-explanation-based learning environment ($Z = -2.72, p < .008$).

CASE ANALYSES: A CLOSER LOOK AT THE LEARNING ENVIRONMENTS

In this section, we take a closer look at the four learning environments representing the four instructional approaches. We present excerpts from learners’ think-aloud protocols to show the effects of instructional approach on the elicitation of learning processes. The protocol excerpts (all translated from Dutch) focus on the aspects of learning that are prototypical for the particular instructional approach.

**Hypermedia Learning Environment**

In the hypermedia learning environment, it was assumed that learners would need all four types of regulative processes in order to make intentional information selections and that they would read, watch, and filter information; check solution steps; and, most important for meaningful learning, relate the new information to existing knowledge and integrate it into a mental representation. In the quantitative analyses, we saw that the learners were devoting most of their processing to superficial processes such as reading, watching, and filtering and to the elaborative process of developing and testing hypotheses, but they did little in the way of (voiced) regulative processing. What is most remarkable, though, is that the
You are on holiday in the country and you happen to watch a running contest by the local boy scouts. There are 7 boys participating in the race. What is the chance that you correctly predict the winners of the gold, silver and bronze medals?

So, there are 7 boys participating in the race and I have to predict the gold, silver and bronze medalist, so three positions, eh. . .

Is that already the answer, at the first individual event, I think they mean with it that, who wins the gold medal . . .

and eh . . . yes, that’s then 1/7,

the silver is 1/6,

and the bronze is, eh, 1/5,

and then you must multiply these, that is 1/7 fraction times 1/6 fraction times 1/5. Yes, that’s right.

Note. Text in italics is text given in the learning environment that is read literally by the learner.

The total number of identified instances of engagement in learning processes in the hypermedia learning environment was low. An explanation for this can be found in the protocols. Table 3 shows a typical example of a learner in the hypermedia learning environment. In this example, Tom is working on the problem requiring the prediction of the first three finishers in a race. He first reads the problem situation (lines 1–3), summarizes that information (lines 4 and 5), and tries to find out what the information given in the learning environment tells (lines 6 and 7). He then merely follows the solution steps presented in the learning environment (lines 8–11) while stating that he understood them (line 12). In other words, he merely checks the solution steps without further elaborating on them.

Another typical example of a learner in the hypermedia learning environment is shown in Table 4. This table shows Susan’s protocol for working on the mountain bike problem. The protocol shows that Susan alternately reads the solution steps provided in the environment and tries to explain the solution steps to herself (reading in line 14 followed by explaining in lines 15 and 16; reading in line 17 followed by explaining in lines 18–22; reading in line 23). Compared to Tom, she elaborates more on the solution steps that were provided in the learning environment.

Finally, inspection of the protocols showed a third typical situation, of which Table 5 gives an example. It is an example from a protocol in which Robin works on the problem on mobile phones. Robin first reads the problem situation (lines 1–6) and summarizes it (lines 7 and 8). She then tries to predict the answer before checking the solution (lines 9–11). Robin finds out that her prediction is incorrect (line 12, line 16, line 18, and line 21), and she tries to understand what went wrong (lines 13–15, line 17, and line 19).
TABLE 4
Think-Aloud Protocol Example of Susan Working in the Hypermedia Learning Environment
(On Problem Category “Order Not Important, No Replacement”)

1. Together with a friend you take part in a two-day mountain bike course. Both days the
instructor has 5 different-colored helmets: green, blue, orange, red, and silver. Each day the
helmets are distributed at random. At the end of the day each participant returns the helmet to
the instructor. Both days you are the first one to get a helmet and your friend is the second
one. What is the chance that the first two helmets to be distributed on the first day are the red
and the green one?

2. What is the chance that the first two helmets to be distributed on the first day are the red and
the green one?

3. Well, there are 5 participants, 5 differently colored helmets, and . . .
4. What is the chance that the first two helmets to be distributed on the first day are the red and
the green one?

5. There are 5 possible outcomes, I just look how they . . . acceptable outcomes, I don’t know if
that . . .

6. Yes, first individual event, 2/5

7. Yes, I do understand the red and the green one are both an acceptable outcome, and 5 helmets,
so that must be 2/5 at the first individual event.

8. And . . . at the second individual event, so still 1/4.

9. Eh, a red and a green one . . . so one has already been returned, distributed, so is going to be
distributed, eh, so one has already been distributed and isn’t being returned, so there are

10. 4 helmets left, and if a red or green one . . . has already been distributed, then only one of
these two can be distributed,

11. so the chance is 1/4.


Note. Text in italics is text given in the learning environment that is read literally by the learner.

Observational Learning Environment

Following the underlying assumptions of observational learning, we expected learners to spend much of their time observing the pedagogical agent solving the task, which would involve the superficial learning processes of reading, watching, and filtering information and checking the solution steps presented by the agent. Furthermore, learners were supposed to reflect on their learning process after each task by rehearsing the task mentally and integrating the newly received information into a mental representation. These latter elaborative learning processes in particular were thought to lead to meaningful learning. In the quantitative analyses, we indeed found that almost half of the utterances of learners in the observational learning environment were devoted to reading, watching, and filtering. About 11% of their processing was spent on reflecting, especially concerning reflection on their knowledge. However, after each task, learners did little in the way of rehearsing the task mentally by self-explaining, relating, and integrating. Instead, they devoted about 20% of their processing to developing and testing hypotheses. The protocol analysis showed a typical pattern of learning processes.
Table 5

Think-Aloud Protocol Example of Robin Working in the Hypermedia Learning Environment
(On Problem Category “Order Not Important, No Replacement”)

1 A factory produces mobile phones. At an assembly line, the phones are provided with
differently colored fronts before they are packed in boxes. Every box contains one red, one
black, one blue, one green, one grey, and one yellow mobile phone. Before the boxes are
transported to the shops, they first go to quality control. At random order, 3 phones are taken
out of a box to be checked. What is the chance that the red, the black, and the blue phone are
taken from a box to be checked?
2 In one box there are one red, a black, blue, green, grey and a yellow, 1, 2, 3, . . . , 6. And
3 phones are taken out. What is then the chance that a red, a blue, and a black phone . . .
4 Well, the first is a red one and there were 6 phones, so 1/6.
5 Then one has gone, then it’s 1/5 for the black one
6 and then 1/4 for the blue phone, I think.
7 Just see if that’s correct, 3 out of 6 . . .
8 Oh yes, for there are of course 3 . . . phones.
9 Oh, it doesn’t matter which order you get, so then you have 3 chances to take that
10 phone out.
11 The chance that the . . . yes, then that second one is 2 out of 5,
12 ‘cause there are two choices left and five phones. Yes.
13 And the last one is then 1 out of 4,
14 ‘cause you still have one choice and there are four phones left.
15 So the number of acceptable . . .
16 Yes, you must multiply these again and then you get 6/120 is 1 out of 20.

Note. Text in italics is text given in the learning environment that is read literally by the learner.

in the observational learning environment. A typical protocol example is given in Table 6. In this protocol, Anne is working on the mobile phone problem. She reads the problem situation (lines 1–6), but before observing the pedagogical agent solving the problem, she thinks about an answer herself (lines 7–15). She then checks her own answer by observing the pedagogical agent (lines 16–28) and discovers that the answer was not correct (line 29). She briefly reflects on her knowledge and explains to herself what went wrong (line 30).

Self-Explanation-Based Learning Environment

In the self-explanation-based learning environment, the learner was expected to read, watch, and filter information provided in the worked-out examples and to check the solution steps in the examples. While doing this, the learner was prompted to self-explain the solution steps. The first problem of each problem category presented assisted self-explanation prompts in which the learner had to fill in the blanks. While working through these problems, the learner was supposed to alternately read and elaborate on what was read by making predictions and drawing conclusions. In the second problem of each problem category, the
A factory produces mobile phones. At an assembly line, the phones are provided with differently colored fronts before they are packed in boxes. Each box contains one red, one black, one blue, one green, one grey, and one yellow mobile phone. Before the boxes are transported . . . transported to the shops, they first go to quality control. At random order, 2 phones are taken out of the boxes to be checked. What is the chance that the yellow and the blue phone are taken from a box to be checked?

Well, eh . . . in one box there are six differently colored phones and it is there is no replacement, because if you have taken a yellow one, you can’t take another yellow one eh, so for that . . . eh yes, and order is not important either so it is 2 individual things again. So at the first one the chance is then . . . eh, 2 out of 6, and at the second 1 out of 5 and then you must multiply these and then eh, just see . . . 3/30 is also the chance 1 out of 10 that it eh that it happens.

The order of selection is not important. It is about the chance that both the yellow and the blue phone are taken for inspection. If first the yellow phone is selected, and then the blue one, or first the blue phone and then the yellow one doesn’t matter so much. It is a selection without replacement. For when the first phone has been checked, you may not put it back. Otherwise you can again select a phone that is already checked. Of course, that’s not the intention. Now there are 5 phones left, from which the second phone can be selected. The order is not important, so I can work here with individual events. The chance at the first individual event is 2 out of 6, the first phone can be blue or yellow. So, 2 of the 6 possibilities are correct. The chance at the second individual event is 1 out of 5.

Suppose, the controller has first drawn a blue phone. The next phone must then be the yellow one. However, there are only 5 phones left in the box. The two events are independent from each other. That’s why the chances must be multiplied, so 2/6 times 1/5. The chance at the complex event is 1/15, or 0.067.

I wasn’t quite correct then, was I?

Oh, how stupid! I said 3/30, and that’s of course 2/30 . . . oh, how silly!

Note. Text in italics is text given by the pedagogical agent that is read literally by the learner.
TABLE 7

Think-Aloud Protocol Example of Sophie Working on an Assisted Prompts Problem in the Self-Explanation-Based Learning Environment (On Problem Category “Order Important, Replacement”)

1. Together with a friend you take part in a two-day mountain bike course. Both days the instructor has 5 different-colored helmets: green, blue, orange, red, and silver. Each day the helmets are distributed at random. At the end of the day each participant returns the helmet to the instructor. Both days you are the first one to get a helmet and your friend is the second one. What is the chance that you get the red helmet on the first day and the green one on the second day?
2. You have acceptable outcomes is 1 every time, as you get 1 of the 5.
3. And, possible outcomes is that you get 5, as there are 5 helmets.
4. On the second day you also have 5 helmets, because the helmets are returned every day.
5. So it’s 1, 5 times 5, so the chance is 1/25.
6. Acceptable outcomes is 1, as you get only 1 helmet.
7. On the second day you also get 1 helmet. So, in the end you also have 1 helmet.
8. The order is . . . eh, the order is . . . important because it’s not important because it does matter on which day you get which helmet.
9. The order is not important because it does not matter which helmet you get.
10. At the first selection 1 acceptable outcome and at the second also 1, because each time you only get 1 helmet and not 2.
11. The number of acceptable outcomes does not change at every selection.
12. This is what you have filled in. The order is not important, the number of acceptable outcomes does not change. Why do you have to multiply in order to calculate the total of the acceptable outcomes?
13. The first outcomes of 5 helmets must occur in combination with exactly 5 first outcomes the first day, the second day, just see . . . 5 times 5 makes 25 . . .
14. with also 5 helmets, because every day the helmets are returned,
15. That’s why the first green branch in the tree diagram forks out in a further green branch.
16. So that’s . . . 5 times 5 . . . branches allowing for every combination.

Note. Text in italics is text given in the worked-out examples and prompts that is read literally by the learner.

self-explanation prompts were given. Sophie first reads the problem situation (lines 1–6) and checks the solution steps (lines 7–12). She then works through the assisted prompts. She alternately reads the prompts (text in italics in lines 13–30) and tries to fill in the blanks by making predictions and drawing conclusions (normal text in lines 13–30). The scaffolded self-explanation prompts forced her to think about why the calculation of the solution in the worked-out example was performed in the way it was.

Table 8 presents another excerpt from Sophie’s protocol, here working on the isomorphic PIN code problem in which support was withdrawn and open
Your bank has protected your bank card with a random four-digit code, better known as PIN code. A thief steals your bank card and immediately tries to take some money from the ATM. What is the chance that the thief correctly guesses your PIN code in one try?

Acceptable outcomes is 1, cause . . . you can only guess 1 digit

because with a PIN code you can use every digit as often as you want, for instance 3333 is also possible

and then you get 1/10 times 1/10 times 1/10 times 1/10, makes 1/10,000, is the chance that he correctly guesses the code in one try.

Acceptable outcomes is therefore 1 every time,

you can only choose 1 digit,

with the second number it’s also 1

because you can only choose 1 digit

with the third number it’s 1 again,

so every time you multiply this, so 1 times 1 times 1, with the fourth digit it’s 1 again, so . . .

is 1 times 1 times 1 makes 1. In the end, I only get 1 acceptable outcome.

Is the order important, or not? Why?

The order is important.

Because it does matter whether you place the digits in the correct order.

Why must you multiply in order to calculate the total number of acceptable outcomes?

Each time you have only eh, you can only enter 1 digit, you only have 1 digit which you can choose,

and so that’s 1 times 1 times 1 times 1, so finally there is only 1 PIN code that’s possible.

Note. Text in italics is text given in the worked-out examples and prompts that is read literally by the learner.

self-explanation prompts were given. In this example, Sophie reads the problem (lines 1–3) and follows and explains the solution steps of the worked-out example (lines 4–17). Then she reads the prompts (line 18 and line 21) and tries to answer them (lines 19 and 20 and lines 22–25). She actively tries to relate the knowledge acquired in the former problem to the present problem. The protocol analysis shows that learners experienced difficulties when the support of filling in the provided blanks was removed. They indicated that they understood the solution to the problem but found it hard to explain why it had to be calculated that way. They were less systematic in answering the questions, but the open self-explanation prompts asking the same questions as the assisted self-explanation prompts stimulated them to relate the current information to knowledge acquired in the former problem.
Inquiry Learning Environment

In the inquiry learning environment, learners were supposed to develop and test hypotheses in the simulations provided and to relate data from multiple experiments and integrate this information with prior knowledge. They were supported in this by the assignments given in the learning environment. In order to regulate the process of performing experiments, learners were also assumed to orient to the environment, plan experiments to test hypotheses, and reflect on the knowledge acquired from the data produced by the experiments performed. In the quantitative analyses, we indeed saw that learners devoted most of their processing to developing and testing hypotheses, and they also attended to relating and integrating. In order to get more insight into this result, we give some protocol examples here.

As there were different types of assignments within the inquiry learning environment, we present three protocols, each involving a different type of assignment. In the first protocol excerpt, presented in Table 9, Peter is working on an assignment in the race example. The assignment concerns a multiple choice question requiring the calculation of the probability that a certain prediction will come true.

**TABLE 9**

<table>
<thead>
<tr>
<th>Protocol Example of Peter Working on a Multiple Choice Question in the Inquiry Learning Environment (On Problem Category “Order Important, No Replacement”)</th>
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<tr>
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</table>

*Note.* Text in italics is text given in the learning environment that is read literally by the learner.
A bank has developed a new security code. The new PIN code can only consist of the following six digits: 0, 1, 2, 3, 6 or 8. Furthermore, the code does not consist of 4, but of 6 digits. What is the chance that the thief correctly guesses your PIN code in one try?

Eh... it can consist of the following digits: 1, 2, 3, 4, 6, 8, that’s 123456 digits in total... and it holds 6 digits... well, you now have a chance of 6 digits and it must hold 6 digits... and then he says 1/6 times 1/6 times 1/6 times 1/6 times 1/6 times 1/6 makes, he says the chance is 1 out of 46.656.

The simulation can be used to answer this question. Peter selects numbers for the variables (line 3 and line 6) and reads off the pattern in the solution steps (lines 7 and 8). He compares the answer acquired in the simulation with those given as answer choices in the multiple choice question and notices that the answer he wants to give based on the probability calculated in the simulation is not one of the alternatives provided (lines 9 and 10). Therefore, he has another look at the problem (lines 11–13), changes the input variables (lines 14–17), reads off the new solution steps (lines 18–20), and finds an answer that is also one of the available alternatives (line 21).

In the second protocol excerpt, presented in Table 10, Eric is working on an assignment on the PIN code problem. Eric is asked to calculate the probability of a thief correctly guessing a particular PIN code. Therefore, he thinks about which values of the variables must be inserted (lines 4–6) and inserts these into the simulation (line 7). He then reads off the chance (lines 8 and 9).

Finally, in the third protocol excerpt, presented in Table 11, Eric works on the section in which all four problem categories are integrated. Eric is asked to determine whether a certain statement is true or false. He inserts values of the variables into the simulation and compares the effect of these variables on the chances for each problem category (lines 8–10). Based on these findings he makes an inference about the truth of the statement (lines 11 and 12).

What becomes salient from these protocols is that learners took the assignments of the learning environment as a starting point and used the simulation as a calculator. As a result, learners did not state hypotheses and test these in the simulation by performing experiments. Instead, they performed experiments and drew conclusions based on the data from these experiments.
TABLE 11
Think-Aloud Protocol Example of Eric Determining the Truth or Falseness of a Statement in the Inquiry Learning Environment (All Four Problem Categories)

<p>| | |</p>
<table>
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<tbody>
<tr>
<td>1</td>
<td>The chance (p) always varies between problem categories. Determine with the aid of</td>
</tr>
<tr>
<td>2</td>
<td>the simulation opposite if the above-mentioned proposition is correct or incorrect.</td>
</tr>
<tr>
<td>3</td>
<td>Type in the space below your conclusion (correct/incorrect) and give at least 1 argument in favor of your conclusion.</td>
</tr>
<tr>
<td>4</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>The chance (p) always varies between problem categories.</td>
</tr>
<tr>
<td>6</td>
<td>Eh... I must just see how I’m going to, eh, see if that’s true.</td>
</tr>
<tr>
<td>7</td>
<td>The chance (p) always varies between problem categories, eh...</td>
</tr>
<tr>
<td>8</td>
<td>Well, he says, if I want 1 eh, helmet, he says, 1 out of 5,</td>
</tr>
<tr>
<td>9</td>
<td>If I want 2 helmets, he says, something else every other category,</td>
</tr>
<tr>
<td>10</td>
<td>With 3 he also says something different,</td>
</tr>
<tr>
<td>11</td>
<td>so this will be the case with the fourth and the fifth as well...</td>
</tr>
<tr>
<td>12</td>
<td>Eh, but that need not be so. So the chance may differ, but eh, that need not be the case.</td>
</tr>
</tbody>
</table>

Note. Text in italics is text given in the learning environment that is read literally by the learner.

DISCUSSION

We started this article by emphasizing the importance of elaborative activities. In our earlier study (Eysink et al., 2009), we found that learners who followed the instructional approaches that required them to generate content (i.e., self-explanation-based learning and inquiry learning) outperformed learners who followed instructional approaches in which all content was presented (i.e., hypermedia learning and observational learning). Although we cannot empirically relate the results of the study on learning outcomes to the results of the study on learning processes, our current study confirms that the way in which learning material is instructionally presented to learners determines which cognitive processes are elicited and how these learning processes are distributed across different activities. More specifically, the results of the present study showed that the self-explanation-based learning environment and the inquiry learning environment elicited significantly more identified instances of engagement in learning processes overall than the hypermedia learning environment and the observational learning environment. This difference held not only for the number of utterances coded as indicative of superficial processes but, more important, also for those taken to indicate elaborative activities. These results seem to contradict the assertions brought forward by Kirschner et al. (2006) that because of limitations in working memory capacity, learners are not able to engage in constructive learning processes in more open learning environments such as environments following an inquiry approach. We now analyze more deeply the learning processes learners applied in the different learning environments, then we discuss the apparent
contradictions between our results and the position of Kirschner et al., and finally we discuss the generalizability issues and the implications of our study.

**Instructional Approaches and Elaborative Activities**

Our results demonstrate that learners in the hypermedia learning environment did not engage in many learning processes; furthermore, they reveal that learners in this learning environment devoted an equal amount of their processing to superficial processing as to elaboration. The think-aloud protocols illustrate that this outcome was particularly due to the fact that learners for the most part merely processed the information superficially instead of alternating superficial processes such as reading with elaborative processes to construct an understanding of what was read. Research on reading comprehension strategies has shown that simultaneously extracting and constructing meaning through questioning, predicting, and explaining is important for understanding texts (Oliver, 2009). However, even though learners were expected to engage in cognitive processes that are the basis for meaningful learning, the hypermedia learning environment apparently did not afford learners enough opportunity or instigation for them to do so. Showing the subject matter in worked-out examples without stimulating learners to actively engage in the subject matter made them passive. Some of the learners could get themselves to try to solve the problem before looking at the solution steps and corresponding solution, but most of them merely followed along with the solution steps, resulting in few identified instances of engagement in learning processes in general and few elaborative activities in particular. As a consequence, learners’ elaborative activities mainly concerned developing and testing hypotheses, whereas we expected the hypermedia learning environment to especially elicit elaborative activities such as relating and integrating. The fact that learners did not relate different resources to one another and integrate them with their prior knowledge matches the findings of Jeong and Hmelo-Silver (2010), who indicated that learners in resource-rich environments such as hypermedia learning environments often do not pass the stage of superficial processing. Getting learners to elaborate on subject matter requires that they be made aware that this is necessary; the mere availability of resources is not sufficient.

Learners in the observational learning environment devoted most of their cognitive resources to superficial processing, and elaboration took up less than 30% of their total processing efforts. Furthermore, just as in hypermedia learning, the total number of identified instances of engagement in learning processes was low. The learners merely watched the animation and filtered information from it. The elaborative activities observed came from learners who tried to solve the problem before watching the expert solving it. Although thinking of a solution in advance is a good thing to do, observational learning places its emphasis on learners’ reflection on the subject matter after each problem. Apparently, cognitive activity such
as reflecting by relating and integrating after each task is something that does not occur spontaneously and that must be stimulated explicitly in order for it to occur.

Learners in the self-explanation-based learning environment spent half of their observed processing on elaborative activities. Although we particularly expected them to self-explain, they mostly performed elaborative activities in the developing-and-testing-hypotheses category and the relating-and-integrating category. What must be taken into account here, though, is that in the assisted self-explanation prompts, learners were asked to make predictions and draw conclusions about possible and acceptable outcomes, which was coded as developing and testing hypotheses. Furthermore, the learners’ self-explanations often included statements identifying the category of a problem, which were coded as relating and integrating. In other words, the giving-(self)-explanations category included only explanations that could not be assigned to one of the other categories, which can explain the lower number of observed processes falling in this category. Nonetheless, it can be concluded that the assistance-giving/assistance-withholding procedure supplementing the worked-out examples in the self-explanation-based learning environment elicits elaborative activities that are assumed to be responsible for the acquisition of deep understanding. Filling in blanks followed by answering open self-explanation prompts is an effective form of sense making. It supports learners in making their thinking explicit so that learning processes can themselves be used as objects for further evaluation and revision (Lin & Lehman, 1999).

Learners in the inquiry learning environment used half of their processing for elaborative activities, in particular activities that were assigned to the developing-and-testing-hypotheses category and the relating-and-integrating category. These were the activities that we expected would be performed. The fact that the learners often used the simulation as a tool to calculate the correct answer to a problem did not prevent them from engaging in elaborative activities. On the contrary, if we follow Quintana et al.’s (2004) line of reasoning, automating calculations gives room for learners to focus on relating data from various simulation runs and making inferences about the underlying model. Furthermore, as also indicated by Hmelo-Silver, Duncan, and Chinn (2007), scaffolding the learners by offering assignments matched with the abilities of the learners and structured the task so that it elicited the right processes and guided the learners in focusing on task aspects that were relevant to the learning objectives.

**Direct Instruction Versus Learner-Generated Content**

The results of this study provide input for the ongoing debate on the value of instructional approaches that provide learners with all necessary information versus ones that require learners to construct their own knowledge (e.g., see Tobias & Duffy, 2009). The most central question in this debate between advocates of direct
instruction such as Kirschner et al. (2006) and those who support more open learning approaches (e.g., Hmelo-Silver, Duncan, et al., 2007; Schmidt, Loyens, van Gog, & Paas, 2007) is whether students are able to cope with the demands of the more open environments. Our two studies, Eysink et al. (2009) and the current one, clearly show that learners are able to perform these processes and that they can gain better results in more open learning environments. How could we come to such different results?

First of all, Kirschner et al.’s (2006) main argument is based on learners working in unsupported environments. This seems a bit of an unrealistic assumption, as it is well known that unsupported learning in open environments does not work (Mayer, 2004). Well-designed environments include support for learners, and the main research efforts in, for example, inquiry learning are on finding the right scaffolds for learners to see that the learning process is efficient and effective (see, e.g., de Jong, 2010b). Also in the current study, we made sure that learners in the learning environments received well-designed support specifically suited to the instructional approach adopted. So in the inquiry learning environment, learners were given assignments that gave them subgoals while investigating the domain. In addition, the domain was made more manageable for the learners in this learning environment by first introducing each problem category separately before presenting the complete domain. In the self-explanation-based learning environment, learners were scaffolded in giving self-explanations by the assistance-giving/assistance-withholding procedure. Moreover, the self-explanation prompts were given in such a way that subgoals were made salient. Learners in the observational learning environment were supported in their reflection processes by presenting the animation in segments and by giving the learners the opportunity to control the animation. Finally, learners in the hypermedia learning environment were given a low level of learner control in order to prevent structural and semantic disorientation. In other words, all instructional approaches were accompanied by scaffolds tailored to the specific approach. As a consequence, the effects that were found can be attributed to neither “pure,” unguided instructional approaches nor specific types of scaffolding. Instead, they must be ascribed to the instructional approaches of which the scaffolds were an integral component.

Second, Kirschner et al. (2006) based their arguments for the ineffectiveness of open learning environments on the limitations of working memory. In practical learning situations, learners have many opportunities to relieve the burden of their working memory, for instance by making notes, replaying episodes, and so on. In most studies in cognitive load theory, this kind of offloading of working memory is prevented (de Jong, 2010a). In our learning environments, however, the learners were supported in offloading their working memory. For example, in all environments, working memory load was automatically decreased for the learner by providing subgoals (e.g., presenting the solution steps to calculate the
probability in succession instead of all at once), and there were, for instance, no time restrictions on processing the solution steps, not even in the dynamic observational learning environment in which the animation could be paused and replayed.

Does It Work for All Learners?

The prior knowledge principle of Kalyuga (2005) states that learners who have previously obtained a considerable amount of knowledge in a specific domain benefit from different design principles than learners who are novices in the domain. Following this principle, one could argue that the effectiveness of instructional approaches may interact with learners’ prior knowledge levels. Park, Lee, and Kim (2009) designed a study in order to see whether learners with different levels of prior knowledge benefited equally from instructional measures. They compared learners with low and high levels of prior knowledge working either in a high-interaction learning environment (i.e., an inquiry learning environment in which interactivity concerned interacting with a simulation) or in a low-interaction learning environment (i.e., a learning environment in which interactivity concerned controlling the pace of an animation). They found that high-knowledge learners understood the concepts in the presented domain better after learning in the high-interaction learning environment than after learning in the low-interaction learning environment, whereas low-knowledge learners understood the concepts better after learning in a low-interaction learning environment than after learning in a high-interaction learning environment. Based on this and other results (e.g., Kalyuga, Chandler, & Sweller, 2001) it would in our case have been reasonable to expect low-knowledge learners to benefit most from direct, low-interaction instructions, such as hypermedia learning and observational learning, and high-knowledge learners to benefit most from high-interaction instructions in which learners have to generate (parts of) the subject matter themselves, such as self-explanation-based learning and inquiry learning. This means that the learners that we used in our earlier study (i.e., learners without prior knowledge of the domain) would benefit most from the hypermedia and observational learning environments, and the learners in the present study (i.e., learners who did have prior knowledge) would benefit most from the self-explanation-based and inquiry learning environments. The results, however, show that both the low-knowledge learners in the former study as well as the high-knowledge learners in the present study performed best (in terms of learning outcomes and learning processes, respectively) when learning in a self-explanation-based learning environment or an inquiry learning environment. Apparently, the instructional approaches implemented in these learning environments stimulate low- as well as high-knowledge learners to deal with the subject matter in such a way that good results can be obtained. Low-knowledge learners are given enough support to
develop familiarity with and knowledge about concepts and procedures needed in the domain, and high-knowledge learners are given enough guidance to engage in elaborative processes needed for meaningful learning. Nevertheless, it would be interesting to see whether these conclusions hold in systematic and controlled experiments designed specifically to investigate the differential effects of prior knowledge on the effectiveness of the four instructional approaches.

Scope of Our Results

All research is conducted under specific circumstances that influence the results in some way. The research presented in this paper compared four instructional approaches that were modeled in a specific way. Take as an example the dolphin in the observational learning environment. If, instead of an intelligent animal, the pedagogical agent had been a human expert, or say a role model for the learners, the results might have been different. Another example comes from the choices concerning the support in each instructional approach. The choices were tailored to the specific approaches, but one could still argue that other choices might have led to different results. For instance, learners in the observational learning environment were supported in their reflection processes by presenting the animation in segments and by giving the learners the opportunity to control the animation. However, reflection could also have been supported by providing reflection prompts. Therefore, all results should be interpreted in light of the full implementation of the approaches as realized in this study. Further research is needed to see whether other choices, such as providing reflection prompts in the observational learning environment, would lead to different results. Moreover, the approaches were implemented in computer-based learning environments in which the role of the teacher was eliminated so that the teacher would not become a confounding variable. It would be interesting to see what happens to the results when the approaches are implemented in a classroom setting in which the teacher can, for instance, decide to stimulate or motivate learners to reflect on the subject matter.

Related to this classroom setting in which learners often work together, it would be interesting to know whether the results found can also be generalized to a collaborative learning setting. In the case of self-explanation-based learning, explaining the subject matter to oneself naturally becomes explaining the subject matter to a partner. As long as the partners have similar levels of prior knowledge and the explanations are understandable to both partners, collaboration in an explanation-based learning environment is likely to lead to similar or even better results. Inquiry learning also fits collaboration naturally. Learners must decide on experiments, and the results of these experiments must be compared and evaluated in such a way that conclusions can be drawn and new experiments can be performed. Exactly those characteristics of inquiry learning environments that lead to elaborative processing match collaboration and can in a collaborative learning setting lead to similar or even better results (cf. Gijlers &
Implementing collaboration in an observational learning environment seems less evident, as watching an instructional animation is an individual activity. Pausing animations to discuss can interrupt the train of thought of the other person. However, one of the basic assumptions of observational learning concerns learners’ reflection on the subject matter after each problem. Although individual learners were not inclined to reflect afterward, one could argue that there is a chance that collaboration would increase this tendency, leading to better results. The same applies for hypermedia learning. Collaboration in this instructional approach could afford learners the opportunity to discuss relations between different resources, activities hardly done by individual learners.

Finally, this study was conducted in the domain of probability theory, which falls within the domain of mathematics. Although learners in this domain often do not go beyond procedural knowledge (i.e., performing the operations in order to come to the right solution without understanding what is done and why; Cheng, 1999), it is imperative in order to gain real understanding of a mathematical domain to be cognizant of the fact that mathematical symbols represent principles and concepts underlying the procedures and to deal with the subject matter in this manner (Ohlsson & Rees, 1991). In light of this, we argue that, from a learning perspective, a mathematical domain is not so different from other domains (e.g., empirical domains such as physics, chemistry, or biology) in which conceptual understanding in addition to procedural knowledge is important for gaining a deep understanding of the domain.

Conclusion

Asking learners to generate (parts of) the subject matter as it happens in inquiry learning and self-explanation-based learning leads to more engagement in elaborative learning processes than more instructivist approaches such as hypermedia learning and observational learning. Related work has shown that the two instructional approaches that stimulate learners to engage in elaborative processes also lead to higher learning outcomes. Well-designed learning environments, however, should not only stimulate elaboration but also focus on means to adequately support learners to avoid potential overload.

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REFERENCES


APPENDIX

1. Superficial processes

1.1. Reading, watching, and filtering

→ learner literally reads texts
→ learner distinguishes major points from side issues
  “10 runners, 3 prizes”
→ learner summarizes
  “the helmets are handed out on two consecutive days”
→ learner memorizes given information
  “I have to remember that I have to multiply instead of adding”

1.2. Checking solution steps
  “That is 1/5 and 1/5 and they again multiply it”

2. Elaborative processes

2.1. Developing and testing hypotheses

→ learner asks himself or herself content-related questions
  “what would happen to the probability if there are more runners in the race?”
→ learner makes assumptions
  “I think the chance will be 1/5 × 1/4 × 1/3”
→ learner draws conclusions
  “the chance decreases with more runners”

2.2. Relating and integrating

→ learner activates prior knowledge
→ learner thinks of examples/makes analogies
→ learner deduces relations between variables that differ between problem categories and between variables that can vary within problem categories
→ learner assigns problems to problem categories
  “so order is important here”
  “The chance that the first two helmets are a blue and a green one . . . so that can be blue and green, but it can also be green and blue”

2.3. Giving (self-) explanations

3. Regulative processes

3.1. Orienting (prior to a task or set of tasks)

→ learner orients to content of the environment
“there are 8 assignments”
“this assignment has been worked out step by step”
→ learner orients to the workings of the environment
“why doesn’t something happen when I push this button?”
“Oh, the animation disappeared already”
→ learner orients to prior knowledge
“I’ve had this with mathematics”
“I don’t know this”
“how did I do this in the last assignment?”

3.2. Planning (planning of actions in the shorter or longer term prior to a task or set of tasks)

→ learner determines a strategy (plans in the longer term)
“I will first read the assignment and then I will . . .”
“I will first try 7 runners in the simulation, and then I will try 1, so I can see what the difference is”
→ learner directs (plans actions performed straightaway)
“I will now try 3 in the simulation”
“let’s have a look at the animation”
“I now move on to the next assignment”

3.3. Monitoring (monitoring ongoing learning as compared to a plan made earlier)
“How many more to go?”
“I haven’t got enough time to do all the assignments”

3.4. Reflecting (after a task or set of tasks)

→ learner reflects on how he or she learned
“Maybe I should have tried to vary one variable at a time instead of more than one”
→ learner reflects on his or her motivation
“this was boring”
→ learner reflects on his or her knowledge
“I still don’t understand what replacement is”
→ learner reflects on the learning environment
“I’ve got the feeling that every time the same information is given”