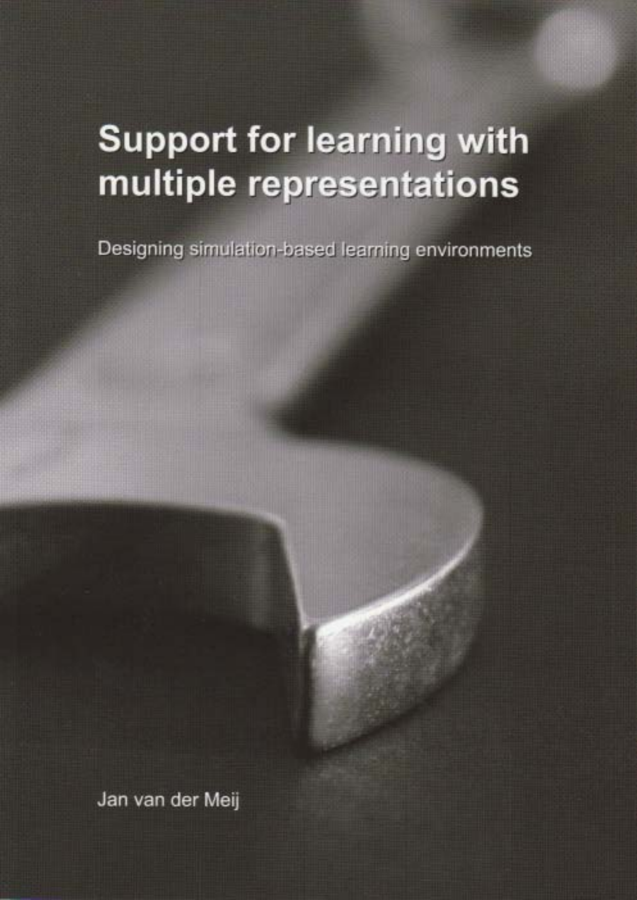

Support for learning with multiple representations

Designing simulation-based learning environments

Jan van der Meij

Support for learning with multiple representations

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SUPPORT FOR LEARNING WITH MULTIPLE REPRESENTATIONS
DESIGNING SIMULATION-BASED LEARNING ENVIRONMENTS

PROEFSCHRIFT

ter verkrijging van
de graad van doctor aan de Universiteit Twente,
op gezag van de rector magnificus,
prof. dr. W.H.M. Zijm,
volgens het besluit van het College voor Promoties
in het openbaar te verdedigen
op donderdag 20 december om 13.15 uur

door

Jan van der Meij
geboren op 29 mei 1970
te Tzum

Dit proefschrift is goedgekeurd door de promotor:
Prof. dr. A.J.M. de Jong

Preface

In November 2000, at the European Academic Software Award finals, I asked both Ton de Jong and Wouter van Joolingen if they had a PhD student position for me. I had worked for CINOP in ‘s-Hertogenbosch for four years at that time and was looking for a new challenge. Ton had just earned his professorship which came with some money to employ a PhD student and he offered me a job. Wouter, working at the University of Amsterdam, also had a PhD position available.

Over that Christmas, Elly and I had a lot to think about. Taking one of the jobs meant moving to either Amsterdam or Enschede, selling our house in ‘s-Hertogenbosch. This also meant a job change for Elly.

After Christmas I called Ton and said yes. We agreed that I would get a contract for five years to work four days a week on my PhD-project and one day a week on other projects and lectures. I started on the first of March 2001. Since Elly was pregnant we decided not to move until she gave birth to our beautiful daughter Emma, in May 2001. Ton kindly offered a three day work week in Enschede and two days at home. Every Monday night I stayed on campus. Those first months, studying, working and even sleeping on campus made me feel like a student again. Which of course I was! Moving to Glanerbrug in November however felt like coming home. I had always loved Twente and now I was living there again.

In December 2001 I was asked to join the OPUT for one day a week. Jules Pieters, who was our dean by that time, agreed that my contract could be extended for a year and I said yes. I now had three days a week left to work on my PhD project. I participated in the OPUT until the first of August 2006. This was the day that I got a job as Assistant Professor in our instructional technology department for which I am very grateful. The new job meant giving more lectures and postponing the promotion date from March to December 2007.

Working 6 and a half years on a PhD-project seems a long time. However, I did not feel like that at all. Of course, a lot of things happened during the past years. I became 6 and a half years older, learned to do research and bought two new motorbikes. Elly also became 6 and a half years older, found a great job in Holten and bought a big Italian car. Emma is over six years old now and is learning to read, write and swim.

This thesis is the result of the research I carried out in the past years. Although my name is on the cover and I am the one who is going to defend it, I did not do all the work alone. There are a lot of people who have contributed to this thesis.

First of all I would like to thank my promotor and supervisor Ton de Jong for his trust in me and his support during my PhD trajectory. Although we did not always agree on the route to follow, we always came to an accord. Ton, you taught me a lot.

Even though Hans van der Meij was not my supervisor, I could always ask him for help on the various ‘problems’ I encountered. He helped me to look critically at my own work and to focus on the main points. He is a colleague and friend who always reminds me to not only see my weak points but to trust in the things I am good at. Hans, thank your for that. I would also like to thank Jos Boeije for his work on the SimQuest simulations. Jos, without your help I would still be struggling to get the simulation models running. During the analyses of my first study Hannie Gijlers and Ard Lazonder helped me with statistical analyses. It had been while since I used statistical tests and Hannie and Ard had to help me with even the simplest things. Thank you both for explaining them to me with much patience. The experiments could not have been done without a working version of SimQuest. Wouter van Joolingen, Paul Weustink and, during the first three years, Koen Veermans were always there to do some just in time fixes and implementations. Thanks to you guys, SimQuest ran smoothly in every school for all three experiments. Although Sarah Manlove and Emily Fox say my English writing is excellent, they did a great job in making my texts better. Thank you both.

Speaking of the schools: The experiments could not have been carried out without them. I would like to thank all teachers and students from ROC Utrecht, ROC A12 Ede, ROC Nijmegen, ROC van Twente locatie Hengelo, ROC van Twente locatie Almelo, Bonhoeffer College Enschede and De Waerdenborch Holten for their participation.

Doing PhD research is often associated with working in solitude. Luckily, thanks to my fellow PhD students and colleagues, I didn’t feel isolated at all. I feel very comfortable in our department and have (had) many interesting discussions about my and their work together with lots of ‘off topic’ and personal talks.

Although I always call my father if I need advice, I am glad that I do not always take it. If I had done so, I would now be a mechanical engineer in some factory in Friesland, which of course might have been a great job. Despite the fact that my father asked me ‘Isn’t it time for you to find a job now?’ after I finished middle vocational training and teacher training, he was always proud that I didn’t listen. Both my parents have always supported my choices. I am very grateful for that.

Finally, I thank Elly and Emma for always being there and standing by me in every way they can. I love you.

Jan van der Meij
November 2007

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1

Introduction

Many learning materials offer multiple representations. Textbooks, for example, use photographic images to illustrate and explain parts of the text. In early computer-based learning environments texts and images were provided in the same way as in textbooks, namely as static images. Therefore, research on representations in textbooks was also valid for these early computer-based learning environments. In modern, computer-based learning environments many additional representation types are available, including: audio, video, animations and dynamically changing graphs and tables. This offers new challenges and opportunities and calls for a new line of research to study the implications for learning when using these multiple dynamic representations. This thesis bundles three studies on supporting learning with multiple representations in simulation-based learning environments.

Representations

When learners study the behaviour of a phenomenon present in the real world they rarely use the real system. A representation[1] of the real system is often used when studying the domain. A representation of a real system describes the system, but is not the system itself. According to Palmer (1978), a representation is something that stands for something else. It is some sort of model of the thing (or things) it represents. Palmer proposes any particular representation should be described in terms of: (1) the represented world, (2) the representing world, (3) what aspects of the represented world are being represented, (4) what aspects of the representing world are doing the modelling and (5) the correspondence between the two worlds. A world, X, is a representation of another world, Y, if at least some of the relations among objects of X are preserved by relations among corresponding objects of Y. Other authors agree with this description of representations. For example, Bechtel (1998), in an article on dynamical systems theory, writes that the function of a representation is to stand in for something else. He also points out that the format of the representation is very important and that it has to be coordinated with the process in which it is used.

[1] In this thesis we focus on external representations as opposed to internal ones. External representations are depictions or descriptions existing outside the learner. Internal representations refer to the learner's stored cognitive structures (Shavelson, 1974). When we use the term representations, we refer to external ones.

There are several reasons for using representations instead of real systems in learning environments. In some cases the system itself is not available or not suitable for teaching. In other cases (the representation of) the real system has to be enhanced, for instance by representations of forces, before it can be used for learning or embedded in other relevant learning material.

Representations in simulation-based learning environments

In our research we focus on learning with multiple representations in simulation-based learning environments. Before describing the benefits and challenges of using multiple representations, we focus on the use of representations in simulation-based learning environments. Simulation-based learning environments offer learners the opportunity to perform experiments in controlled settings. They are safe to work with, may increase the availability of inaccessible or expensive systems, use minimal resources, are modifiable and may allow for experimentation with systems that normally cannot be physically manipulated. Moreover, simulations offer new instructional opportunities. For example, simulations visualize processes that are invisible in natural systems by, for instance, showing animations of speed vectors or graphs of quantities such as energy or impulse. In this way, multiple views and multiple representations of the simulated system can be offered.

The representations in simulation-based learning environments are often dynamic. This means the information they hold changes based on manipulations in the learning environment. Simulation-based learning environments contain an executable model of a (natural) system. They simulate the behaviour of the modelled system. Learners explore the simulation model by manipulating values of (input) variables and observing the behaviour of other (output) variables. By understanding the relations between the variables, it is expected that learners acquire a deeper understanding of the domain and are able to transfer this knowledge to similar ‘problems’ in other (real) situations.

In simulation-based learning environments the real system is described by a simulation model. The simulation model is an abstract representation of the real system that describes its behaviour. In many situations this simulation model is too complex to let novice learners learn the simulated domain. Moreover, the simulation model only shows the mathematical relations between the variables. This is seldom sufficient for learning a (new) domain. This is the reason that the simulation model is not visible for the learner in most simulation-based learning environments. The learner interacts with the model through additional representations such as animations, numerical outputs, graphs and tables. As a result, in simulation based learning environments the real system is represented by a model which is itself also represented (see Figure 1-1).

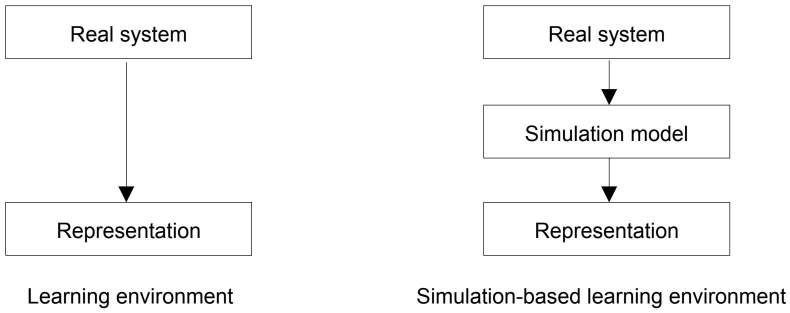

Figure 1-1 Representations of learning environments

Multiple representations

We speak of multiple representations when two or more representations are used to represent real systems or processes. These representations can represent different aspects of the real system or can represent the same aspects in different ways. According to Palmer (1978), combining two or more representations of the represented world can model the same set of objects in three ways. First, representations are *non-equivalent* if each representation models different relations among the represented objects. Second, representations are *informationally equivalent* if they model the same relations in different ways. Third, if representations model the same relations in the same way they are *completely equivalent*. Despite this, they may appear different because of the context they are used in and/or operations performed on them. According to Palmer it is important that the learner always realise a representation is not the real system. Information discovered in the representation should always be translated (back) to the real system.

An illustration of a simulation-based learning environment using multiple representations is shown in Figure 1-2. The figure shows the interface of a simulation concerning the braking distance of a scooter with different initial speeds, different braking power, different masses and different road conditions.

The different representations in this simulation-based learning environment present different aspects of the subject matter. *Numerical fields* are used for both setting the initial speed and braking power and to observe mass, current speed, and distance. A *graph* is used for representing the actual (real time) speed against time. *Animations* are used to represent the scooter and for showing the current speed (speedometer). Beneath the animation of the scooter riding in the landscape a *slider* represents the braking distance of the scooter. These aspects concern the “view” of the simulation model which is the focus of the studies in this thesis. Additional representations are available for operating the simulation. Learners can scroll the graph and store or erase the current run with *action buttons* under the graph. Action buttons are also used to start, stop, and reset the simulation. They are located in the left bottom corner of the window. *Radio buttons* are used for setting the road condition and the mass of the scooter.

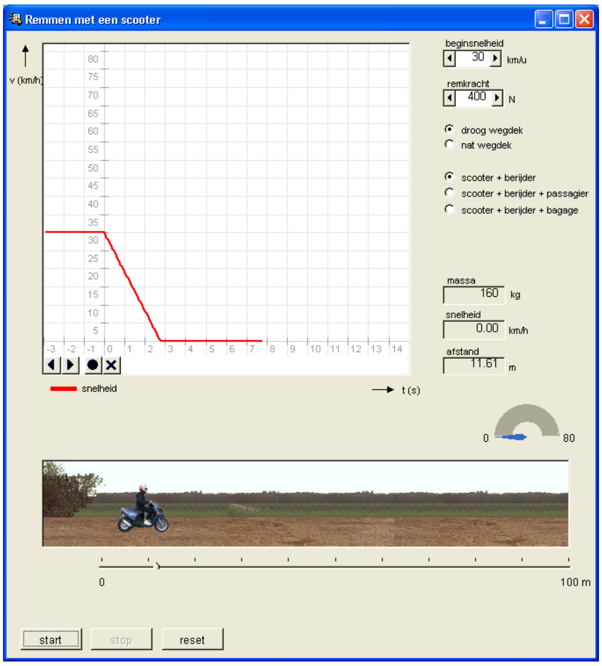

Figure 1-2 Interface showing scooter braking distance

In this learning environment the representations are partially informationally equivalent. For example, the magnitude of the initial speed is shown in an input field, in the graph, and in the animation of the speedometer. The initial speed is also visible in the animation of the scooter, but the magnitude cannot be read off this representation.

Presenting two representations is not automatically better than one (Petre, Blackwell, & Green, 1998). These authors point out that a single representation uses less screen space, avoids problems of switching from one representation to the other and of finding the right place in each one and avoids the problem of working out which parts of the representations are equivalent. So, the question is: Why use multiple representations?

Reasons for using multiple representations

The basic idea of using multiple representations is that learners can benefit from the properties of each representation. If learners are capable of mentally integrating the information from several representations they have a more complete picture of the represented domain compared with learning the domain with only one representation. It is expected that this will lead to a deeper understanding of the subject being taught (Ainsworth, Bibby, & Wood, 1997; de Jong et al., 1998; Seufert, 2003; van Labeke & Ainsworth, 2001). We believe acquiring deeper knowledge is the main reason for using multiple representations. Learning with more than one representation is assumed to encourage learners to reason with and reflect on the similarities and differences between the representations in order to gain better understanding of the domain. We believe this so-called translation between representations is the most important process in learning with multiple representations. According to Petre, Blackwell and Green (1998), translation between multiple representations forces reflection beyond the boundaries and details of the separate representations. In her multiple representations framework, Ainsworth (2006) also identifies the construction of deeper knowledge as one of its main functions. She argues that multiple representations support deeper knowledge construction that leads to a more abstract and extended understanding of the domain. Other key functions according to both Ainsworth and Petre et al. are the so-called complementary and redundancy function and the constraining function. We argue that these two functions are supportive of the main function: constructing deeper knowledge. In addition, the *forms* of the representations are equally as important as their *functions* in multi-representational learning environments. One cannot consider the function of a representation without referring to its form.

In the remainder of this section we describe the three main functions of multiple representations in more detail with reference to the functional taxonomy of Ainsworth (1999), to the reasons for using multiple representations according to Petre et al. (1998) and to Palmers' (1978) classification of multiple representations. In addition, we clarify each of the functions by giving examples of how they can be integrated in a specific type of multi-representational learning environment: computer simulations.

Construct deeper knowledge

As indicated above, we consider constructing deeper knowledge to be the main reason for using multiple representations. According to Ainsworth (2006) multiple representations support the construction of deeper knowledge when learners integrate information from several representations to achieve insight that would be difficult to achieve with one representation. Citing Bransford and Schwartz (1999), she writes that insight derived in this way increases the likelihood of transferring this knowledge to new situations. Petre et al. (1998) use the term "useful awkwardness" for the process of integrating information from different representations in order to acquire deeper understanding of the domain. They believe the use of multiple representations forces learners to reflect beyond the boundaries and details of a first representation to anticipate correspondences in a second one. While Petre et al. do not elaborate on deeper knowledge construction, Ainsworth does. She distinguishes three sub-functions that lay the foundations for deeper knowledge construction: abstraction, extension and relation.

Abstraction

It is expected that when learners build references across multiple representations they acquire knowledge about the underlying, more abstract, structure of the domain represented. When learners have a more abstract understanding of the domain, it is believed that they can use this understanding in new situations. If learners studied the simulation of the hoisting crane shown in Figure 1-3 without the graphs represented simultaneously with the other representations, it could well be the case that they would not notice the linear relation between the length and torque and between the force and torque. It is assumed that learners study the correspondences (and differences) between the representations when multiple representations are presented simultaneously and thereby get a more abstract understanding of the domain.

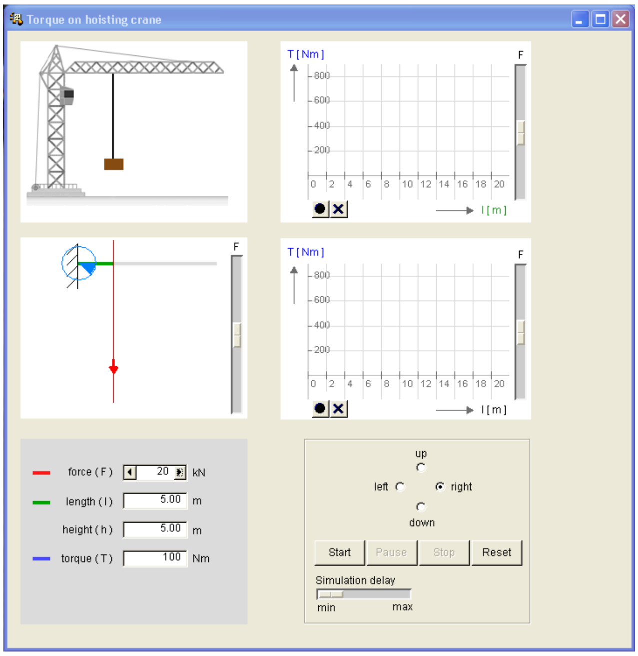

Figure 1-3 Interface of simulation on torque

Extension

It is expected that, by using multiple representations, subjects can transfer their knowledge of the domain presented in the learning environment to other, comparable, situations (e.g., Ainsworth, 1999; Petre et al., 1998). By using multiple representations it should be easier to apply knowledge to new situations because learners acquired their knowledge at a more abstract level (see the section on Abstraction, page 6). When learners have studied the behaviour of torque on a hoisting crane with the simulation shown in Figure 1-3, it is expected that they are then able to apply their knowledge to the simulation shown in Figure 1-4. In this simulation learners study the behaviour of torque on a nut when operating an open-end spanner. Learners can change the position of the hand (length), and can change the value and direction of the force. However, extension can also lead to misconceptions, as when learners use the operators appropriate for reading a table for reading the information of a graph.

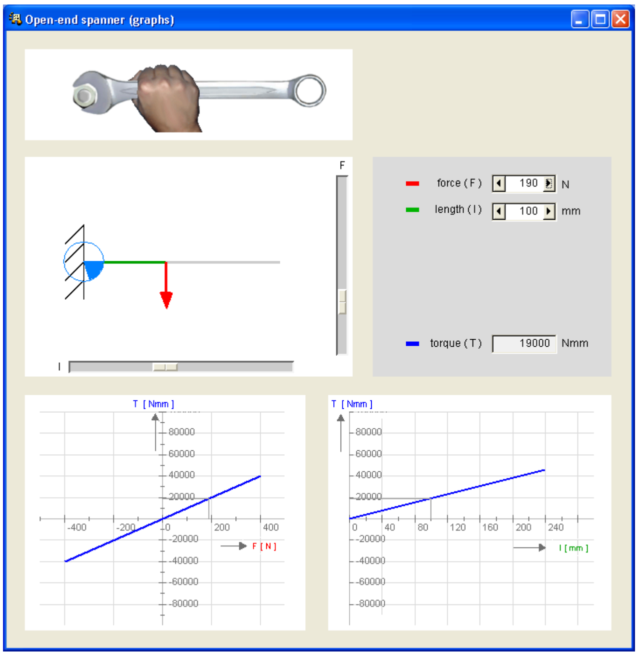

Figure 1-4 Interface showing torque on nut

Relation

Ainsworth (2006) describes relation as the association of two representations without reorganisation of knowledge. She considers relating representations to be one of the processes that lead to the construction of deeper knowledge. In her framework, Ainsworth does not make clear whether she considers relating representations to include reasoning about the relations or to involve only finding the relations between representations at a surface level. If she defines relation as the former, we do agree this can lead to deeper understanding; however, we would not call this relating. We would call it translating between representations (see the section on Translating between representations, page 19). If she defines relation as finding similarities and differences in two or more representations on a surface level, as we do (see the section on Processing multiple representations, page 17), we do not agree with her that this leads to deeper understanding. In learning with multiple representations, relating representations is very important, but relating alone is not enough. A learner has to reason about the relations in order to construct deeper knowledge. That is why we do agree with Ainsworth when she also writes that relating may serve as the basis for abstraction. In the section on Processing multiple representations on page 17, we describe the process of relating representations in more detail when we describe the four tasks learners have to perform to be able to learn from multiple representations.

Complementary and redundancy function

When using multiple representations, each representation can show specific aspects of the learning material or can show the same aspects of a domain in different forms (e.g., an animation showing, technically, the same information as a graph). Ainsworth (1999) uses the term 'complementary functions' for describing both complementary and redundant functions of multiple representations. Since 'complementary functions' does not cover both, usually combined, functions, we speak of 'complementary and redundancy function'. Even when representations complement each other, in most multi-representational learning environments there is considerable information overlap between the representations. In fact, redundancy is essential to be able to relate different representations. Because Palmer (1978) only focuses on the information a representation contains, in his view the complementary and redundancy function is the essential function of multiple representations.

By combining representations that contain different information or support different processes (Ainsworth, 2006), it is assumed learners can benefit from the advantages of each of the representations (Tabachneck-Schijf, Leonardo, & Simon, 1997). In their discussion of reasons to use multiple representations, Petre et al. (1998) mention only support for different information. They speak of both 'multiple identical representations' and so-called 'heterogeneous inference' which they borrowed from Stenning and Oberlander (1995). With 'multiple identical representations' they mean that different representations can provide different views on the same objects. Architects, for example, can provide multiple simplified 2 dimensional views of three dimensional objects. With 'heterogeneous inference' they mean that the learner has to integrate two or more representations in order to encompass the whole of the problem.

Different types of representations may be useful for different purposes, as they differ in their representational and computational efficiency (Larkin & Simon, 1987). Text and pictures, for example, are good representations for presenting the context of a problem. Diagrams are well suited for presenting qualitative information. They can hold information that supports computational processes by indexing of information (Larkin & Simon, 1987). Graphs, formulas and numeric representations can be used to show quantitative information. Graphs, in particular, are important tools in enabling learners to predict relationships between variables and to show the nature of these relationships (McKenzie & Padilla, 1984). Graphs show trends and interaction more successfully than alphanumeric representations. An example is the distinction between an equation such as '$y=x^2+2x+5$' and an informationally equivalent graph. The equation does not explicitly show the variation, which the graph does. According to Cox and Brna (1995) the cognitive effect of graphical representations is the reduction of search and working memory load by organising information by location. For example, tables make information explicit and can direct attention to unsolved parts of a problem (e.g., empty cells of a tabular representation).

Ainsworth (1999) distinguishes between different information and different processes. We illustrate these with examples from simulation-based learning environments.

Different information

There are many reasons for using multiple representations showing both complementary and redundant information. In this section we give the following examples:

1. When one representation is insufficient to show all domain aspects.
2. When one representation becomes too complex to show all the information.
3. To show the domain from different perspectives.
4. To vary domain precision or complexity.

When one representation is insufficient to show all domain aspects. Many domains have different aspects that are each best shown through a specific type of representation. By only showing a graph of a process, for example, the process itself is not shown. If it is important to show the process, a second representation can be used. An example is presented in Figure 1-5.

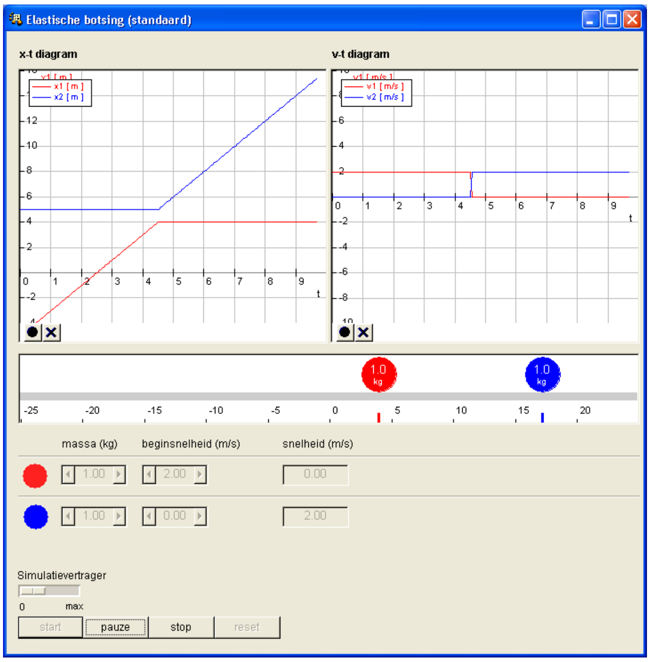

Figure 1-5 Interface of simulation on collisions

The animation shows the position of the balls, their initial speed and end speed, and their masses (as numbers inside the balls). The animation gives a ‘real life’ representation of the domain, but cannot show all important aspects of the domain. An important aspect of the domain collisions is to understand the relation between mass and initial speed in the collision. The animation can give an idea of this relation, but the exact relation cannot be read off the animation. A graph is an appropriate representation to read off relations, but it cannot show the real life situation. While the single representation cannot show all aspects of the domain, the combination of both can.

When one representation becomes too complex. To learn a domain containing many variables, the domain information can be distributed over several representations. This results in representations that are easier to process.

The sewage plant (Figure 1-6) is a complex system in which different processes are involved. In order to understand the system, the learning environment first provides an overview of the complete system and then zooms in on the separate parts. Figure 1-7 shows an example of one of the parts. With this representation learners can study the behaviour of a sandtrap.

When the behaviour of several variables in a complex process is presented by graphs, using multiple graphs showing the behaviour of different variables is often preferable over using a single graph showing all variables. With multiple graphs the learner can easily study the behaviour of one variable. A drawback is that it is harder to compare two variables that are presented in different graphs, even when these graphs are presented simultaneously.

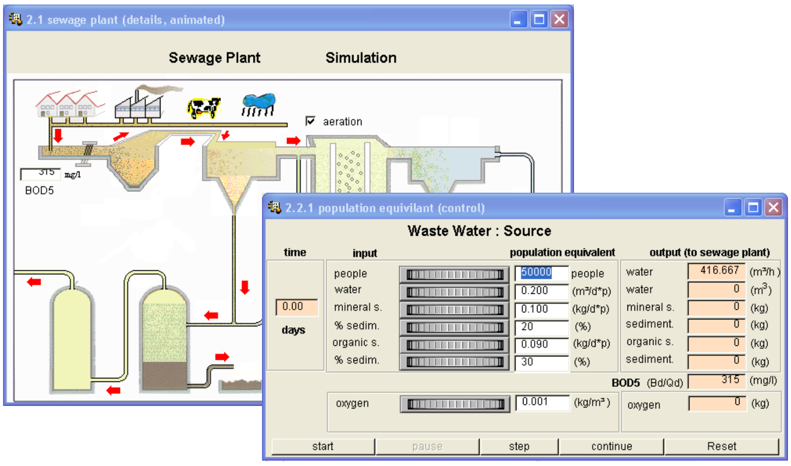

Figure 1-6 Interface showing overview of sewage plant

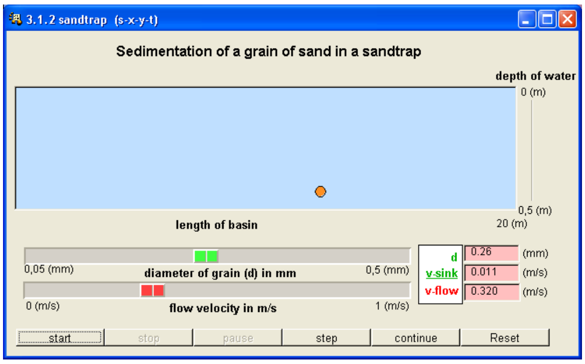

Figure 1-7 Interface showing sedimentation of sand grain in a sandtrap

Showing the domain from different perspectives. Multiple representations can show a domain from different perspectives. Showing a domain from different perspectives can mean showing it from different angles or showing different functionalities of a domain. Figure 1-8 shows a lathe from different angles.

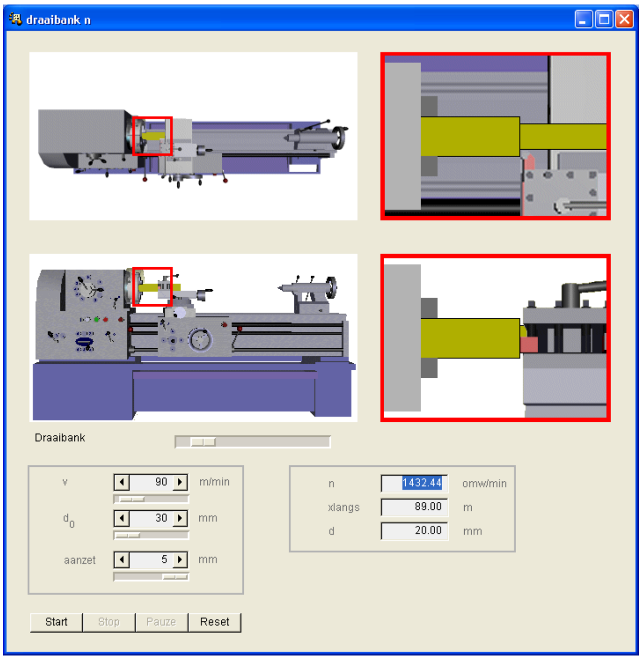

Figure 1-8 Interface showing lathe from different perspectives

By doing this, the learner is expected to have a better idea of how the machine works. The left representations show the complete machine from the side and from above, and the right representations zoom in on the important part of the machine. An example of showing different functionalities would be showing the engine of a car from a mechanical and electrical perspective. In simulation-based learning environments, the simulation model needs to be suitable for modelling different perspectives of the domain (see White & Frederiksen, 1990).

Varying the precision or complexity of the domain. When a learner explores a new domain it can be useful to present the domain first in a qualitative way before introducing the values of the variables involved. Examples are shown in Figure 1-9. The interfaces presented belong to a simulation where the learner first explores the simulation by doing several assignments that encourage the learner to explore the simulation in a qualitative way. In a second stage the values of the variables are introduced and the learner can then explore the relation between the variables in a quantitative way.

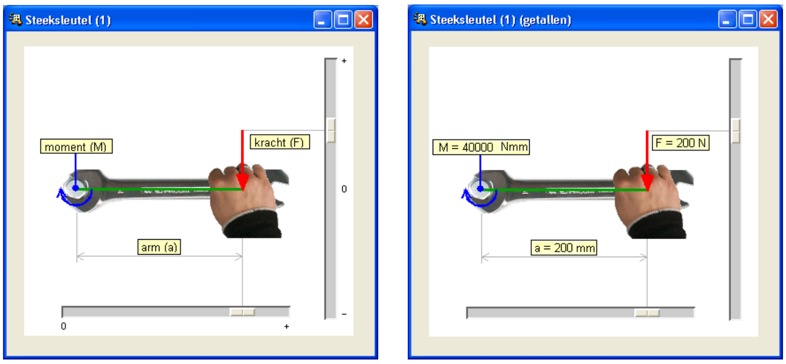

Figure 1-9 Interface showing qualitative (left) and quantitative (right) variables

In this example the representations are shown in sequence. Another example would be to present an animation showing the domain qualitatively alongside an equation showing the same domain quantitatively.

Domain precision can also mean the domain is sequenced from simple to complex to support learners in learning the domain gradually. In this case different representations are used to support so-called model progression (White & Frederiksen, 1990). One type of model progression is increasing the model complexity step-by-step. In this case a first representation only shows some variables, whereas successive representations show more variables.

Different processes
Ainsworth (1999) subdivides support for different processes into three categories:

1. Strategies
2. Individual differences
3. Tasks

Strategies. Using multiple representations can encourage learners to use more than one strategy to solve a problem (Ainsworth, 2006). An example is shown in Figure 1-10. To find the phase shift in a given electrical circuit learners may switch between the graph and the vector diagram to find the right answer.

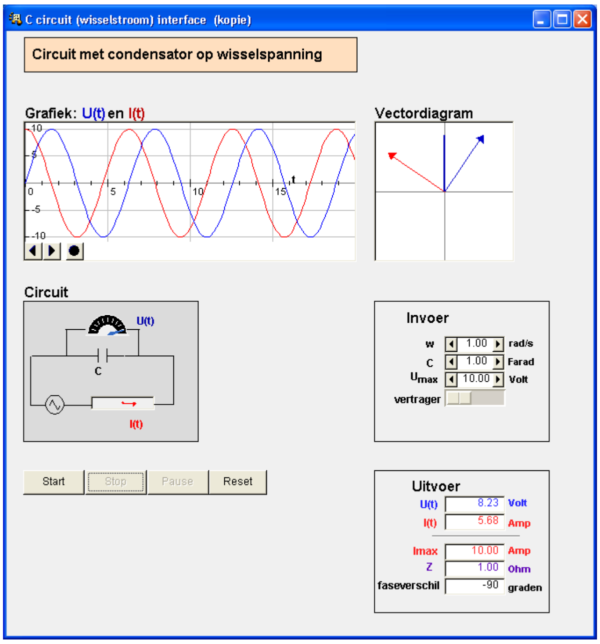

Figure 1-10 Learners are able to switch their strategy by using a different representation

Individual differences. Different learners may have different preferences for representations. For one learner a formula may be the preferred representation for understanding the domain, while for another it is an informationally equivalent graph (see Figure 1-11 for an example). Providing multiple representations allows learners to explore the domain using the representation(s) of their choice. However, preference for specific types of representations has to be handled with care. Schuyten and Dekeyer (2007) found that learners with preference for textual information had lower performance in statistics. Moreover, preferences for specific representations might lead to the processing of only one of the provided representations (see e.g., Tabachneck-Schijf & Simon, 1998).

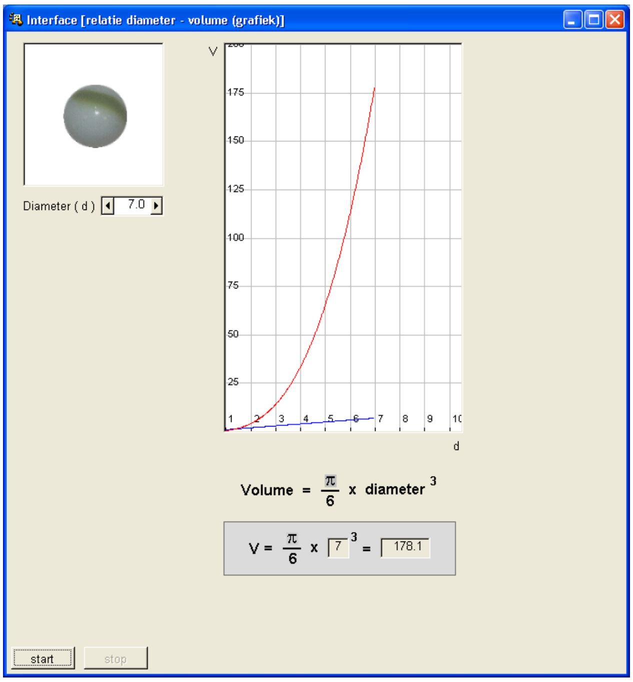

Figure 1-11 Interface showing both a formula and a graph

Multiple tasks. In many learning environments learners have to perform a number of different tasks to achieve a particular goal. The goal in simulation-based learning environments often is that learners learn to understand the underlying model by exploration. Frequently, the underlying model is explored by performing different tasks on multiple representations representing some aspects of the simulation model. One representation is typically not sufficient to support the different tasks the learners have to perform. Particular representations facilitate performance on certain tasks.

When the task for the learner using the interface shown in Figure 1-12 is to position the people on the seesaw at the same distance from the fulcrum, it's easier to do that with the animation than with the numerical representation. When the task is to find out the value of the moment in a given situation, this cannot be done by using the animation. In this case learners need the numerical representation to find the answer.

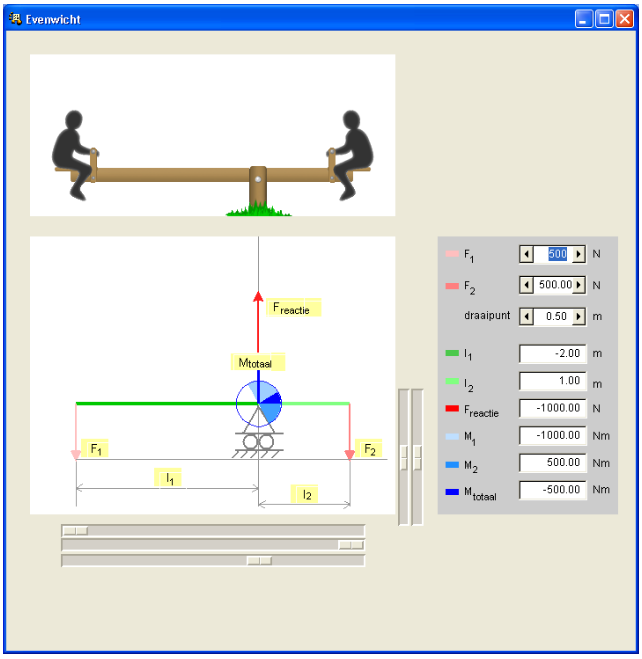

Figure 1-12 Interface of simulation on balance

Constrain interpretation

By the constraining function of multiple representations, a first representation can be used to constrain the information presented in a second. Petre et al. (1998) use the term 'bridging representations' when a second representation helps the learner to reason about a first. In her functional taxonomy Ainsworth (1999) distinguishes between constraining by familiarity and constraining by inherent properties.

Constrain by familiarity

An example of constraining by familiarity is an animation constraining the interpretation of a graph. There is a strong tendency among learners to view graphs as pictures rather than as symbolic representations (Kaput, 1989; Mokros & Tinker, 1987). When the animation shows a car riding up a hill with constant power, it constrains the interpretation of the speed shown in a line graph. The animation can show learners the line graph is representing not a valley but the speed of the car; they can see that the car slows down going up the hill and it accelerates going down the hill. The purpose of the constraining representation is not to provide new information but to support the learners' reasoning about the less familiar representation (Ainsworth, 1999).

Figure 1-13 shows an example of an animation of a car constraining the interpretation of the graphs above it. The animation helps the learner to understand the behaviour of the variables presented by the graphs.

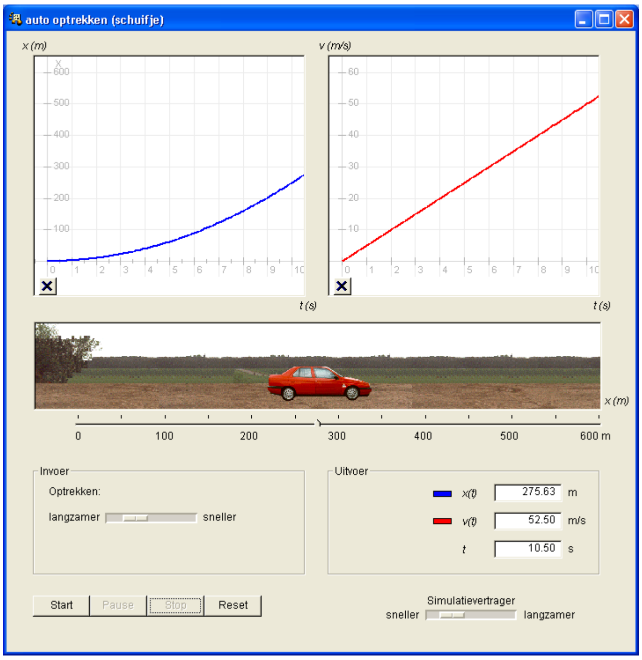

Figure 1-13 Interface showing accelerating car

Constrain by inherent properties

Sometimes a more abstract or unfamiliar representation can be used to constrain interpretation of a second representation. Ainsworth (2006) uses an example from Stenning and Oberlander (1995) which shows that graphical representations are generally more specific than textual ones: "The phrase 'the cat is by the dog', is ambiguous about which side of the dog the cat is sitting, but in a picture, the cat must be either on the left or the right of the dog. So, when these two representations are presented together, interpretation of the first (ambiguous) representation may be constrained by the second (specific) representation." (p. 189).

In Figure 1-14 the text on the right is describing the context of the situation: "A hoisting crane is carrying a load". This description does not make clear what the horizontal and vertical position of the load is. The animation in the left window constrains the interpretation of the text by showing these positions. It makes clear that the load is located at the right side, at a fourth of the maximum length from the jib fixation, and that it hangs at a fourth of the maximum height.

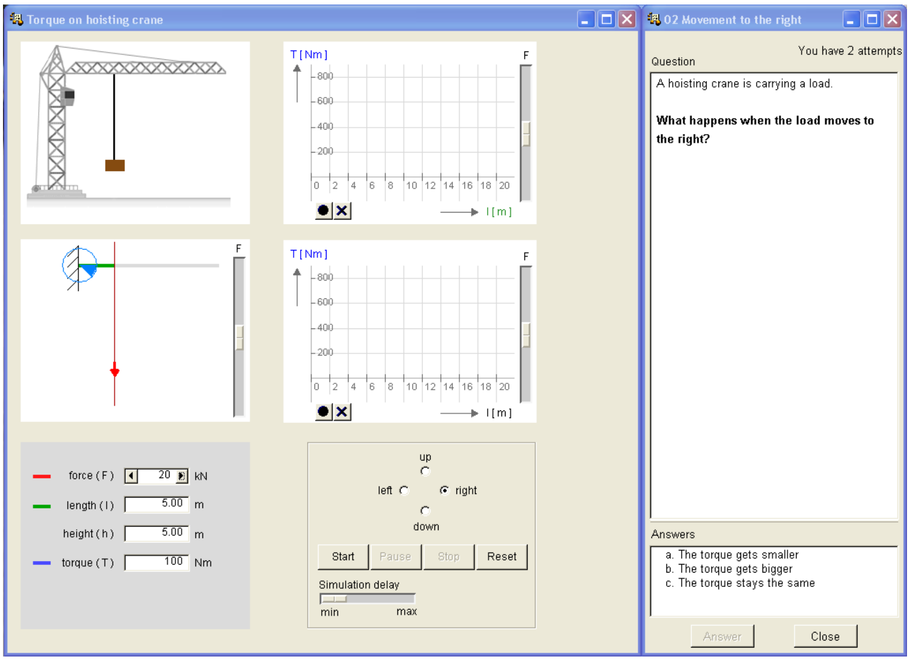

Figure 1-14 Interface showing the context described by the text on the right

Processing multiple representations

According to Ainsworth, Bibby and Wood (1997), learners are faced with three tasks when learning with multiple representations. They have to: (1) learn to understand each representation, (2) understand the relation between the representation and the domain it is representing and (3) must come to understand how representations relate to each other. We adapted this to four tasks, since we believe that in order to understand the relations learners have to perform two separate tasks: relating representations and translating between them. Therefore, we distinguish four tasks for learning with multiple representations. In our view, learners have to: (1) understand the syntax of each representation, (2) understand which parts of the domain are represented, (3) relate the representations to each other if the representations are (partially) redundant and (4) translate between the representations.

Understanding the syntax

In order to understand the syntax of a representation, learners must learn the format and operators of the representation. Moreover, operations on a representation must be coordinated with the format of the representation. So, the learner must understand which operations to carry out on particular representations. The format of a graph, for example, would include attributes such as labels, number of axes, and line shapes. Examples of graph operators are finding the gradients of lines, minima and maxima, and intercepts. Meaningful operators depend on the type of representation. Operators for tables, for example, differ from operators for graphs. When learners are unfamiliar with the representations used in a learning environment, the operators for one representation are often used inappropriately to interpret a different representation. This results in common mistakes such as viewing a graph as a picture (see Mokros & Tinker, 1987). In the already mentioned example of a car riding up a hill with constant power, novice learners could easily misinterpret the slope of the graph as the representation of a car riding down a hill.

Understanding which parts of the domain are represented

To learn from a representation, learners have to understand which parts of the domain are being represented. This could be either a complete domain with all its variables and relations or only a specific part of the domain. To do this, learners must have sufficient knowledge of the domain. When learners do not have this knowledge, the learning environment must provide at least the information learners need to be able to 'read' the representation. For many domains it is important that learners at least know which variables play a role. If the learner does not have this knowledge yet, the variables have to be introduced explicitly or learners should be able to look them up in a help system, for example. Relations between domain variables can be either presented to the learner or explored by the learner.

Relating representations

We define relating as finding similarities and differences of different representations at a surface level. In a simulation about a car in motion, for example, the learner has to relate the slope of the line in a speed-time graph to the right property of the moving car. A relevant question would be: Does the line represent the acceleration of the car or does it represent the speed of the car?

When different representations are presented together, it is not always clear whether learners are supposed to relate them to each other. This depends on the functions the provided representations have in the learning environment (see the section on Reasons for using multiple representations, page 4). When representations complement each other, for example, representation elements are not supposed to be mapped into each other. In this case learners have to combine the elements presented in the representations to get the 'full picture'.

Especially for novice learners, not familiar with the domain characteristics, it is hard to identify if the elements shown in the representations have to be linked or not. In a learning environment where learners were supposed to relate representations, Tabachneck-Schijf and Simon (1998) found that rather than relating representations, novice students tended to reason with only one representation at a time.

Even if learners know which elements to relate, problems may arise. One of these problems is the split-attention problem as studied by Chandler and Sweller (1991) and Mayer and Moreno (1998). When learning with separate representations, learners are required to relate disparate sources of information, which may generate a heavy cognitive load that may leave fewer resources for actual learning (Sweller, 1988, 1989). This, however, is not always problematic, since one of the benefits of using multiple representations is that learners – once they manage to relate the representations in the right way – are believed to gain a better understanding of the domain by studying the relations between the representations.

Translating between representations

We define translating as having to interpret the similarities and differences of corresponding features of two or more representations. Translating between representations is expected to lead to knowledge about the underlying, more abstract, structure of the domain represented.

A number of studies have reported difficulties novices have in translating between representations. Tabachneck, Leonardo, and Simon (1994) reported that novices learning with multiple representations in economics did not attempt to translate information between line graphs and written information. Experts, in contrast, tied graphical and verbal representations closely together. Similar results were reported by Kozma (2003), who reviewed experimental and naturalistic studies examining the role of multiple representations in understanding science. He looked at the differences between expert chemists and chemistry students in their representational skills and in their use of representations in science laboratories. Experts coordinated features within and across multiple representations to reason about their research. Students, on the other hand, had difficulty moving across or connecting multiple representations, so their understanding and discourse were constrained by the surface features of individual representations.

Supporting learning with multiple representations

Learning with multiple representations can be supported in several ways. This section reviews literature suggesting different kinds of support for different purposes and proposes a categorization of support types.

According to Ainsworth (1999) the type of support depends on representation use. She suggests that when multiple representations are used to support complementary roles and information, the learning environment should automatically perform translation between the representations if translation is necessary for learning the domain. This frees the learner from this task, which might tax working memory. Alternatively, it may be appropriate to present the representations sequentially to discourage attempts at coordination if translation between the representations is not necessary to learn the domain (e.g., when specific aspects of a domain can be learned separately from others). When multiple representations are used to constrain interpretation, the relations between representations should be made very explicit. This could be achieved by either automatic translation or dynamic linking. If neither representation is used for these actions, the relations between the representations should be made explicit by visual cues, such as highlighting correspondent components. If learners are required to link the representations themselves, representations that are easily coordinated should be selected. These are representations with more or less the same representational codes (Ainsworth, Wood, & Bibby, 1998).

Kozma (2003) suggests three design principles that could increase the drawing of connections between representations and which support learners' domain understanding: (1) provide at least one representational system that has features that explicitly correspond to the entities and processes that underlie the physical phenomena being taught, (2) have learners use multiple, linked representations in the context of collaborative, authentic, laboratory experiments, (3) engage learners in collaborative activities in which they generate representations and coordinate the features of representations to confirm and explain the findings of their investigations. They implemented these design principles in one of their early learning environments called 4M:Chem. 4M:Chem uses four different but linked symbolic spaces to represent chemical phenomena that learners must investigate. These consist of a chemical equation, a dynamic real-time graph, a molecular animation, and a video of a web lab experiment. Colour and dynamic linking were used to link the representations.

In a pilot study Kozma (2000) looked at the material and social affordances of the environment. Students worked in pairs on simulated experiments and were guided by a manual which asked them to make predictions, record observations, give explanations, and draw conclusions. If students disagreed, they were instructed to try and convince each other of their position, using whatever evidence was available. The pilot study showed how a pair of students constructed shared meaning from observed surface features across multiple representations. They both achieved a scientific understanding of the entities and processes that underlie a scientific phenomenon and they replicated the discourse practices of scientists.

Kozma and Russell (1997) asserted that instruction can foster the development of "representational competence" through explicitly engaging students in the production of various representations and encouraging them to reflect on their meanings. They defined representational competence as a set of representational skills concerning the ability to represent a domain (in their case: chemistry) in multiple ways.

Ardac and Akaygun (2004) also performed research in the domain of chemistry. In their study students had to integrate three representations into one consistent representation. These authors believe that when learners are expected to learn from visual displays, instruction should include opportunities for learners to generate their own representations and check for the consistency between these representations. Adding such a reflective component would also provide valuable information for teachers about how learners interpret, relate, and integrate representations depicting the macroscopic, molecular, and symbolic levels of chemical phenomena. Further instructional support may be required to highlight the correspondence between related representations. Explanatory texts can help learners organise the information into a coherent representation and integrate it with existing knowledge. Like others such as Tabachneck-Schijf and Simon (1998), they found learners do not always attend to the correspondence between the representations. Showing the related representations in connection to each other does not guarantee that learners perceive and encode them in a related manner.

In their study on genetics reasoning with multiple external representations, Tsui and Treagust (2003) make several claims about the positive effect of using multiple representations. They conclude that the use of multiple external representations in the learning environment “BioLogica” led students to construct deeper understanding of genetics as well as motivating their learning and constraining their interpretation of the phenomena of genetics. The authors argue that as students were intrinsically motivated in their learning of genetics, they were likely to be more engaged in reasoning and problem-solving tasks than in an otherwise normal classroom situation without these computer-based multiple representations. However, not all students liked genetics and BioLogica activities did not motivate them in their learning. They found that only students who had ‘mindful’ interaction with the representations benefited from them. Learners’ mindfulness in interacting with multiple representations appeared to be crucial in the development of genetics reasoning and in the transfer of that reasoning to new problem situations.

Of the 4 tasks presented in the section on Processing multiple representations on page 17, relating and translating are unique for learning with multiple representations. In our research we focus on these two processes. Since learners do not automatically relate different representations and translate between them, they need to be supported in both processes. In the remainder of this section we describe types of support aimed at supporting such relating and translating between representations.

Support for relating

We define relating as finding similarities and differences of different representations at a surface level. Surface level support is aimed at making the relations between multiple representations visible for the learner (see e.g., Seufert, 2003; Seufert & Brünken, 2006). Surface feature level support only shows the relations between representations, it does not explain them. Relating representations can be supported in the following ways:

1. Dynamic linking
2. Colour coding
3. Integration
4. Hyperlinks

Support for relating can be passive or active (e.g., Bodemer, Ploetzner, Feuerlein, & Spada, 2004). Passive support tries to make the relations between the representations visible for the learner. With active support learners decide when the relations between the representations are made visible. Dynamic linking, colour coding and integration can be characterised as passive support, whereas the support of relating with hyperlinks can be characterised as active support.

Dynamic linking

Dynamic linking makes relations between representations explicit by continuously updating all representations. If a learner, for example, presses a start button to start a car moving in an animation, a corresponding graph can show the time and distance travelled simultaneously. By doing so, the learner can observe both representations and learn the relation between the moving car and the graph.

Although several authors suggest dynamic linking as powerful support for relating representations, it also has its drawbacks. Lowe (1999) warns that dynamic linking may lead to cognitive overload, since learners need to attend to and relate changes that occur simultaneously in different regions of different representations. In our opinion this is only problematic if the learner has limited control over the learning environment. A solution could be to give learners more control over the learning environment. In the example mentioned earlier, the learner could be given the opportunity to move the car stepwise; in that way the learner can attend to the changes at his or her own pace.

Another problem with dynamic linking is mentioned by Ainsworth (1999). She points out that dynamic linking may hinder learners in understanding the relations between the representations, as it may discourage reflection. This is the reason why we categorise dynamic linking as passive surface level support. It does not explicitly support learners in understanding the relations between representations. It only makes the relations visible. Since understanding of the relations between representations is necessary to get a deeper understanding of the domain, it is important that a learning environment does not rely on dynamic linking solely. For understanding, additional deep level support is needed.

Colour coding

Colour coding is a powerful information mapping technique. It is a very effective support measure to show relations between objects (e.g., Kozma, 2003; Kozma, Russell, Jones, Marx, & Davis, 1996; Lohse, 1993). When corresponding representation objects are shown in the same colour, learners are supported in finding the relations. As Lohse (1993) found, colour coding can help to reduce the cognitive overhead involved in associating elements to each other. He compared use of symbols with colour coding and found colour coding facilitated the association better. Since colour has no specific meaning of its own, it does not add additional meaning to the representation(s). Symbols can have their own meaning and, therefore, learners can give meaning to symbols that is not intended by the designers. Moreover, symbols can be interpreted differently by different learners.

Integration

In multi-representational learning environments, split-attention effects (e.g., Chandler & Sweller, 1991) should be considered. In a multi-representational learning environment information is varied over different representations and learners have to relate and translate between the representations to acquire an integrated mental model of the domain. Chandler and Sweller argue that ineffective instruction occurs if learners are unnecessarily required to mentally integrate disparate sources of information such as separate text and diagrams. They state that such split-source information may generate a heavy extraneous cognitive load, because material must be mentally integrated before learning can commence. Therefore, designers should consider if it is necessary to split the information over different representations. Chandler and Sweller suggest that sometimes it is better to integrate the different sources of information. Physical integration of representations makes relations between representations explicit by placing corresponding elements close to each other. By physical integration of information the cognitive effort required to mentally integrate disparate sources of information can be reduced or eliminated, resulting in availability of resources for productive learning (Ayres & Sweller, 2005; Mayer, 2005). With regard to the translation process, having all related elements in the same place makes it easier to interpret the similarities and differences of corresponding features.

It is, however, not always useful to integrate different sources of information, especially when the learning goal is for learners to find relations between different representations themselves. Moreover, Chandler and Sweller (1991) found that physical integration is important only where the disparate sources of information are unintelligible unless integrated. If it is not necessary to integrate sources of information to understand them, a redundant source of information may need to be removed. This may sound obvious, but it is not easy to identify whether learners need to integrate different sources of information to understand the domain. This depends heavily on the learners' prior knowledge and the represented domain. Therefore, it is not always possible to predict beforehand if integration will be beneficial or not.

The complexity of the representation may be a problem for integration. An important reason to use multiple separate representations is that providing one (integrated) representation would become too complex. Whether a representation becomes too complex depends on the represented domain and the target group.

Hyperlinks

In a series of experiments Seufert, Jänen and Brünken (2007) implemented hyperlinks for learners to make relations between multiple representations visible. According to the authors, inter-representational hyperlinks may foster the visual search for correspondences. Relevant concepts were marked as a hyperlink in a text. When clicking a link, arrows pointed to corresponding parts in a picture. They found the use of hyperlinks was only effective when the learning task was not complex or when the learners had high expertise. It seems hyperlinks can be used effectively if the learners can make sense of the relations. If they are unable to interpret the correspondences shown, additional support is necessary.

Support for translating

We define translating as having to interpret the similarities and differences of corresponding features of two or more representations. By translating between representations, learners are processing the learning material at a deep level. Deep level support is aimed at explaining the relations between the representations (see e.g., Seufert, 2003; Seufert & Brünken, 2006). Explanations can come from the system or learners can be asked to come up with explanations. Translation between representations can be supported in the following ways:

1. Explanatory texts
2. Active integration
3. Hints and prompts

Just as with support for relating, support for translating can be either passive or active. With passive translation, the translation process is done for the learner. The translation from one representation to the other is explained by the learning environment. With active translation, learners have to explain the relations between the representations themselves and reason with them.

Explanatory texts

Explanatory texts describe the relations between two or more representations in text and, therefore, can be considered as passive translation. Seufert (2003), who uses the term 'verbal descriptions', examined whether directive and non-directive textual help had different effects on coherence formation. A typical example of a directive text would be: "The change of electrons is visible in both pictures.". A typical example of a non-directive text would be: "Are there corresponding processes in both pictures and where are the differences?". She found that directive help supported both recall performance as well as comprehension processes whereas she had expected non-directive help to be more effective for the latter. As non-directive help is believed to be more demanding than directive help, non-directive help may be hard to implement successfully in a complex learning environment, which was the case in Seufert's study.

Seufert and Brünken (2006) used explanatory texts to explain how to globally link information between representations. The descriptions were aimed at stimulating the process of integrating multiple representations. The authors compared the following combinations of surface level help (SLH) and deep level help (DLH): no help, SLH only, DLH only and SLH plus DLH. They did not find significant differences between the experimental conditions, although the combined condition showed the highest post-test scores.

Although we categorise textual support as deep level support, the question arises whether explanatory texts alone support deeper understanding. We believe it is more effective to try to encourage learners to relate and translate between multiple representations actively.

Active integration

With active integration, learners construct an integrated representation from two separate sources of information. A learner can be asked, for example, to drag labels to the right positions in a diagram in order to construct an integrated representation. The learning environment could provide feedback on whether the labels were dragged to the right places. According to Bodemer et al. (2004) presenting static versions of dynamic representations before dynamic ones gives learners time to identify the important elements and become familiar with them. Moreover, the integration of static representations has the purpose of relating unfamiliar representations to familiar ones before working with the actual learning material. The authors argue that viewing the relations between representations does not direct support learners in constructing meaningful knowledge. The learners might remain rather passive and thus might not mentally process and integrate the learning material in an adequate way.

In a series of experiments Bodemer et al. (2004) and Bodemer and Faust (2006) found positive learning results when students had the opportunity to actively integrate multiple representations. However, they only found good results when the students were capable of integration. When students had low prior knowledge and therefore were not able to integrate the representations, a non-integrated or pre-integrated format resulted in better learning outcomes.

Hints and prompts

Giving hints and prompts to relate and translate between representations might be a good way to support learners to benefit from multiple representations. Giving these hints and prompts may help learners to realise that the purpose of using multiple representations is for them to learn from relating and translating between representations. Hints and prompts look like the non-directive support described earlier with the difference that learners are asked to explicitly answer the questions asked. An example of a prompt would be: "You saw that the value of moment changes in the equation as soon as you change the angle of the force in the animation. Please explain why this happens." In this example learners are asked to link the change of the angle to the change of the arm in the animation first (within-representation link) and then link this to the change of arm (and therefore moment) in the equation (between-representation link).

We believe it is important that learners realise that the purpose of providing them with multiple representations is for them to integrate these representations. Several studies have shown that learners often reason with one representation at a time (e.g., Tabachneck-Schijf & Simon, 1998), whereas the intended value of the multiple representations lies in their combination. Explicitly asking learners to relate or translate two or more representations may solve this problem. Moreover, prompting learners in this way may also result in (prompted) self-regulation (Azevedo, 2005; Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Chi, Deleeuw, Chiu, & Lavancher, 1994) in the sense that they have to think about the relations between representations and have to formulate an answer to the question(s) asked. Many authors agree that learning from multiple representations "… is not a passive process, but requires that the learners actively engage in the processing of the representations." (Van Meter, Firetto, & Higley, 2007, p. 7). Explicitly asking learners to process the information from different representations may help.

However, an unanswered question is: Are learners capable of doing this? We assume that learners can do this when additional surface feature support is provided in the form of dynamic linking, physical integration and/or sequencing representations.

SimQuest

The studies presented in this thesis were all carried out in the simulation-based learning environment SimQuest. This section describes the basic idea behind inquiry learning and the processes involved. Thereafter, a description of a typical SimQuest learning environment will be given.

Simulation-based inquiry learning

The basic idea behind inquiry learning is to provide learners with an environment in which they can discover a domain by exploration (de Jong & van Joolingen, 1998). In inquiry learning learners are in control of their own learning process. They construct their own knowledge of the domain by stating hypotheses, doing experiments and interpreting the data. Doing experiments on natural systems is an important source of information to construct scientific knowledge and plays an important role in science education (van Joolingen & de Jong, 2003).

However, there are many situations where computer simulations have advantages compared to natural systems (Alessi & Trollip, 1985; de Jong, 1991). Computer simulations offer learners the opportunity to perform experiments in controlled settings. They are safe to work with, increase the availability of inaccessible or expensive systems, use minimal resources, are modifiable, and allow for experimentation with systems that normally cannot be physically manipulated. Moreover, simulations offer new instructional opportunities. For example, simulations visualize processes that are invisible in natural systems by, for instance, showing animations of speed vectors or graphs of quantities such as energy or impulse. In this way, multiple views and multiple representations of the simulated system can be offered (see e.g., Ainsworth, 1999; van der Meij & de Jong, 2006).

Computer simulations contain an executable model of a (natural) system. They simulate the behaviour of the modelled system. Learners explore the simulation model by manipulating values of (input) variables and observing the behaviour of other (output) variables. By understanding the relations between the variables, it is expected that learners acquire a deeper understanding of the domain and are able to transfer this knowledge to similar ‘problems’ in other (real) situations.

Inquiry learning processes

In our work we distinguish two types of learning processes that are important for inquiry learning: transformative processes and regulative processes (de Jong, 2006; Njoo & de Jong, 1993). Transformative processes directly yield knowledge, whereas regulative processes are necessary to manage the inquiry learning process.

Transformative processes

Transformative processes include orientation, hypothesis generation, experimentation, data interpretation and evaluation.

Orientation. During the orientation process, learners build their first ideas of the domain and the learning environment. Learners might read an introductory text or background information, might identify the variables that are involved and might manipulate the variables in the simulation to get a first impression of the possible relations between the variables.

Hypothesis generation. Hypothesis generation is regarded as an important process in inquiry learning. Learners formulate a statement about the relation between two or more input and output variables by using the knowledge acquired in the orientation phase. Learners' hypotheses form the basis for performing experiments.

Experimentation. During the experimentation process the learners design and perform experiments to test their hypotheses. To do so, they decide which variables to manipulate and observe.

Data interpretation. During the data interpretation process learners try to make sense of the data collected during the experimentation process. This can involve the extraction and interpretation of data from several representations, such as graphs, numerical outputs, animations and tables.

Evaluation. During the evaluation process learners compare the data to the predictions made during hypothesis generation. Based on the gathered data they have to decide if their hypothesis holds or not. This may lead to revision of hypotheses and/or generation of new ones.

Regulative processes

Regulative processes are the processes that learners have to employ to keep track of their progress during the transformative processes. Regulative processes include planning and monitoring.

Planning. Planning the inquiry activities is imperative. Since learners are responsible for their own learning process in inquiry learning environments, they have to plan this process themselves. Planning involves making decisions as to which steps to take in what order. Learners have to plan their activities before they carry them out.

Monitoring. Monitoring is the process of keeping track of the steps taken and the actions done. During all transformative processes, learners must look back and monitor what they have done so far.

Cognitive scaffolds

Despite its potential, learners have considerable difficulties with simulation-based inquiry learning. As a result, inquiry learning does not always lead to better learning results compared to other types of learning. De Jong and van Joolingen (1998) provide an extensive overview of the problems associated with inquiry learning. Learners have particular problems with: hypothesis generation, setting up experiments, data interpretation and regulation.

Cognitive scaffolds can help to prevent or overcome the problems associated with simulation-based inquiry learning (de Jong & van Joolingen, 1998; Mayer, 2004). The basic idea is to embed the simulation in an instructional environment that supports the processes of inquiry learning. In such a supportive environment the behaviour of the simulation and that of the instructional support should be in line. This leads to the concept of integrated simulation learning environments (de Jong, van Joolingen, Veermans, & van der Meij, 2005). In such an environment, simulations and instructional support measures cooperate to offer just-in-time and adequate support for the learners' learning processes. The instructional support measures provide the cognitive scaffolds needed for successful learning. Scaffolds for the transformative processes include giving domain information during the orientation process, providing tools to support hypothesis generation and providing experiment hints. Scaffolds for the regulative processes include model progression, planning support, monitoring support and structuring the learning process. These integrated simulation learning environments can be built with our authoring system SimQuest.

Inquiry learning with SimQuest simulations

SimQuest simulations allow learners to engage in inquiry learning activities with a simulation, supported by cognitive scaffolds. A typical SimQuest simulation consist of: (1) a simulation model, (2) a simulation interface providing one or more visual representations of the simulation model to control, manipulate, and observe the behaviour of the simulation model and (c) instructional support measures to support the inquiry learning process. In this section we will give examples of cognitive scaffolds used in the studies reported in this thesis.

Support for orientation

Support for orientation can be provided in a number of ways. Figure 1-15 shows a possible introduction of a simulation on the physics topic of moments. With use of hypertext and corresponding pictures, learners are introduced to the topic of moments by presenting an everyday life example: someone carrying a crate far from the body and close to the body. In this simulation the topic is presented as a problem: "Why does the crate feel heavier when you carry it far from your body?" Learners are then introduced to variables involved and are told they are going to find the solution to the problem with the simulation learning environment.

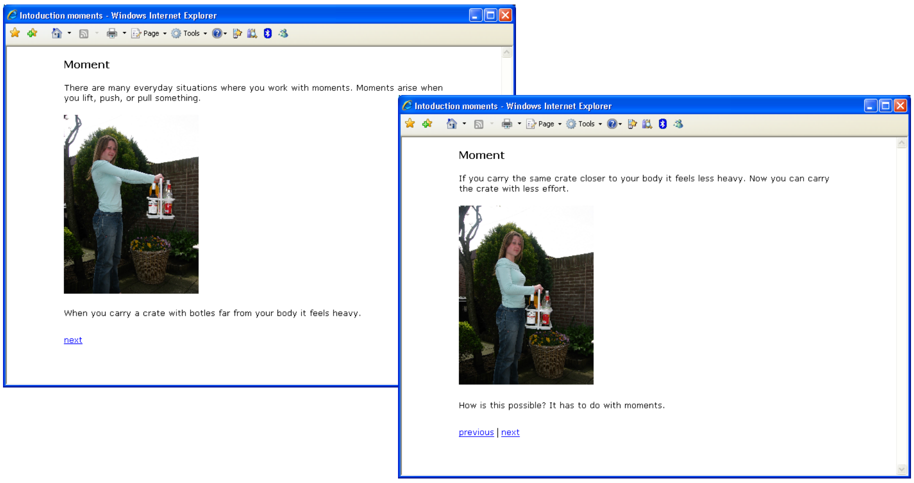

Figure 1-15 Introduction of SimQuest simulation Moments

After the introduction, learners are asked to open the first assignment, which introduces them to the simulation interface (see Figure 1-16). During the orientation process the most basic version of the simulation model is used to restrict the number of (new) variables and relations. In the case of the Moments simulation only moment (M), force (F) and arm (a) are present during the orientation process. Learners therefore only need to orient themselves to these variables and the role they play in the domain. The assignment supports learners in getting familiar with both the simulation interface and the variables.

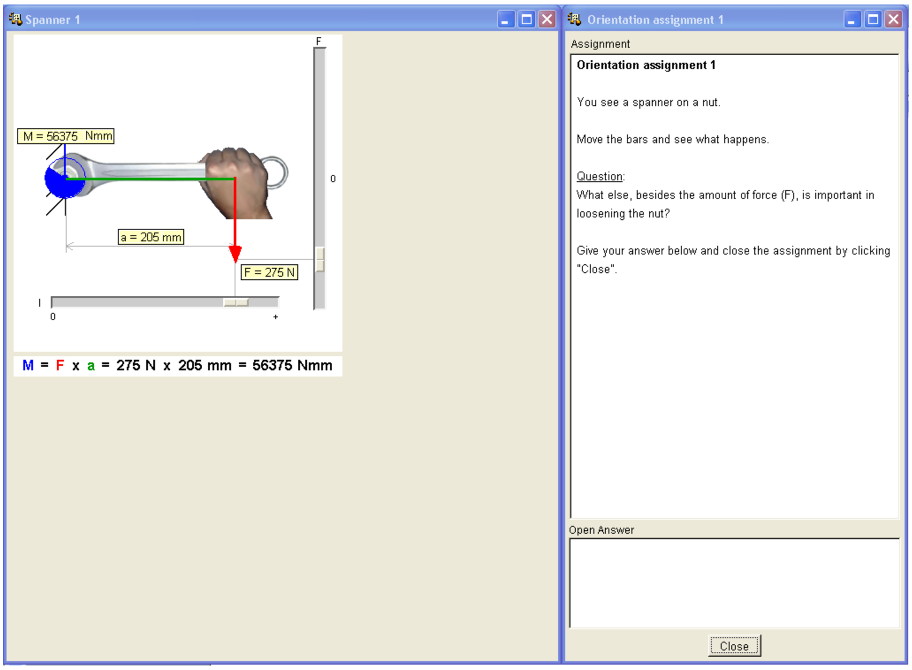

Figure 1-16 Orientation in SimQuest simulation Moments

Assignments can support transformative and regulative inquiry processes. They support transformative processes, for example, by giving domain information. They support regulative processes by providing learners with short-term goals for their learning progress. SimQuest offers a range of different assignment types.

Do it/Do them assignments present their goal to the learner without asking for a direct answer. Do it assignments present the learner with one initial state of the simulation model. With Do them assignments, learners are asked to compare two or more pre set initial states.

Open answer assignments ask the learner to give an answer in text.

Investigation/Explicitation assignments ask the learner to inquire about the relation between two or more variables. The assignments offer several possible hypotheses that can explain the observed phenomena, from which the learner has to select one or more possibilities. The assignments can trigger specific feedback based on the answer(s) chosen. The assignments differ in the number of initial states of the simulation model.

Specification assignments ask the learner to predict the values of certain variables when the simulation reaches a state defined by the author.

Optimisation assignments require learners to perform a task within given constraints and with a set target. The learner has to vary the variables such that the constraints are not violated and the target is reached.

After answering the assignment, learners are given feedback on their answer. In SimQuest feedback can be combinations of text, images, videos and/or sound. In our simulations we provide learners with informative feedback. After learners give an answer, we always explain why it is correct or incorrect.

Support for hypothesis generation

Although SimQuest offers specific tools for hypothesis generation (see Gijlers, 2005; van Joolingen & de Jong, 1991), in our studies we have decided to support hypothesis generation with assignments because we did not want to overwhelm the learners with specific tools.

Support for experimentation

Support for experimentation can have two forms: general experimentation hints such as “do not vary too many variables at the same time” or specific experimentation hints describing the precise conditions of the experiment. Figure 1-17 shows an example of a specific experiment hint.

The experiment hint is provided by an assignment asking the learner to perform a specific experiment and to give the answer by choosing the right alternative plus an explanation. After giving the answer, the learner receives informative feedback.

When performing experiments learners can use the hint(s) to explore the simulation. Although in our simulations it is not obligatory to do the assignments, we often see learners do them all. On the one hand, this is positive, since several studies (e.g., Swaak, van Joolingen, & de Jong, 1998) have confirmed that this type of support helps learners to gain better learning results compared to working with simulations without support. On the other hand, this is problematic, since many learners only do the assignments and are not exploring the simulation to the extent we would like them to do, that is, setting up their own experiments and thereby exploring the simulation themselves. In our recent studies we have specifically focused on this aspect. We are trying to motivate learners to use the assignments as starting points for designing and carrying out their own experiments.

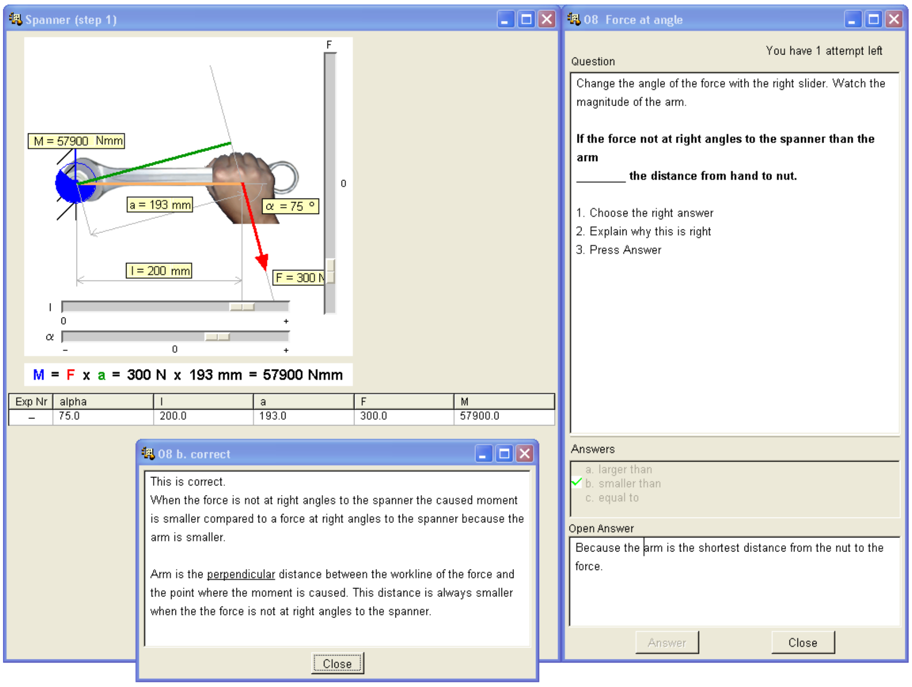

Figure 1-17 Example of a specific experiment hint

Support for data interpretation
Data interpretation can be supported by different tools. Again, assignments can fulfil this function by asking learners to answer a specific question and giving them feedback on the answer given. Investigation, specification and optimization assignments can be especially useful for data interpretation. Another supportive tool is the SimQuest monitoring tool (see Veermans, 2002), shown in Figure 1-18. With the monitoring tool learners can save experimental data and compare it. To make comparison easier they can rerun saved experiments without having to set up the experiment again.

Support for evaluation
Support for evaluation in SimQuest can have different forms. The most basic type of support is asking learners to draw conclusions. This can be supported by an open answer assignment. Learners can be asked to revisit the hypotheses they stated earlier and comment on them in their conclusion. A summary containing all key aspects of the domain could be provided as feedback.

Additional tools for evaluation are a SimQuest modelling tool (see e.g., Löhner, van Joolingen, & Savelsbergh, 2003) and SimQuest concept map tool (see e.g., Gijlers, 2005).

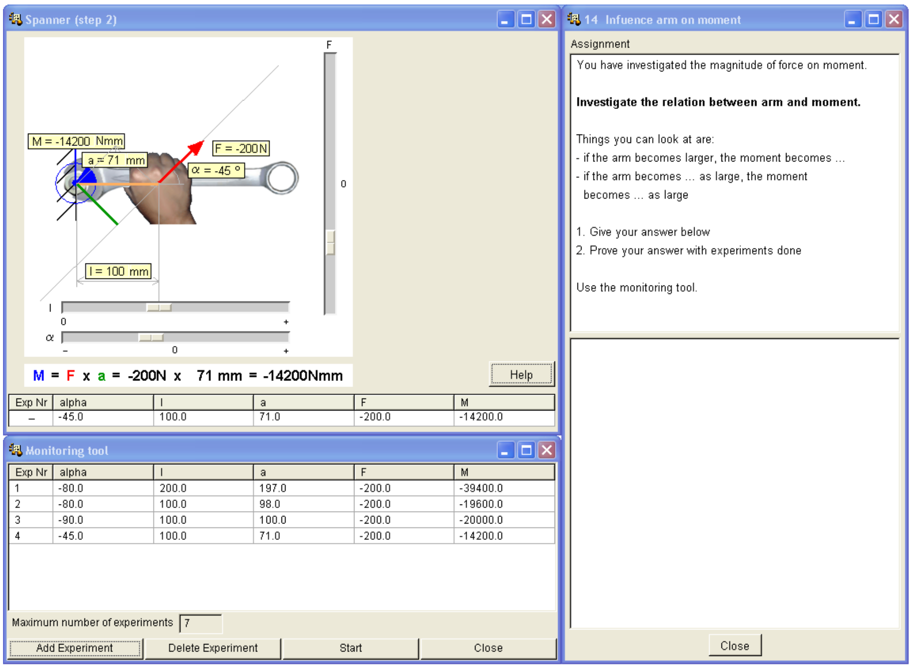

Figure 1-18 Assignment with monitoring tool for data interpretation

Support for regulation

Learners' regulation of the inquiry process can be supported by structuring the transformative processes, following the inquiry cycle of orientation, hypothesis generation, experimentation, data interpretation and evaluation. Assignments, explanation and dedicated tools can guide the learner through the learning environment. The seemingly simple SimQuest monitoring tool is a good support tool for keeping track of experiments done. When using this tool learners can easily observe what they have done so far and can replay their experiments with two mouse clicks instead of setting up the complete experiment again.

Another way to structure the inquiry process is by providing model progression (White & Frederiksen, 1990). With model progression the learning environment can be sequenced from simple to complex by increasing the complexity of the simulation model step-by-step. Figure 1-19 shows a representation of an oscillatory motion model with increasing number of variables acting on the system.

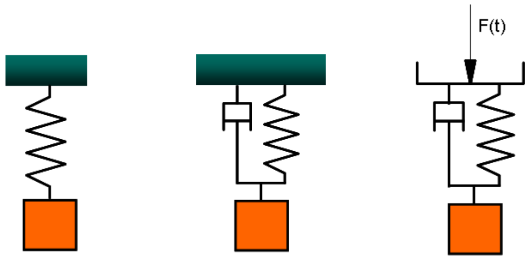

Figure 1-19 Example of model progression

The 'best' support

Although, most researchers agree that learners need support in inquiry learning environments, the question remains: What is the best way to implement this support? In the previous sections we gave examples of support in SimQuest based on the inquiry processes identified by Njoo and de Jong (1993). In our research we have found that these tools can help learners to overcome the problems associated with inquiry learning. However, supporting learners in inquiry learning always affects the learning process. Designers of integrated simulation learning environments need to find the right balance between freedom and guidance. Njoo and de Jong (1993) identified three dimensions for support: non-directive versus directive, stimulating versus restricting, and obligatory versus non-obligatory.

Directive support stimulates the learner to perform a task, whereas non-directive support does not. An example of directive support is asking learners to investigate specific relations between given variables. An example of non-directive support is giving the learners definitions of investigation, relation and variables.

Restrictive support constrains the learners in what they are allowed to do in order to prevent them from floundering. This can be accomplished, for example, by providing model progression or presenting them with a pre-specified hypothesis list as opposed to allowing them to express hypotheses in natural language.

Obligatory support is imposed upon learners, as opposed to leaving the use of instructional measures as their own decision. An example of obligatory support is to force learners to state a hypothesis before an experiment can be carried out.

In order to maximize learner initiative, support in inquiry learning should be ideally non-directive, stimulating and non-obligatory (Veermans, 2002). A problem with this kind of support is that learners, especially the ones that need support most, often fail to recognize or neglect the offered support. The practical consequence is that support is usually located more towards the other ends of these dimensions.

Purpose of our research

In this introductory chapter we described the potentials and challenges of learning with multiple representations. To successfully learn with multiple representations in general and in simulation-based learning environments in particular, support is needed. This thesis reports three studies in which we examined how learners can be supported to relate and translate between multiple representations. To do this, three research questions were posed:

Does integrating and/or linking dynamic multiple representations have an effect on learning outcomes?

The goal of the first study was to determine if integrating and/or linking dynamic multiple representations has an effect on learning outcomes. In three experimental conditions, the same learning environment, that of the physics topic of moments, was presented with separate, non linked representations (S-NL condition), with separate, dynamically linked representations (S-DL condition), and with integrated, dynamically linked representations (I-DL condition). The learning environment was divided into low complexity and high complexity parts. The results and implications of this study are discusses in chapter 2.

Does sequencing dynamic representations have an effect on learning outcomes?

In the second study, described in chapter 3, we used the findings of study 1 as a starting point and examined if sequencing dynamic representations has an effect on learning outcomes. Two versions of the same simulation-based learning environment, that of the physics topic of moments, were compared: a learning environment providing the representations step-by-step (R-Step condition) and a learning environment providing all representations at once (R-Once condition).

Does sequencing dynamic representations combined with explicit instruction to relate and translate between representations have a positive effect on learning outcomes?

Where study 1 and 2 focused on surface level support, in study 3 we examined the effect of providing hints and prompts to encourage the subjects to translate between representations. This study is described in chapter 4. Two versions of the same simulation-based inquiry learning environment on the physics topic of moments were compared. One learning environment provided all representations at once and instructional support focused solely on relations between the domain variables (R-Once condition). The second learning environment provided the subjects with representations step-by-step and with instructional support that focused additionally on relating representations and translating between them (R-Step condition).

Chapter 5 presents a review of the results and conclusions of the three studies, followed by a discussion of the general findings. After this, similarities and differences between the studies as well as limitations are discussed. The chapter concludes with sections on implications and further research.

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2

Integrating and dynamic linking[2]

Abstract - In this study, the effects of different types of support for learning from multiple representations in a simulation-based learning environment were examined. The study extends known research by examining the use of dynamic representations instead of static representations and it examines the role of the complexity of the domain and the learning environment. In three experimental conditions, the same learning environment, that of the physics topic of moments, was presented with separate, non-linked representations (S-NL condition), with separate, dynamically linked representations (S-DL condition), and with integrated, dynamically linked representations (I-DL condition). The learning environment was divided into low complexity and high complexity parts. Subjects were seventy-two students from middle vocational training (aged 16 to 18). Overall, the I-DL condition showed the best learning performance. Subjects in the I-DL condition, compared with the S-NL condition, showed better learning results on post-test items measuring domain knowledge. A trend in favour of the I-DL condition compared with the S-NL condition was found on post-test items measuring subjects' ability to translate between different representations. A subjective measure of experienced difficulty showed that subjects in the I-DL condition experienced the learning environment as easiest to work with. The complexity of the learning environment and domain interacted with the effects of the experimental conditions. Differences between conditions were only found on the test items that corresponded to the high complexity part of the learning environment.

[2] van der Meij, J., & de Jong, T. (2006). Learning with multiple representations: Supporting students' learning with multiple representations in a dynamic simulation-based learning environment. *Learning and Instruction, 16*, 199-212.

Introduction

Many learning materials offer multiple representations. Textbooks, for example, often use photographic images or diagrams to illustrate and explain parts of the text. In early computer-based learning environments, texts and images were provided in the same way as in textbooks, namely as static images. Therefore, research on representations in textbooks was also valid for these early computer based learning environments. In modern, computer-based learning environments many dynamic representations are available, including: audio, video, animations, dynamically changing graphs and tables (Lowe, 2003), and interactive dynamic visuals. This development poses new challenges and opportunities and calls for a new line of research to study the implications for learning using these multiple dynamic representations (Ploetzner & Lowe, 2004).

Benefits of multiple representations

Different types of (dynamic) representations exist, and combining different representations in one interface may have several advantages (e.g., Ainsworth & van Labeke, 2004).

First, each representation can show specific aspects of the domain to be learned. Different types of representations may be useful for different purposes, as they differ in their representational and computational efficiency (Larkin & Simon, 1987). Text and pictures, for example, are good representations for presenting the context of a problem. Diagrams are well suited for presenting qualitative information, and graphs, formulas, and numeric representations can be used to show quantitative information. Graphs, in particular, are important tools for enabling learners to predict relationships between variables and to show the nature of these relationships (McKenzie & Padilla, 1984). It is expected that learners benefit from the properties of each representation and that this will lead to a deeper understanding of the subject being taught (Ainsworth, Bibby, & Wood, 1997; de Jong, Ainsworth, Dobson, van der Hulst, Levonen, Reimann, Sime, van Someren, Spada, & Swaak, 1998; Seufert, 2003; van Labeke & Ainsworth, 2001).

A second benefit of a multi-representational learning environment is that one representation can constrain the interpretation of another representation. An animation, for example, can constrain the interpretation of a graph. There is a strong tendency among learners to view graphs as pictures rather than as symbolic representations (Kaput, 1989; Mokros & Tinker, 1987). When the animation shows a car riding up a hill with constant power, it constrains the interpretation of the speed shown in a line graph. The animation can show learners that the line graph is not representing a valley but the speed of the car; they can see that the car slows down going up the hill and that it accelerates going down the hill. The purpose of the constraining representation is not to provide new information but to support the learners' reasoning about the less familiar representation (Ainsworth, 1999).

A third advantage of the use of multiple representations is that by translating between representations, learners build abstractions that may lead to a deeper understanding of the domain (Ainsworth & van Labeke, 2004).

Problems with multiple representations

When learning with multiple representations, learners are faced with four tasks. First, they have to understand the syntax of each representation. They must learn the format and operators of the representations. For example, the format of a graph would include attributes such as labels, number of axes, and line shapes. Examples of graph operators are finding the gradients of lines, minima and maxima, and intercepts (Ainsworth et al., 1997). Second, learners have to understand which parts of the domain are represented. In a simulation about a car in motion, for example, the learner has to relate the slope of the line in a speed-time graph to the right property of the moving car. A relevant question would be: Does the line represent the acceleration of the car or does it represent the speed of the car? In addition, the operators for one representation are often used inappropriately to interpret a different representation. This results in common mistakes such as viewing a graph as a picture (see Mokros & Tinker, 1987). Third, learners have to relate the representations to one another if the representations (partially) present the same information. We define relating as linking the surface features of different representations. When, for example, a numerical representation and a graph have to be related, learners must find the corresponding variables in both representations. Fourth, learners have to translate between the representations. We define translating as having to interpret the similarities and differences of corresponding features of two or more representations.

A first problem that learners may encounter when learning with multiple representations is that they have difficulties relating different representations. This problem is related to the split-attention problem as studied by Chandler and Sweller (1991) and Mayer and Moreno (1998). When learning with separate representations, learners are required to relate disparate sources of information, which may generate a heavy cognitive load that may leave fewer resources for actual learning (Sweller, 1988, 1989).

Second, a number of studies have reported problems that novices have in translating between representations. Tabachneck, Leonardo, and Simon (1994) reported that novices learning with multiple representations in economics did not attempt to translate information between line graphs and written information. Experts, in contrast, tied graphical and verbal representations closely together. Similar results were reported by Kozma (2003), who reviewed experimental and naturalistic studies examining the role of multiple representations in understanding science. He looked at the differences between expert chemists and chemistry students in their representational skills and in their use of representations in science laboratories. Experts coordinated features within and across multiple representations to reason about their research. Students, on the other hand, had difficulty moving across or connecting multiple representations, so their understanding and discourse were constrained by the surface features of individual representations.

Types of support

The problems that were mentioned in the preceding section in regard to relating and translating representations traditionally (with static representations) are approached by integrating representations. Dynamic presentations offer the possibility of connecting representations not only by integrating them, but also by linking them so that a change in one representation is concurrent with a change in another representation.

Integrating

One way to make relations between representations explicit for the learner is to physically integrate the representations (e.g., Chandler & Sweller, 1991). Multiple representations, when integrated, appear to be one representation showing different aspects of the domain. Through integration, relations between the representations are directly shown to the learner. Integrating representations also supports learners in the translation process. Having all related elements in the same place makes it easier to interpret the similarities and differences of corresponding features. Several studies conclude that learning with integrated representations leads to better knowledge than learning with representations that are not integrated (Ainsworth & Peevers, 2003; Chandler & Sweller, 1991; Mayer & Moreno, 1998; Tabbers, Martens, & Van Merriënboer, 2000). Different results were found by Bodemer et al. (2004). They compared learning from a situation in which learners had to integrate representations themselves to learning from a non-integrated format and a pre-integrated format. Bodemer et al. found that learners in the integrated condition did not learn more than learners in the non-integrated condition, unless learners had to actively integrate the representations themselves. In their study, the active integration was done with static representations, whereas the learning environment contained dynamic representations.

Dynamic linking

A second way to make the relation between different representations explicit for the learner, in the case of dynamic representations, is by providing the learner with dynamic linking (Ainsworth, 1999). With dynamically linked representations, actions performed on one representation are automatically shown in all other representations. If a learner, for example, changes the value of a force in a numerical representation, the corresponding representation of the force in an animation is updated automatically. It is expected that dynamic linking helps the learner to establish the relationships between the representations (e.g., Kaput, 1989; Scaife & Rogers, 1996). An environment using multiple linked representations can facilitate novices' learning even if their understanding of symbolic expressions draws heavily on an incomplete or inaccurate knowledge of the domain (Kozma, Russell, Jones, Marx, & Davis, 1996). Some literature, however, also mentions disadvantages of dynamic linking. Ainsworth (1999), for example, asserts that a constructivist approach to education might argue that dynamic linking leaves a learner too passive in the process. Dynamic linking may discourage reflection on the nature of the translations, leading to a failure by the learner to construct the required understanding (p. 133). Another problem with dynamic linking might be that with multiple dynamically changing representations, learners need to attend to and relate changes that occur simultaneously in different regions of various representations, which may lead to cognitive overload (see Lowe, 1999).

Research questions

The goal of this study was to determine if integrating and/or linking dynamic multiple representations has an effect on learning outcomes. This was examined in a (simulation based) learning environment with dynamic representations. Most of the studies on integrating representations (Chandler & Sweller, 1991; Mayer & Moreno, 1998; Tabbers et al., 2000) investigated the integration of one diagram and text. Only the environment used by Ainsworth and Peevers (2003) consisted of more than two representations. These representations were also more complex than the representations used in the other studies. The study by Bodemer et al. (2004) suggested that the complexity of the domain and learning environment might influence the effects of integrating representations on learning. They found effects of integrating representation in a low complexity environment, but not in an environment of a higher complexity. In this study, we took complexity into account by dividing the learning environment into low and high complexity parts.

The context of the study was a guided inquiry simulation-based learning environment called ‘Moment’. Learners studied the physics topic of ‘moments’ by means of multiple representations of an open-end spanner tightening a bolt and of a crane hoisting a load. Three versions of the same simulation-based learning environment were compared: a learning environment with separate, non-linked representations (S-NL condition), a learning environment with separate, dynamically linked representations (S-DL condition), and a learning environment with integrated, dynamically linked representations (I-DL condition). We did not include a fourth (integrated, non-linked) condition, because integration and non-linking cannot be combined (see materials section). All learning environments contained the same content. We expected that the S-DL and I-DL learning environments would lead to better learning results than the S-NL learning environment. We expected that the I-DL learning environment would lead to the best learning results.

With regard to complexity, we expected a positive effect of integration as long as the interface did not become too complex. We expected larger differences between conditions in the high complexity part of the learning environment compared with the low complexity part, because in the high complexity part, more representations are presented simultaneously and/or more variables are introduced, which leads to more complex representations and relations. This would mean that support in the form of integration or linking would be more necessary and have a larger impact (Lowe, 1999). It could, however, also be the case that the integration of representations hinders learning when the representation becomes too complex (see Bodemer et al., 2004). In that case, subjects in the I-DL condition would not perform as well as subjects from the S-DL condition. To assess this effect, we measured the subjectively experienced complexity of the different parts of the learning environment.

Method

Subjects

Subjects were Dutch students from four middle vocational training schools. The subjects were between 16 and 18 years old. They were all taking a course on mechanical engineering. One-hundred-twenty-eight subjects started the experiment; 36 subjects missed the session of working with the learning environment and two subjects did not take part in the pre-test, which resulted in 90 subjects participating in all three phases of the experiment. Subjects who worked with the learning environment were randomly assigned to one of the three experimental conditions.

This paper reports analyses done with 72 subjects. From the set of 90 subjects participating in all phases of the experiment (pre-test, working with the learning environment, and post-test), 18 subjects were removed from the sample because they did not work through all five progression levels in the learning environment and, therefore, did not explore all parts of the simulated domain. Table 2-1 shows how the subjects were distributed across conditions and schools.

Table 2-1 Distribution of subjects per condition

	Condition			
School	S-NL	S-DL	I-DL	Total
1 (m/f)	4 (4/0)	7 (7/0)	6 (6/0)	17 (17/0)
2 (m/f)	5 (5/0)	4 (4/0)	5 (5/0)	14 (14/0)
3 (m/f)	7 (6/1)	6 (4/2)	5 (3/2)	18 (13/5)
4 (m/f)	8 (8/0)	7 (7/0)	8 (8/0)	23 (23/0)
Total	24 (23/1)	24 (22/2)	24 (22/2)	72 (67/5)

m = male, f = female

Materials

Computers

The experiments were conducted in computer classrooms with IBM compatible Pentium III 450 MHz processors and 256 MB RAM computers. During the experiments, all subject actions with the computer program were logged automatically.

SimQuest learning environment Moment

Subjects worked with the learning environment, Moment, that was built in the authoring environment SimQuest (de Jong, van Joolingen, Veermans, & van der Meij, 2005; van Joolingen & de Jong, 2003). Learners studied the topic of moments in mechanical engineering. The learning environment is based on guided inquiry learning (de Jong & van Joolingen, 1998). Because it contains a simulation model that is not directly visible to the learner, the learner has to engage in inquiry activities in order to learn about the properties of this model, and the learner is guided in the inquiry process by ‘cognitive tools’ such as model progression, assignments, and explanations. Learners explore the simulation model by manipulating values of (input) variables and observing the behaviour of other (output) variables. It is expected that learners acquire a deeper understanding of the domain by understanding the relations between the variables, and are able to transfer their knowledge to similar 'problems' in other (real) situations.

The learning environment has five progression levels. Table 2-2 gives an overview of these levels.

Table 2-2 Overview of progression levels of learning environment

	Level				
	1	2	3	4	5
Complexity	low	low	high	high	high
Representations*	1 - 3	1 - 3	1 - 5	1 - 3	1 - 5
Context	spanner	spanner	spanner	spanner	crane
Number of variables	3	3	3	6	4
Qualitative / Quantitative	qualitative	quantitative	quantitative	quantitative	quantitative
Number of assignments	7	7	6	3	7

* see Figure 2-2

Learners start exploring a specific aspect of the domain by choosing an assignment from the menu. When opening an assignment, a corresponding simulation interface opens. Each assignment starts with a short description of an aspect of the domain, asks the learner to explore this aspect, and asks the learner to answer a question about it. Figure 2-1 shows an example of an assignment with corresponding simulation interface.

Figure 2-2 shows an example of an S-NL and corresponding I-DL simulation interface. The simulation interface contains a maximum of five representations: (1) diagrammatic representation, (2) concrete representation, (3) numerical representation[3], and (4, 5) two graphs (moment-force and moment-arm or moment-force and moment-height).

Learners can manipulate the input variables in all types of representations by either using the provided sliders (concrete and diagrammatic representations) or by using the arrow keys (numerical representation). If a learner manipulates a slider or arrow key, the corresponding changes are shown in the representations in real time. So, if a learner moves the force-slider, the element representing force is updated continuously and immediately, as is the change in moment. Learners can compare situations by moving the slider back and forth between different states of the simulation.

[3] In progression level 1, the numerical representation contains sliders with the indications: minimum, zero, and maximum. The values of input variables can be changed by these sliders.

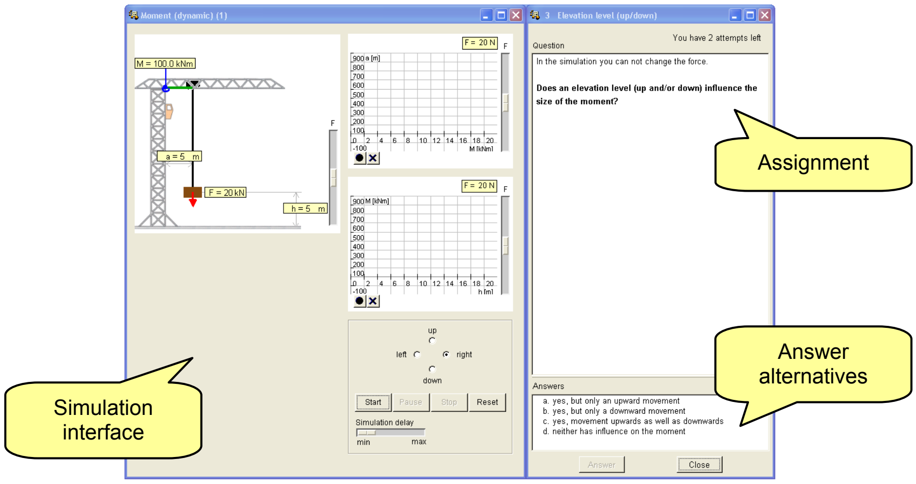


Figure 2-1 Example of Moment assignment (representations from I-DL condition)

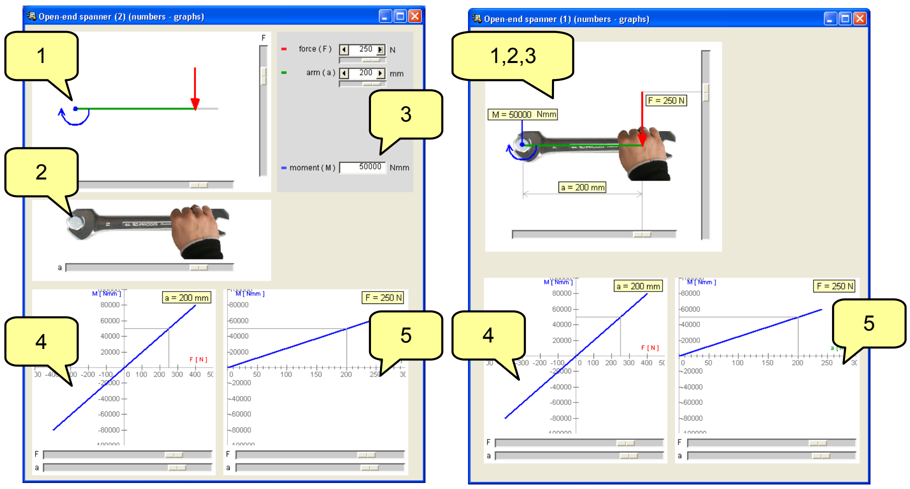


Figure 2-2 Example of simulation interface. Left: representations from S-NL and S-DL condition. Right: representations from I-DL condition

Representations 1, 2, and 3 are representations that are usually found in textbooks. These representations are the basic types presented to learners studying the domain of moments. They all support learners in getting insight into the domain from different perspectives. The concrete representation is a learner-controlled animation that provides the learner with a context for the simulated task. This representation links the learning material to a real life experience. In the first four levels (see Table 2-2) the concrete representation is an animation of an open-end spanner, because most of the learners in the target group have experience using this tool. In the fifth level of the learning environment, a hoisting crane is introduced, because this gave us the opportunity to introduce a new variable (height) and because we wanted to provide a new concrete context to give learners the opportunity to apply their knowledge in a new situation. In addition, this representation is less learner-controlled; it changes over time after pressing a start button. The diagrammatic representation helps learners go beyond the concrete situation to a more abstract understanding of the relation between the variables involved. By providing this type of representation, it is expected that learners can use their acquired understanding in new situations. Both the concrete and diagrammatic representation present the domain in a qualitative way. The numerical representation gives a quantitative view of the variables involved. The contribution of this representation is in showing the values of the variables to support the numerical relations between the variables. The graphs are provided to help learners predict relationships between the variables. In the graphs, any 'pictorial' similarity to the represented domain has disappeared; therefore, graphs represent the domain in a more abstract way than do the concrete and diagrammatic representations (Bernsen, 1994). The graphs, however, give the learner more direct information about the relations between the variables than do the other representations.

The representations in the S-NL learning environment are not linked. Within a representation changing an input variable (e.g., length) leads to a real time update of an output variable (moment). However, changing values of variables in one representation does not lead to changes in the other representations. In this learning environment learners need to relate representations themselves. Changing values of variables in one representation in the S-DL learning environment, by contrast, leads to a change in all representations. When, for example, a learner changes the value of the force in the numerical representation, not only the value of the moment in the numerical representation but also the force and moment in all other representations change accordingly. In the I-DL learning environment, the diagrammatic, concrete, and numerical representations (representations 1, 2, and 3 shown in Figure 2-2) are integrated. These representations are placed ‘on top of one another,’ resulting in one representation showing these three representation in an integrated format. Of the five representations used, only the diagrammatic, concrete, and numerical representations could be integrated. The diagrammatic and realistic representations could easily be integrated because they share the same spatial properties. The numerical representations were also integrated because they could be placed near the objects in the other two representations. But, because the formats of the graphs differ from the diagrammatic and concrete representations, they could not be integrated and, therefore, are represented separately in this learning environment. We chose to dynamically link the graphs and the integrated representation, because the other representations are also dynamically linked by integrating them into one representation.

In all learning environments, colour coding is used to indicate similar variables. Force is coloured red, length is coloured green, and moment is coloured blue in all but the concrete representation.

The learning environment has low and high complexity parts (see Table 2-2). In the low complexity part, learners explore moment caused by force and length by investigating the behaviour of moment on a bolt caused by a force on an open-end spanner. They do this in a qualitative (level 1) and a quantitative way (level 2). Levels 3 to 5 form the high complexity part of the learning environment. In level 3, a moment-force and a moment-arm graph are introduced. In level 4, a second force is introduced, resulting in more complex representations. In this level, the graphs are not used in order to avoid cognitive overload. Therefore, the number of representations in level 4 is three. In level 5 learners explore moment caused by force, length and height by investigating moment on a hoisting crane caused by a load. In this level there are four variables and five representations.

Tests and questionnaire

A paper-and-pencil pre-test assessed the subjects' prior domain knowledge. It was administered a week before working with the learning environment. A paper-and-pencil post-test was administered directly after working with the learning environment. Both tests consisted of 38 multiple-choice items with four answer possibilities, divided into three item types: 7 items on subject matter content, 17 items with transfer problems, and 14 items on the translation between representations. The domain items tested the subjects' domain knowledge. The content of the items was analogous to the content of the learning environment. Transfer items tested the ability of the subjects to apply their acquired knowledge in new situations: new contexts and relations between variables that were not asked for in the learning environment but could be derived from the domain knowledge. These items were included because the goal of scientific inquiry learning is not only to help subjects acquire domain knowledge but also to enable them to apply their knowledge in new situations. The representation items tested the subjects' ability to relate and translate between different representational formats.

For each pre-test and post-test item a subject received a score of 1 if the item was answered correctly or a score of 0 if the answer was incorrect. The maximum score was 38.

Figure 2-3 shows examples of three test items.

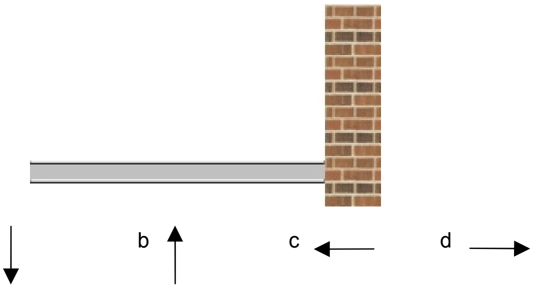
The post-test differed slightly from the pre-test in that it contained minor changes in the item order and the order of the answer alternatives. Because subjects did not know which items were changed, they could not rely on a memory strategy.

1. If you tighten a bolt with an open-end spanner, then where is the moment the largest?

a b c d

a. At the bolt
b. Between the hand and the bolt
c. At the hand
d. At the end of the open-end spanner

2. What is the direction of the force if the moment is positive?



a b c d

3. In the picture you see a hand exercising a negative force on an open-end spanner.

Which of the following figures is the right reproduction of length, force, and moment?

a b

c d

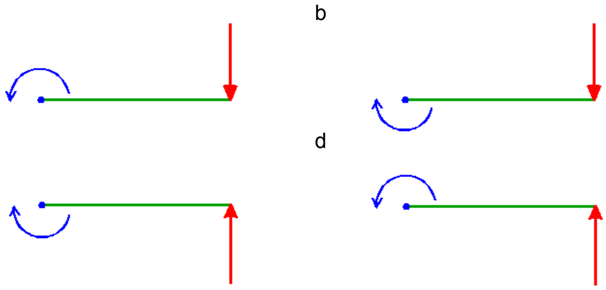


Figure 2-3 Example of a (1) domain, (2) transfer, and (3) representation item

An electronic questionnaire based on Swaak's S.O.S. scale (Swaak, 1998) was used to assess the subjects' opinions of the learning environment and the domain. The questionnaire contained seven questions (Q1-7) that asked subjects to rate topic, simulation, and assignment complexity. In particular it asked subjects to score the topic as easy, average, or difficult (Q1), whether they found working with the simulation easy, average, or difficult (Q2), and whether they found the assignments clear (Q3) and useful (Q4) (yes or no). Additionally, subjects were asked if they could always find the arm (Q5), force (Q6), and moment (Q7) in the simulation (yes or no). The questionnaire was given five times to subjects while they worked with the learning environment, after the last assignment of each progression level. Subjects had to complete the questionnaire before they could continue. For the first two questions in the electronic questionnaire, a three point scale was used. Possible answers were: easy, average, or difficult, which were coded as 1, 2, or 3. For the other five questions a two point scale was used. Possible answers were: yes or no, which were coded as 1 or 2.

Procedure

The experiments were held at the four participating schools and consisted of three experimental sessions: pre-test, working with the learning environment and post-test.

The pre-test session lasted a maximum of 45 minutes. Subjects were informed about the experiment and were told that the test measured their prior knowledge of force, arm, and moment. Subjects were asked whether they were already familiar with the term, 'moment,' and got a brief description if they were not. Subjects were asked to answer all test items, even if they were unsure about the right answer.

The learning environment session took place a week after the pre-test session and lasted a maximum of one hour. Subjects were randomly assigned to one of the three conditions using their seating placement. Subject did not know beforehand in which condition they were going to be placed. At the start of the session, the subjects were told that their task was to learn with the learning environment. They worked on their own and could question the teacher or experiment leader about operating the learning environment. The experiment leader gave a short introduction on how to control the learning environment. The electronic questionnaire had to be filled in five times while working with the learning environment. The subjects were asked to work through all of the progression levels and were asked to do all of the assignments. When they were ready, they could ask to do the post-test.

The post-test took place directly after the learning environment session. The subjects could work a maximum of 45 minutes on this test. The subjects were not allowed to use the learning environment during the test and were asked to fill in all test items, even if they were unsure about the right answer.

Results

Pre-test and post-test

The overall mean score on the pre-test was 22.15 out of 38 multiple-choice items (SD = 3.97). These data indicate that the subjects had some prior knowledge in the domain. The overall mean score on the post-test was 25.00 out of 38 multiple-choice items (SD = 4.52). Table 2-3 shows the means and standard deviations of the scores on the three different item types in the pre-test and post-test.

Table 2-3 Means and standard deviations of pre-test and post-test scores

	Pre-test			Post-test		
	Mean	(SD)	%	Mean	(SD)	%
Domain items (max. 7)	4.94	(1.28)	71	5.63	(1.17)	80
Transfer items (max. 17)	9.68	(2.10)	57	10.18	(2.27)	60
Representation items (max. 14)	7.53	(2.10)	54	9.18	(2.39)	66
Total (max. 38)	22.15	(3.97)	58	25.00	(4.52)	66

n = 72

A repeated measures ANOVA showed that the overall post-test score of the 72 subjects was significantly better than the overall pre-test score ($F(1,71) = 30.90$, $p < 0.01$). Repeated measures ANOVAs showed that the post-test score on domain and representation items was significantly better than the pre-test scores on these item types ($F(1,71) = 17.96$, $p < 0.01$ and $F(1,71) = 36.34$, $p < 0.01$). Scores on transfer post-test items were not better than pre-test scores ($F(1,71) = 2.08$, $p = 0.15$). Table 2-4 shows the means and standard deviations of the pre-test and post-test scores for the three different item types per condition.

One way ANOVAs showed no significant differences between the experimental conditions on pre-test domain scores, transfer scores and representation scores ($F(2,69) = 0.76$, $p = 0.47$; $F(2,69) = 0.922$, $p = 0.40$; $F(2,69) = 0.24$, $p = 0.79$). This means that subjects in the experimental conditions did not differ in prior knowledge. One way ANOVAs showed no significant relations between overall pre-test scores and schools and overall pre-test scores and gender ($F(3,68) = 0.98$, $p = 0.41$ and $F(1,70) = 1.91$, $p = 0.17$)[4]. Therefore, there was no need to correct for these variables.

One way ANOVAs on the post-test scores showed the following results. A significant difference was found between conditions on domain item scores ($F(2,69) = 3.23$, $p < 0.05$). Tukey HSD post hoc analyses showed that subjects in the I-DL condition scored significantly better than the S-NL condition. Differences between the other conditions were not significant. No difference was found between conditions on transfer item scores ($F(2,69) = 0.26$, $p = 0.78$). A trend was found for the difference between conditions on representation item scores ($F(2,69) = 2.63$, $p = 0.08$). Tukey HSD post hoc analyses showed that the trend on representation items was in favour of the I-DL condition compared to the S-NL condition.

[4] For all 126 subjects: $F(3,122) = 0.46$, $p = .71$ and $F(1,124) = 0.35$, $p = 0.56$.

Table 2-4 Means (standard deviations) of pre-test and post-test scores per condition

	Condition					
	S-NL		S-DL		I-DL	
Pre-test						
Domain items (max. 7)	5.20	(1.14)	4.83	(1.27)	4.79	(1.44)
Transfer items (max. 17)	9.21	(2.60)	9.88	(1.99)	9.96	(1.57)
Representation items (max. 14)	7.29	(2.05)	7.59	(2.26)	7.71	(2.05)
Pre-test total (max. 38)	21.71	(4.36)	22.29	(4.20)	22.46	(3.41)
Post-test						
Domain items (max. 7)	5.25	(1.39)	5.58	(1.21)	6.08	(0.72)
Transfer items (max. 17)	10.25	(2.42)	9.92	(2.22)	10.37	(2.24)
Representation items (max. 14)	8.54	(2.22)	8.95	(2.69)	10.04	(2.05)
Post-test total (max. 38)	24.04	(4.94)	24.46	(4.51)	26.50	(3.83)

n = 72

Post-test scores based on complexity

The learning environment was divided into low and high complexity parts. Based on this distinction, we divided the corresponding post-test items into low and high complexity categories. Twenty-three post-test items corresponded to the low complexity part and 15 items corresponded to the high complexity part. A one way ANOVA showed a significant difference between the experimental conditions on the overall scores on the post-test items corresponding to the high complexity part of the learning environment ($F(2,69) = 3.37$, $p < 0.05$). However, Tukey HSD post hoc analyses did not show where the differences were found. No difference was found on the low complexity part. Comparing the post-test scores between conditions for the different item types (domain, transfer and representation) based on complexity, a one way ANOVA showed a significant difference between the experimental conditions on the high complexity domain item post-test scores ($F(2,69) = 1.54$, $p < 0.05$). Tukey HSD post hoc analyses showed that subjects in the I-DL condition scored significantly better than subjects in the S-NL condition. No significant differences were found between conditions on the other item types.

Experienced domain complexity

The experienced domain complexity was measured by the questionnaire question: “I find the topic at this moment: easy, average, or difficult.” The question appeared at the end of each of the five progression levels. We calculated a mean score for the five answers given (see Table 2-5, question 1). A one way ANOVA showed a significant difference between the experimental conditions on experienced domain complexity ($F(2,69) = 3.45$, $p < 0.05$). Tukey HSD post hoc analyses showed that subjects in the I-DL condition experienced the domain as easier than subjects in the S-DL condition. Differences between the other conditions were not significant.

Table 2-5 Means (standard deviations) of questionnaire answers

	Condition					
	S-NL		S-DL		I-DL	
Question 1*	1.65	(0.41)	1.78	(0.47)	1.46	(0.38)
Question 2*	1.55	(0.36)	1.62	(0.47)	1.23	(0.32)
Question 3**	1.19	(0.23)	1.40	(0.31)	1.09	(0.19)
Question 4**	1.18	(0.35)	1.38	(0.39)	1.26	(0.33)
Question 5**	1.13	(0.22)	1.15	(0.23)	1.03	(0.09)
Question 6**	1.17	(0.27)	1.17	(0.26)	1.03	(0.13)
Question 7**	1.14	(0.23)	1.20	(0.28)	1.03	(0.13)

* n = 72

** n = 69 (3 subjects removed because they answered the question less than 3 times)

Subjects experienced the domain complexity differently throughout the learning environment. If subjects scored higher on ‘easy’ the complexity was rated as low. If subjects scored higher on ‘average’ and ‘difficult’ the complexity was rated as high. Progression levels one and two were experienced as low complexity. Progression levels three to five were experienced as high complexity. Based on this experienced complexity, we calculated the means of scores from the first and second appearances of the questionnaire (domain experienced as low complexity) and the means of scores from the third, fourth and fifth appearances of the questionnaire (domain experienced as high complexity). A one way ANOVA on these mean scores showed a significant difference between the experimental conditions on the high complexity part of the learning environment ($F(2,69) = 4.11$, $p < 0.05$). Tukey HSD post hoc analyses showed that subjects in the I-DL condition experienced the domain as easier than subjects in the other conditions in the high complexity part of the learning environment. No significant differences were found between the conditions in the low complexity part ($F(2,69) = 0.83$, $p = 0.44$).

Experienced learning environment complexity

The experienced learning environment complexity was measured by the questionnaire question: “I find working with the simulation at this moment: easy, average, or difficult”. The question appeared at the end of each of the five progression levels. We calculated a mean score for the five answers given (see Table 2-5, question 2). A one way ANOVA showed a significant difference between the experimental conditions in experienced complexity when working with the learning environment ($F(2,69) = 6.87$, $p < 0.01$). Tukey HSD post hoc analyses showed that subjects in the I-DL condition experienced working with the learning environment as easier than subjects in the linked and separate conditions. Differences between the other conditions were not significant.

A one way ANOVA on these mean scores showed a significant difference between the experimental conditions in the high complexity part of the learning environment ($F(2,69) = 6.80$, $p < 0.01$). Tukey HSD post hoc analyses showed that subjects in the I-DL condition experienced working with the learning environment as easier than subjects in the other conditions in the high complexity part of the learning environment. A trend was found between the conditions in the experienced low complexity part ($F(2,69) = 2.72$, $p = 0.07$). Tukey HSD post hoc analyses showed that subjects in the I-DL condition experienced working with the learning environment as easier than subjects in the S-DL condition. This confirms our presumption that progression levels 1 and 2 had a low complexity and that levels 3 to 5 had a high complexity.

Usefulness of assignments and finding variables

A mean score for each of questions three to seven was calculated for all appearances of the questionnaire (see Table 2-5). One way ANOVAs showed a significant difference between conditions on questions three (I find the assignments clear: yes, no) and seven (I can find the moment in the simulation everywhere: yes, no) ($F(2,66) = 9.42$, $p < 0.01$; $F(2,66) = 3.86$, $p < 0.05$)[5]. Tukey HSD post hoc analyses showed that subjects in the S-DL condition experienced the assignments as less clear than subjects in the other conditions and that subjects in the I-DL condition could find the moment more frequently than those using the linked version, but not more frequently than those using the separate version. No differences were found between conditions on questions four (I find the assignments useful: yes, no), question five (I can find the arm in the simulation everywhere: yes, no) and question six (I can find the force in the simulation everywhere: yes, no).

Subjects' interaction with the learning environment

Table 2-6 shows the means and standard deviations of the time subjects spent on working with the learning environment, the number of assignments they did and the calculated time spent per assignment.

A one way ANOVA showed a significant difference between the experimental conditions on the average time spent working with the simulation ($F(2,69) = 4.23$, $p < 0.05$). Tukey HSD post hoc analyses showed that subjects in the S-DL condition worked for a significantly shorter duration in the environment than subjects in the other conditions. One way ANOVAs on the number of assignments done and time per assignment showed no differences between conditions.

[5] Three subjects were removed from the sample because they answered the questionnaire less than three times.

Table 2-6 Means (standard deviations) of questionnaire answers

	Condition							
	S-NL		S-DL		I-DL		Total	
Total time (min)	39.71	(6.71)	33.79	(7.72)	40.17	(10.53)	37.89	(8.85)
Assignments done (max. 31)	29.71	(2.14)	28.54	(3.64)	30.04	(1.65)	29.43	(2.66)
Time per assignment (s)	80.34	(12.70)	71.62	(16.38)	80.08	(19.64)	77.34	(16.76)

Because time on task may have affected post-test scores, ANCOVAs were performed with time on task as covariate, showing similar results as the reported ANOVAs. A significant difference was found between conditions on domain item scores ($F(2,68) = 4.35$, $p < 0.05$). No difference was found between conditions on transfer item scores ($F(2,68) = 0.04$, $p = 0.96$). A trend was found for the difference between conditions on representation item scores ($F(2,68) = 2.58$, $p = 0.08$).

Discussion

The aim of this study was to examine ways to support learners in the translation between different representations in a simulation-based learning environment. Three versions of the same simulation-based learning environment were compared: a learning environment with separate, non linked representations (S-NL condition), a learning environment with separate, dynamically linked representations (S-DL condition) and a learning environment with integrated, dynamically linked representations (I-DL condition). We expected that dynamic linking would free the subjects from mentally relating the representations and, therefore, we expected to find a larger learning effect for the S-DL learning environment compared with the S-NL version. We also predicted that the I-DL learning environment would lead to the best learning results as long as the integrated representations were not too complex for the subjects.

Overall, we found that subjects learned from working with the learning environment. Post-test scores were significantly better than pre-test scores, but only on domain and representation items. We found that dynamic linking alone (S-DL condition) did not lead to better learning outcomes than non-linking. We found that subjects in the I-DL condition had the best scores on post-test domain items. They scored significantly better than subjects in the S-NL condition, but not better than those in the S-DL condition. A trend was found for representation items. The trend was again in favour of the I-DL condition, but again only in comparison with the S-NL condition.

As expected, complexity of the learning environment interacted with the effects of the experimental conditions. The differences seen on the domain items were only found on items that corresponded to the high complexity part of the learning environment, but not on the items that corresponded to the low complexity part. The contingency that the integrated representation could become too complex when more variables were introduced was not supported by our data. To the contrary, subjects in the I-DL condition experienced level 4 of the learning environment, where a second force was introduced, as easier than subjects in the other conditions. It looks like finding the relations between representations in the separate and linked conditions was more complex than the complexity of the integrated representation. In the S-NL and S-DL conditions, the subjects had to relate nine variables that were presented separately. Linking these variables helped the subjects to find their relations, but not enough to experience this as less difficult than the I-DL condition.

The fact that we did not find better results for dynamic linking in comparison with non-linking seems in contrast with other studies reporting positive effects of linking representations (e.g., Kozma, 2003; Kozma et al., 1996; Tsui & Treagust, 2003; Wu, Krajcik, & Soloway, 2001). There are, however, two issues that make these studies different from ours. First, in our study the S-DL condition differed from the S-NL condition only by the presence of *dynamic* linking. Apart from dynamic linking we used colour coding to relate representations, but this colour coding was present in both the S-DL and S-NL conditions. Other studies (e.g., Kozma et al., 1996) combined different ways to relate representations, including dynamic linking, and did not examine the effect of dynamic linking alone. Taken together, these results may suggest that in our case colour coding may have been sufficient and, because of that, the dynamic linking had no additional effect.

A second aspect of our learning environments that could have helped subjects to relate and translate representations could have been the instructional support in our environments. Instructional support, such as the assignments that we provided the subjects with, may highlight the correspondence between related representations (see e.g., Ardac & Akaygun, 2004). The assignments in our learning environments were the same for all conditions.

Where dynamic linking did not lead to better learning effects, integration plus linking did. We found significant differences on domain items, which indicates that the learners learn the domain better if the representations are integrated (and linked). This is in accordance with Chandler and Sweller (1991), who found that integrating instruction led to better learning results than separate instruction, as long as the materials chosen were unintelligible without mental integration. The trend found on representation items may indicate that integrating representations supports learners in relating different representations.

The results on the transfer items were not as expected. An important motivation to use multiple representations is that they should encourage learners to construct a deeper knowledge of a domain (e.g., Ainsworth, 1999; Petre, Blackwell, & Green, 1998). Petre et al. (1998) asserted that having to make the mental transference between representations (and possibly between paradigms) forces reflection beyond the boundaries and details of the first representation and an anticipation of correspondences in the second. The deeper level of cognitive processing can reveal glitches that might otherwise have been missed. We expected that by using multiple representations, subjects could transfer their knowledge of the domain presented in the learning environment to other, comparable, situations. However, we did not find significant differences on transfer items between the pre-test and post-test. This could possibly be explained by the fact that subjects worked with the learning environment for a short period of time (the average learning time was 38 minutes) and therefore did not explore the domain deeply. Subjects, therefore, did not obtain enough insight in the relations between the domain variables to be able to transfer their knowledge to new situations. A second aspect could be that in the learning environments the domain was presented in specific contexts. Representation 2 (see Figure 2-2) showed the physics system under study; an open-end spanner with a hand tightening a bold or a hoisting crane. It showed the domain in a way it would appear in a real-world situation. This representation was meant to constrain the interpretation of the other representations. A drawback could have been that subjects related the domain to the presented contexts too much and were therefore not able to transfer their new knowledge to other contexts.

Although their pre-tests and post-tests contained transfer items, Wu et al. (2001), Ainsworth et al. (1997) and van Labeke and Ainsworth (2002) did not look explicitly for learning effects of (dynamically) linked multiple representations on these items. Tsui and Treagust (2003), doing research on genetics reasoning, found that some but not all subjects scored better on transfer items. When analysing their interviews, they found that the subjects who did not improve showed no mindful interaction with the multiple representations in their learning environment. According to Tsui and Treagust, learners' mindfulness in interacting with multiple representations is a theme which appeared to be crucial in the development of genetics reasoning and in the transfer of that reasoning to new problem situations.

Like, for example, Petre et al. (1998), we believe that having to make mental translations between representations is a good way to acquire deeper knowledge in a domain. It is worthwhile to further investigate the effects of different types of support when offering learners multiple representations. Integrating representations looks promising, but, as Lowe (2004) also asserts, additional support is probably needed to let learners have mindful interaction with the representations.

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3

Progression in multiple representations

Abstract - Relating multiple representations and translating between them is important for acquiring deeper knowledge in a domain. To relate representations, learners must mentally search for similarities and differences. To translate between representations, learners need to interpret the effects that changes in one representation have on corresponding representations. The question is how the design of representations influences the processes of relation and translation. In this study we examined the effect of sequencing dynamic representations on learning outcomes. Two versions of the same simulation-based learning environment, that of the physics topic of moments, were compared: a learning environment providing the representations step-by-step (experimental condition) and a learning environment providing all representations at once (control condition). The subjects were 88 students from secondary vocational education (aged 15 to 21). Overall, we found that the subjects learned from working with the learning environment; the post-test scores on the domain and transfer items were significantly better than the pre-test scores. Despite our expectations, no differences were found between the two experimental conditions. The subjects learned equally well regardless of the way in which the representations were presented. Also, the extent to which the subjects experienced complexity of both the topic and the learning environment did not differ between the experimental conditions.

Introduction

Many learning environments contain multiple representations such as: text, static pictures, animations, graphs, tables and formulas. By using multiple representations, learners are assumed to acquire deeper knowledge in a domain and therefore to be able to use their knowledge in other learning situations. Mental transference between representations forces learners to reflect beyond the boundaries and details of the first representation to anticipate correspondences in the second (Petre, Blackwell, & Green, 1998). This is believed to lead to a deeper level of cognitive processing. In addition to this, multiple representations can comprise different roles. First, a familiar representation can support understanding and reasoning with unfamiliar ones (the constraining function; Ainsworth (1999, 2006)). Second, representations can complement each other by containing complementary information or by supporting different complementary processes (the complementing function; Ainsworth (1999, 2006)).

To be able to learn from multiple representations, learners must: (1) understand the syntax of each representation, (2) understand which parts of the domain are represented, (3) relate the representations to each other if the representations are (partially) redundant and (4) translate between the representations, that is, interpret similarities and differences of corresponding features of two or more representations (van der Meij & de Jong, 2006). Several studies (e.g., Kozma, 2003; Tabachneck, Leonardo, & Simon, 1994) have shown that the last two tasks – relating and translating between representations – are difficult for learners. This is problematic, because these cognitive processes are important for deeper learning to occur. Learners find most difficulty in translating between representations with different *representational codes* (for example, pictorial, arithmetical or textual) (Ainsworth, 1999).

This leads to an interesting question for instructional designers: can the way in which multiple representations are presented facilitate the cognitive processes of relating and translating?

Supporting the relating and translating process

An important requirement for learning with multiple representations in simulation-based learning environments is how to support learners in the process of relating and translating. Both integration and dynamic linking of representations (Ainsworth & Peevers, 2003; Chandler & Sweller, 1991; Mayer & Moreno, 1998; van der Meij & de Jong, 2006) are of proven value. However, both also have their limitations and drawbacks.

Integrating

Physical integration of representations can make relations between representations explicit for the learner (e.g., Chandler & Sweller, 1991). Integrated representations appear to be one representation showing different aspects of the domain. By integrating representations, relations between them are shown directly to the learner. Having all related elements in the same place makes it easier to interpret the similarities and differences between corresponding features and therefore integration also supports the translation process. Several studies conclude that learning with integrated representations leads to better knowledge compared with learning with non-integrated representations (Ainsworth & Peevers, 2003; Bodemer, Ploetzner, Feuerlein, & Spada, 2004; Chandler & Sweller, 1991; Mayer & Moreno, 1998). However, integration does not always lead to better learning outcomes. Bodemer et al. (2004) found that students working with integrated representations only learned more compared with students working with non-integrated ones when they had to actively integrate the representations themselves. Moreover, Bodemer and Faust (2006) only found positive effects of active integration when students were able to integrate the representations correctly. Chandler and Sweller (1991) only found positive effects of integration when individual units could not be understood separately.

Dynamic linking

For simulation-based learning environments with dynamic representations (representations that change over time or change according to input of the learner), dynamic linking can be provided to make the relations between different representations explicit for the learner (Ainsworth, 1999). With dynamically linked representations, actions performed on one representation are automatically shown in all other representations. If a learner, for example, changes the value of a force in a numerical representation, the corresponding representation of the force in an animation is updated automatically. It is expected that dynamic linking decreases cognitive load by freeing learners from having to establish the relationships between the representations (e.g., Kaput, 1989; Scaife & Rogers, 1996). However, a potential problem with dynamic linking might be learners' selective attention (see Lowe, 1999). With multiple dynamically changing representations, learners need to attend to and relate changes that occur simultaneously in different regions of various representations. Another problem might be that dynamic linking allows a learner to be too passive in the relating and translating processes (Ainsworth, 1999). Dynamic linking may discourage mental relation and translation, hindering the learner from constructing the required understanding. Despite the potential problems, dynamic linking seems to be a promising approach to support learning with multiple representations.

Integrating plus dynamic linking

In a previous study comparing three simulation-based learning environments, we extended known research on integration by examining its role using dynamic representations instead of static representations (van der Meij & de Jong, 2006). In three experimental conditions, the same learning environment on the physics topic of moments was presented using separate, non-linked representations, using separate, dynamically linked representations and using integrated, dynamically linked representations. Furthermore, we examined the role of the complexity of the domain and the learning environment. The learning environment was divided into a low complexity and a high complexity part. We found better learning results on domain knowledge when the representations were integrated plus dynamically linked. In addition, we found a trend between experimental conditions on so-called representation items – where subjects had to relate or translate between representations – in favour of the integrated plus dynamically linked condition. We did not find differences between conditions on test items measuring transfer. The learning environments we used can be characterized as guided inquiry learning environments (e.g., Mayer, 2004; van Joolingen & de Jong, 2003). In inquiry learning environments, learners are engaged in active exploration of the learning materials in order to understand the concepts of a domain. It is expected that learners who explore a domain themselves acquire deeper knowledge of that domain. However, they only gain from the inquiry process if it is adequately guided by, for example, assignments and explanations.

Representation progression

Another way to support learners in simulation-based learning environments is to provide them with model progression (White & Frederiksen, 1990). With model progression the learning environment can by sequenced from simple to complex. This study was a first attempt to relate model progression to representational progression. Based on the model progression used, we increased the number of representations gradually. As a result, the number of relations and possible translations increased likewise. Starting with a few relations and possible translations and then introducing more relations and possible translations step-by-step might support learners in relating the representations and translating between them. In addition, sequencing the representations might be a solution to the selective attention problem mentioned earlier.

Research questions

The goal of this study was to determine if sequencing dynamic representations has an effect on learning outcomes. This was examined in a simulation-based learning environment with dynamic representations.

The context of the study was a guided inquiry simulation-based learning environment called Moments. Subjects studied the physics topic of moments by means of multiple representations of an open-end spanner tightening a bolt. Two versions of the same simulation-based learning environment were compared: a learning environment providing the learners with representations introduced step-by-step (experimental condition – R-Step) and a learning environment presenting all the representations at once (control condition – R-Once).

Method

The primary group in this study were subjects without prior knowledge of the domain. These subjects were at the start of their first year of secondary vocational education. Since our materials were ready three months before the start of the first semester, we had the opportunity to carry out our study also with two groups of students at the end of their first year. We took this opportunity to explore how these students, who had prior knowledge of the domain, would perform on our tests and would work with our learning environments.

Subjects

Primary group - subjects without prior knowledge in the domain

The subjects were students at the start of their first year of secondary vocational education. They were between 15 and 21 years old and took either a course in mechanical engineering (classes 1 and 2) or architecture (classes 3 and 4). Subjects came from two schools and from one class at school one and three classes at school two. A between subjects design was used, in which participants were randomly assigned to one of the two experimental conditions. Ninety-five students started the experiment; two subjects were not representative because they were repeaters, two subjects had no Internet access and as a result were not able to do the pre-test and post-test, subject identifications of two subjects were probably mixed up and one subject was removed from the analyses as an outlier (score of 1 on the pre-test); resulting in the analyses being performed with 88 subjects. Table 3-1 shows how the subjects were distributed across the conditions.

Table 3-1 Distribution of subjects without prior knowledge across conditions

		Condition		
Class	School	R-Step (m/f)	R-Once (m/f)	Total (m/f)
1	1	11 (11/0)	12 (12/0)	23 (23/0)
2	2	7 (7/0)	8 (8/0)	15 (15/0)
3	2	13 (13/0)	13 (13/0)	26 (26/0)
4	2	14 (13/1)	10 (10/0)	24 (23/1)
Total		45 (44/1)	43 (43/0)	88 (87/1)

m = male, f = female

Exploratory group - subjects with prior knowledge in the domain

The subjects were students at the end of their first year of secondary vocational education. They were between 16 and 19 years old and took either a course in mechanical engineering (class 1) or architecture (class 2). Subjects came from two schools and from one class at each school. A between subjects design was used, in which participants were randomly assigned to one of the two experimental conditions. Thirty-five students started the experiment; two subjects were not representative because they were in orientation for the course and the post-test results of one student were lost, resulting in analyses being done with 32 subjects. Table 3-2 shows how the subjects were distributed across the conditions.

Table 3-2 Distribution of subjects with prior knowledge across conditions

Class	School	Condition R-Step (m/f)	Condition R-Once (m/f)	Total (m/f)
1	1	9 (9/0)	8 (8/0)	17 (17/0)
2	2	6 (5/1)	9 (8/1)	15 (13/2)
Total		15 (14/1)	17 (16/1)	32 (30/2)

m = male, f = female

Materials

Learning environment

Subjects worked with the Moments learning environment that was built in the SimQuest authoring environment (de Jong, van Joolingen, Veermans, & van der Meij, 2005; van Joolingen & de Jong, 2003). Subjects studied the physics topic of moments in the context of mechanical engineering. The learning environment is based on guided inquiry learning (de Jong & van Joolingen, 1998). The learner has to engage in inquiry activities in order to learn about the properties of the simulation model and is guided in the inquiry process by 'cognitive tools' such as model progression, assignments and explanations. Learners explore the simulation model by manipulating values of the input variables and observing the behaviour of output variables. By understanding the relations between the variables, it is expected that learners acquire a deep understanding of the domain and are able to transfer their knowledge to similar problems in other situations.

The learning environment consists of an introduction and 16 assignments. The introduction gives an overview of 'moments' by giving everyday examples in which moments play a role. After this introduction, learners explore specific aspects of the domain by choosing an assignment from the menu. When opening an assignment, a corresponding simulation interface opens. Each assignment starts with a short description of an aspect of the domain, asks the learner to explore this aspect and asks the learner to answer a question about it. After answering the question, the learner gets feedback in the form of the right answer with an explanation. With multiple choice questions, the learner receives a hint when the first attempt is wrong. If the second attempt is wrong as well, the right answer is given with an explanation.

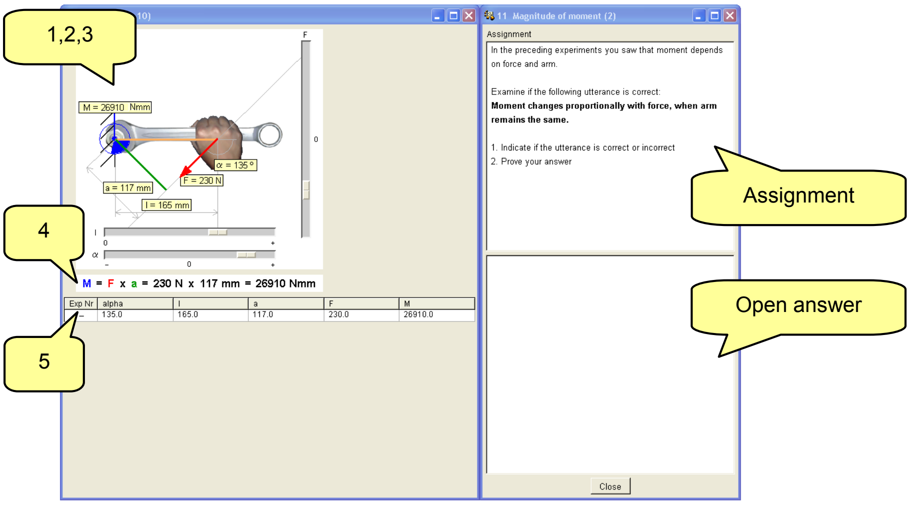


Figure 3-1 Assignment with simulation interface showing all representation types

The learner can perform experiments in the simulation interface (left screen in Figure 3-1) supported by assignments (right screen in Figure 3-1). The learner can manipulate the force and length input variables and can observe the moment output variable. The assignments stimulate learners to explore the relation between the variables in the simulation model. The types of representations used are: (1) a concrete representation (animation of an open-end spanner), (2) a diagrammatic representation (an abstract representation of the variables playing a role in the concrete situation), (3) a numerical representation (showing the values of the variables involved), (4) a dynamically changing equation and (5) a dynamically changing table (showing one row that is dynamically updated when variables are manipulated by the learner). Table 3-3 gives an overview of the instructional support with corresponding representations. The assignments are the same for both experimental conditions.

Representations 1, 2 and 3 (see Figure 3-1) are representations usually found in textbooks. These representations are the basic types presented to learners in this domain. They support learners in getting insight into the domain from different perspectives. We were able to integrate these representations because of their formats. The concrete and diagrammatic representations could easily be integrated because they share the same spatial properties. The numerical representations could be placed near the objects in the other two representations. The concrete representation (1) provides the learner with a context for the simulated task. This representation links the learning material to a real-life experience. The choice of an open-end spanner in this learning environment was made because most of the students in the target group have experience in using this tool. The diagrammatic

Table 3-3 Instructional support with corresponding representations

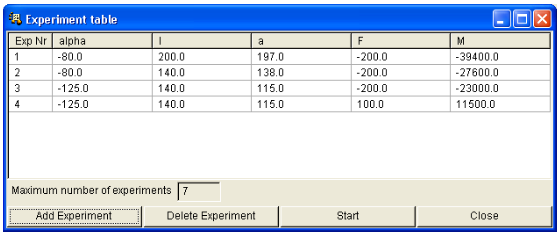
Instructional support (text)	Representations R-Step	Representations R-Once
00. Introduction	Text and pictures	Text and pictures
01. Explanation what is moment	1	1, 2, 3, 4, 5
02. Fixed clamp	1, 2 (clamp)	,,
03. Moment caused by place hand	1, 2 (clamp and M)	,,
04. Introduction arm	1, 2 (clamp, M and a)	,,
05. Introduction force	1, 2 (clamp, M, a and F)	,,
06. Orientation moment by force	,,	,,
07. Introduction angle (90°)	1, 2 (clamp, M, a, F and α)	,,
08. Introduction distance	1, 2	,,
09. Magnitude moment	1, 2, 3	,,
10. Variables that play a role	1, 2, 3, 4	,,
11. Relation force and moment	1, 2, 3, 4, 5	,,
12. Introduction Experiment table	,,	,,
13. Double the force	,,	,,
14. Relation a and M	,,	,,
15. Combination M, a and F	,,	,,
16. Influence angle on moment	,,	,,

Representations:

1. concrete representation (animation of open-end spanner)
2. diagrammatic representation (an abstract representation of the variables playing a role in the concrete situation)
3. numerical representation (showing the values of the variables involved)
4. dynamically changing equation
5. dynamically changing table (showing one row that is dynamically updated when variables are manipulated by the learner)

representation (2) helps learners to go beyond the concrete situation to a more abstract understanding of the relation between the variables involved. By providing this type of representation, it is expected that learners can use their acquired understanding in new situations. Both the concrete and diagrammatic representations present the domain in a qualitative way. The numerical representation (3) gives a quantitative view of the variables involved. The contribution of this representation is showing the values of the variables to support the numerical relations between the variables. The dynamically changing equation (4) represents the domain as a formula with dynamically changing numerical values. It shows the actual values of the variables together with their relations in a direct way. The dynamically changing table (5) also supports the understanding of numerical relations. It contains one row representing the actual values of all variables involved. The dynamically changing equation and table could not be integrated with representations 1 to 3 because their forms are too divergent. We chose to dynamically link all the representations.

In addition to the table, an experiment table is introduced in assignment 12 (see Figure 3-2). This table has the same format as representation number 5 (the dynamically changing table), except that learners can save, compare, structure, replay and delete their experiments. Experiments are saved by clicking a save button; this adds a row to the table showing the variables' values in a static fashion. Learners can replay an experiment by selecting a table row and clicking a start button. All representations then represent the values of the table row.



Exp Nr	alpha	l	a	F	M
1	-80.0	200.0	197.0	-200.0	-39400.0
2	-80.0	140.0	138.0	-200.0	-27600.0
3	-125.0	140.0	115.0	-200.0	-23000.0
4	-125.0	140.0	115.0	100.0	11500.0

Figure 3-2 Experiment table

Learners can manipulate the input variables by using the provided sliders. If a learner manipulates a slider, the corresponding changes are shown in the representations in real time. For example, if a learner moves the force-slider, the element representing force is updated continuously and immediately, as is the change in moment. Learners can compare situations by moving the slider back and forth between different states of the simulation. They can also compare situations when they have access to the experiment table (see Figure 3-2).

In the experimental condition, the representations are introduced one by one; starting with the concrete representation, followed by the diagrammatic, then the numerical and ending with the table (Figure 3-3 shows the first step; Figure 3-1 showed the final step).

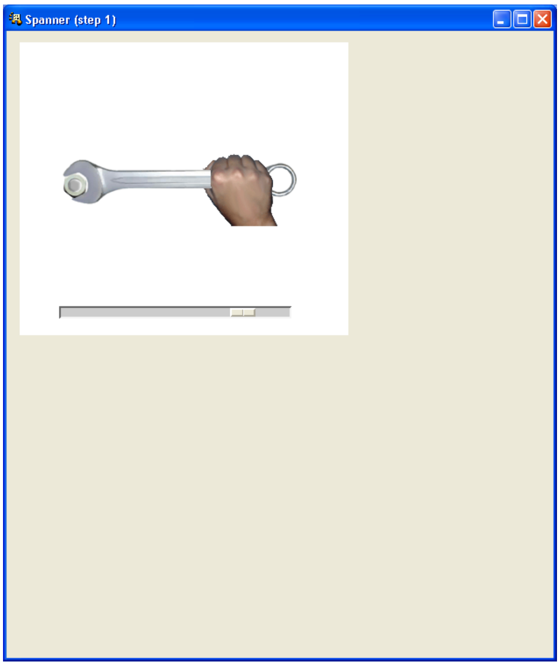


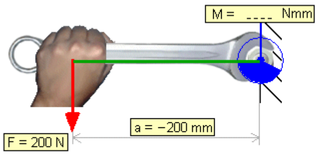
Figure 3-3 First representation progression step (experimental condition)

Tests and questionnaire

Subjects' prior domain knowledge was assessed using an online pre-test. This was administered directly before working with the learning environment. An online post-test was administered directly after working with the learning environment.

The pre-test consisted of 20 items, both multiple-choice and open answer items; 10 items testing domain knowledge and 10 items testing transfer knowledge. The post-test consisted of 40 items, both multiple-choice and open answer items; 10 domain items, 10 transfer items, 10 items testing the ability to relate representations and 10 items testing the ability to translate between representations. The *domain items* tested whether the subjects were able to reproduce the content they were explicitly asked to explore in the learning environment. The *transfer items* tested the ability of the subjects to apply their acquired knowledge in new situations. These were new contexts and/or relations between variables that were not directly asked for in the learning environment, but that could be derived from the domain knowledge. The *relate items* tested whether the subjects were able to relate different representations. These items asked the subjects to relate similar variables of representations with different representational codes. To be able to answer *translate items* correctly, the subjects had to make a mental translation from manipulations on one representation to the effects in another representation having a different representational code. Figure 3-4 shows examples of the test items.

(1) How big is the moment on the nut shown in the example below?

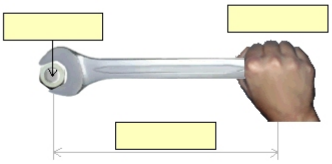


- − 40000 Nmm
- 0 Nmm
- 400 Nmm
- 40000 Nmm

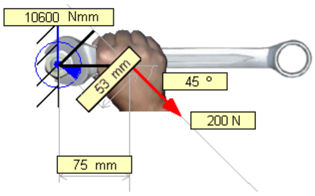
(2) In the figure below the long bar is supported exactly in the middle by the second bar. The length of the long bar is 4 meters. The weight of the long bar is 1000 N. What is the magnitude of the moment in the connection?

a. 0 Nm
b. 250 Nm
c. 500 Nm
d. 4000 Nm

(3) Drag "a" to the correct position.



(4) In the example below someone moves the hand twice as far from the nut.



Which of the following experiments corresponds to this example?

Exp Nr	alpha	l	a	F	M
1	45.0	75.0	53.0	200.0	10600.0
2	45.0	106.0	75.0	200.0	15000.0
3	45.0	150.0	106.0	200.0	21200.0
4	45.0	212.0	150.0	200.0	30000.0

- 1
- 2
- 3
- 4

Figure 3-4 Examples of (1) domain, (2) transfer, (3) relate and (4) translate items

The domain and transfer items corresponded to the post-test items. The post-test items differed slightly from the pre-test by changing the item and alternative answer orders. Since subjects did not know which items had been changed, they could not rely on a memory strategy.

For each pre-test and post-test item, a subject received a score of 1 if the answer was correct or a score of 0 if the answer was incorrect. The maximum scores for the pre-test and post-test were 20 and 40 respectively.

An electronic questionnaire based on Swaak's S.O.S. scale (Swaak, 1998) was used to assess the subjects' opinions of the complexity of the learning environment and the domain. The questionnaire asked subjects to score the topic as easy, average, or difficult (Q1) and whether they found working with the simulation easy, average, or difficult (Q2). The questionnaire was given three times to subjects while they worked with the learning environment: after assignments 6, 11 and 16. Subjects had to complete the questionnaire before they could continue.

Procedure

The experiments were held at the participating schools and consisted of three experimental sessions: pre-test, working with the learning environment and post-test. Subjects were randomly assigned to one of the two conditions using their seating placement.

Before the pre-test participants were informed about the experiment and were told the test measured their prior knowledge of force, arm and moment. If necessary, a brief description was given. Participants were asked to fill in all test items, even if they were unsure about the right answer. Subjects had a maximum of 45 minutes to complete the pre-test.

The learning environment session took place approximately 45 minutes after the start of the pre-test session, so that all subjects had at least a 10-minute break between the sessions. Subjects could work in the learning environment at their own pace, but not longer than an hour. They worked on their own and could question the teacher or experiment leader on operating the learning environment. Subjects were asked to do all 16 assignments. When ready, the subjects could ask to do the post-test.

The post-test took place directly after the learning environment session. The participants could work a maximum of 45 minutes on this test. The participants were not allowed to use the learning environment during the test and were asked to fill in all test items, even if they were unsure about the right answer.

Results

Pre-test and post-test

Primary group - subjects without prior knowledge in the domain

The overall mean score on the pre-test was 9.65 out of 20 test items (SD = 2.88). These data indicate the subjects had relatively little prior knowledge in the domain. The overall mean score on the post-test domain plus transfer items was 11.64 out of 20 test items (SD = 3.10). Table 3-4 shows the means and standard deviations of the scores on the item categories in the pre-test and post-test.

Table 3-4 Means and standard deviations of pre-test and post-test scores

	Pre-test			Post-tests		
	Mean	(SD)	%	Mean	(SD)	%
Domain items (max. 10)	5.70	(1.62)	57	6.99	(1.68)	70
Transfer items (max. 10)	3.96	(1.78)	40	4.65	(1.91)	47
Total (max. 20)	9.95	(2.88)	48	11.64	(3.10)	58
Relate items (max. 10)				7.82	(1.50)	78
Translate items (max. 10)				2.95	(1.39)	30

n = 88

A repeated measures ANOVA showed that the overall combined domain and transfer post-test score of the 88 subjects was significantly better than the overall pre-test scores ($F(1,87) = 60.68$, $p < 0.01$). Repeated measures ANOVAs for each item category showed that the post-test scores on domain and transfer items were significantly better than the pre-test scores on these item types ($F(1,87) = 67.51$, $p < 0.01$ and $F(1,87) = 15.54$, $p < 0.01$). Table 3-5 shows the means and standard deviations of the pre-test and post-test scores for the four item categories for each condition.

One-way ANOVAs showed no significant differences between the experimental conditions on pre-test domain scores and transfer scores ($F(1,86) = 2.05$, $p = 0.16$; $F(1,86) = 0.05$, $p = 0.82$). This means that subjects in the experimental conditions did not differ in prior knowledge.

One-way ANOVAs showed no significant differences between the experimental conditions on post-test domain scores, transfer scores, relate scores and translate scores ($F(1,86) = 0.33$, $p = 0.57$; $F(1,86) = 0.64$, $p = 0.43$; $F(1,86) = 0.94$, $p = 0.33$; $F(1,86) = 0.09$, $p = 0.77$).

Table 3-5 Means and standard deviations of pre-test and post-test scores

	R-Step		R-Once	
	Mean	(SD)	Mean	(SD)
Pre-test				
Domain items (max. 10)	5.93	(1.76)	5.44	(1.44)
Transfer items (max. 10)	3.91	(1.73)	4.00	(1.85)
Pre-test total (max. 20)	9.84	(2.97)	9.44	(2.80)
Post-test				
Domain items (max. 10)	7.09	(1.62)	6.88	(1.75)
Transfer items (max. 10)	4.49	(1.73)	4.81	(2.09)
Relate items (max. 10)	7.67	(1.49)	7.98	(1.50)
Translate items (max. 10)	2.91	(1.47)	3.00	(1.31)
Post-test total (max. 40)	22.16	(4.01)	22.67	(5.29)

n = 88

Exploratory group - subjects with prior knowledge in the domain

This section reports the results for the exploratory group. Although the learning environment was designed for learners without prior knowledge in the domain, this group was included because we had the opportunity to carry out our study with two groups with prior knowledge in the domain and we were eager to see how these students would perform on the tests and work with the learning environment.

The overall mean score on the pre-test was 12.16 out of 20 test items (SD = 2.99). These data indicate the subjects had moderate prior knowledge in the domain. The overall mean score on the post-test domain plus transfer items was 13.31 out of 20 test items (SD = 2.81). Table 3-6 shows the means and standard deviations of the scores on the item categories in the pre-test and post-test.

Table 3-6 Means and standard deviations of pre-test and post-test scores

	Pre-test			Post-test		
	Mean	(SD)	%	Mean	(SD)	%
Domain items (max. 10)	6.97	(1.51)	70	7.50	(1.44)	75
Transfer items (max. 10)	5.19	(1.94)	52	5.81	(2.07)	58
Total (max. 20)	12.16	(2.99)	61	13.31	(2.81)	67
Relate items (max. 10)				8.63	(1.21)	86
Translate items (max. 10)				3.78	(1.98)	38

n = 32

A repeated measures ANOVA showed that the overall combined domain and transfer post-test score of the 32 subjects was significantly better than the overall pre-test scores ($F(1,31) = 9.07$, $p < 0.01$). Repeated measures ANOVAs for each item category showed a trend for pre-test to post-test scores on domain items ($F(1,31) = 3.89$, $p = 0.06$). Post-test scores on transfer items were significantly better than pre-test scores on these item types ($F(1,31) = 7.52$, $p < 0.05$). Table 3-7 shows the means and standard deviations of the pre-test and post-test scores for the four item categories for each condition.

Table 3-7 Means and standard deviations of pre-test and post-test scores

	R-Step		R-Once	
	Mean	(SD)	Mean	(SD)
Pre-test				
Domain items (max. 10)	7.33	(1.63)	6.65	(1.37)
Transfer items (max. 10)	5.53	(1.51)	4.88	(2.26)
Pre-test total (max. 20)	12.87	(2.70)	11.53	(3.17)
Post-test				
Domain items (max. 10)	7.53	(1.30)	7.47	(1.59)
Transfer items (max. 10)	5.73	(1.53)	5.88	(2.50)
Relate items (max. 10)	8.60	(1.12)	8.65	(1.32)
Translate items (max. 10)	3.73	(1.87)	3.82	(2.13)
Post-test total (max. 40)	25.60	(4.42)	25.82	(5.88)

n = 32

One-way ANOVAs showed no significant differences between the experimental conditions on pre-test domain scores and transfer scores ($F(1,30) = 1.68$, $p = 0.21$; $F(1,30) = 0.90$, $p = 0.35$). This means that subjects in the experimental conditions did not differ in prior knowledge.

One-way ANOVAs showed no significant differences between the experimental conditions on post-test domain scores, transfer scores, relate scores and translate scores ($F(1,30) = 0.02$, $p = 0.90$; $F(1,30) = 0.04$, $p = 0.84$; $F(1,30) = 0.01$, $p = 0.92$; $F(1,30) = 0.02$, $p = 0.90$).

Comparison of subjects with and without prior knowledge

A one-way ANOVA showed that subjects with prior knowledge scored significantly higher on the pre-test than subjects without prior knowledge ($F(1,118) = 17.49$, $p < 0.01$). The same effect was found for the post-test ($F(1,118) = 11.17$, $p < 0.01$).

Experienced domain complexity

The experienced domain complexity was measured by the questionnaire question: "I find the topic at this moment: easy, average, or difficult." The question appeared three times during working with the learning environment. One-way ANOVAs for all three appearances showed no significant differences between the experimental conditions on experienced domain complexity for subjects with prior knowledge and subjects without prior knowledge.

Experienced learning environment complexity

The experienced learning environment complexity was measured by the questionnaire question: "I find working with the simulation at this moment: easy, average, or difficult". The question appeared three times during working with the learning environment. One-way ANOVAs for all three appearances showed no significant differences between the experimental conditions on experienced learning environment complexity for subjects with prior knowledge and subjects without prior knowledge.

Discussion

The aim of this study was to determine if sequencing dynamic representations has an effect on learning outcomes. This was examined in a simulation-based learning environment on the physics topic of moments.

Overall, we found that subjects learned from working with the learning environment; post-test scores on the domain and transfer items were significantly better than pre-test scores. This was the case for both the subjects with and without prior knowledge in the domain. It was interesting to find that the pre-test scores of subjects with prior knowledge were higher than the post-test scores of the subjects without prior knowledge and that their knowledge still improved significantly. This may indicate that the subjects without prior knowledge might have scored higher on the post-test had they had more time to work with the learning environments.

In contrast with our expectations, no differences were found between experimental conditions. So, subjects learned equally well regardless of the way the representations were presented. Also, subjects' complexity experience of both the topic and learning environment did not differ between the experimental conditions.

This leaves us with the question: Why did sequencing representations not support learners in relating and translating between representations? In search of an answer to this question we analysed the log files to get insight into the way learners worked through the learning environments. The log files showed that almost all subjects worked through the learning environment in the order in which we presented the assignments. This was not surprising since these students are used to doing this and we asked them to do all assignments. This was also the preferred order, since the assignments were sequenced from simple to complex, introducing variables and relations between variables step-by-step. The assignments were the same in both conditions and followed the step-by-step introduction of the R-Step condition. The assignments directed the subjects' attention to the newly introduced representations and variables in the R-Step condition. It looks like subjects' attention in the R-Once condition also seems to have been directed to these representations and variables. Answers the subjects gave on the assignments and the experiments they saved in the experiment table showed that all subjects did only experiments we explicitly asked them to do. Taking these findings together, our conclusion is that the instructional support provided by the assignments played a very important role in this study. The instructional support had a great impact on how learners worked with the learning environment and may have overshadowed the possible effect of sequencing.

Although we tried to encourage the subjects to explore the simulation and reflect on their actions by asking them to prove their answers by experiments done and to provide an explanation for the answers they gave, the log files showed that learners did not explore the simulation for other features than those explicitly indicated in the assignments and their reflections were very brief. In short, the instructions guided the subjects through the learning environment with little else being attended to. As a result, the subjects seem not to have focused on relating representations and translating between them.

Despite our attempt to engage the subjects in relating representations and translating between them, they do not seem to do so if they are not explicitly asked to. We believe the intervening effect of instructional support in the present study can help us to improve the effects of providing multiple representations in the future. In a follow-up study we will use the current results to adapt the instruction. Instead of focusing on domain knowledge in the instruction, we are going to try to encourage learners to relate and translate between representations by explicitly asking them to do so. We believe that sequencing the representations can give additional support. Sequencing the representations avoids overloading the learners by directing their attention only to those representations they are asked to relate and translate between.

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4

Prompts to translate between representations

Abstract - Learners who learn with multimedia learning environments are almost always confronted with multiple representations. The processing of these representations is an important part of the learning activity. Therefore, the design of these learning environments should support the learner in adequately processing the representations. In this study we examined the effect of presenting learners with sequences of multiple representations combined with explicit instruction, at each step of the sequence, to relate and translate between the different representations. Two versions of the same simulation-based inquiry learning environment on the physics topic of moments were compared. One learning environment provided all representations at once and instructional support focused solely on relations between the domain variables (R-Once condition). The second learning environment provided learners with representations step-by-step and with instructional support that focused additionally on relating representations and translating between them (R-Step condition). Subjects were 86 students from secondary vocational education and 125 students from pre-university education. Overall, the R-Step condition showed the best learning results. Subjects in the R-Step condition performed better on post-test items measuring domain knowledge. A trend in favour of the R-Step condition was found on post-test items asking subjects to relate two different representations. No differences were found between the experimental conditions on post-test transfer items and post-test items asking subjects to translate between two different representations.

Introduction

Computer-based learning environments often combine several representations such as text, static pictures, animations, graphs, tables and formulas. To be able to learn from multiple representations, learners must perform four tasks in sequence: (1) understand the syntax of each representation, (2) understand which parts of the domain are represented, (3) relate the representations to each other if the representations are (partially) redundant and (4) translate between the representations (van der Meij & de Jong, 2006a; chapter 2).

Tasks three and four are unique for learning with multiple representations and we believe that these processes are the main reasons for using multiple representations. When learners are capable of relating and translating between representations they are much more likely to acquire deeper understanding of the domain. A potential explanation for this is that these processes of relating and translating force learners to reflect beyond the boundaries and details of a first representation to anticipate correspondences in a second one (Petre, Blackwell, & Green, 1998). However, to be able to relate and translate between representations, learners first must fulfil tasks one and two.

Understanding the syntax means that learners must comprehend the format (e.g., labels, axes and line shapes) and operators (e.g., plus, minus and divide) of the representation. In a multi-representational learning environment learners must at least have experience with one of the representations. If they don't have this experience, the format and operators of at least one representation must be taught. Not knowing the format and operators of (the) other representations should not be a problem if the learning environment is carefully designed; the learning environment should support learners in finding the format and operators of (the) other representations by somehow linking them with the familiar representation(s).

To *understand which parts of the domain are represented* learners must have sufficient knowledge of the domain. When learners do not have this knowledge, the learning environment must provide at least the information learners need to be able to 'read off' the representation(s) that represent the domain. For many domains it is important that learners at least know which variables play a role. These variables need to be introduced explicitly or learners should be able to look them up in a help system, for example. Relations between domain variables can be either presented to the learner or explored by the learner.

To be able to *relate representations*, learners must mentally search for similarities and differences. We believe that having some prior knowledge in the domain is imperative for finding meaningful relations. Of course, learners can relate elements of different representations without having domain knowledge (e.g., because they have the same colour), but then relating them does not have any educational value. To make sense of the relations, learners need to know what a particular variable in one representation represents, to be able to make sense of a corresponding element in a second representation. Knowing what a particular element represents in one representation also helps the learner to distinguish corresponding elements from non-corresponding elements in a second representation. Although the learners must do the actual relating, the learning environment can provide direct support for the relation process.

To be able to *translate between representations*, learners need to interpret the effects that changes in one representation have on corresponding representations. By translating, learners are supposed to gain deeper understanding of the domain by articulating what happens to a second representation when a first is manipulated and/or by reflecting upon the similarities and differences between the representations. For example, learners should grasp that if in an animation a hand tightening a nut with a spanner is placed twice as far from the nut, this doubles the value of moment in an equation. Learners can only make this translation when they understand what the influence of arm on moment is. To do this, they must translate the concrete situation represented by the animation, via an abstract (mental) representation of the situation and a doubled value of arm in the equation, to the doubled value of moment. Translating between representations is a process that the learner must do mentally and/or explicitly. The learning environment cannot do the translation for the learner; it can only support the learner in the translation process, for example, by giving hints or prompts, explaining the relations or providing worked out examples of ‘interesting’ phenomena. Based on previous research (van der Meij & de Jong, 2006a, 2006b) we believe that learners need to be both prompted to translate between representations and guided in the translation process.

It is important that the design of multiple representations offer support for learners in the knowledge generating processes of relating and translating. For simulation-based learning environments, both integration and dynamically linking representations (Ainsworth & Peevers, 2003; Chandler & Sweller, 1991; van der Meij & de Jong, 2006a) are of proven value for helping learners to relate representations.

Integration of representations can make relations between representations explicit for the learner. Integrated representations appear to be one representation showing different aspects of the domain. By integrating representations, relations between them are shown directly to the learner. Having all related elements in the same place makes it easier to interpret the similarities and differences between corresponding features; therefore, integration is also believed to support the translation process. Bodemer et al. (2004) found that students working with integrated representations only learned more when they had to actively integrate the representations themselves. Bodemer and Faust (2006) only found positive effects of active integration when students were able to integrate the representations correctly. Chandler and Sweller (1991) only found positive effects of integration when individual units could not be understood separately.

With *dynamically linked representations*, actions performed on one representation are automatically shown in all other representations. If a learner, for example, changes the value of a force in a numerical representation, the corresponding representation of the force in an animation is updated automatically. A problem with dynamic linking might be that with multiple dynamically changing

representations, learners need to attend to and relate changes that occur simultaneously in different regions of various representations (Lowe, 1999).
To facilitate the processes of relating and translation, representations can be introduced step-by-step. As a result, the number of relations and possible translations is increased likewise. Starting with a few relations and possible translations and then introducing more relations and possible translations step-by-step might support learners in relating the representations and translating between them. In a previous study (van der Meij & de Jong, 2006b; chapter 3) we examined the effect of sequencing dynamic representations on learning outcomes. Two versions of the same simulation-based learning environment were compared: a learning environment providing the representations step-by-step (experimental condition) and a learning environment providing all representations at once (control condition). Both learning environments used the same integrated and dynamically linked representations. No differences were found between the two conditions. Moreover, post-test scores on translate items were low (3 out of 10 items correct). Log file analysis revealed that an intervening variable might have played an important role: the instructional support consisting of assignments and explanations that were present in the environment. This instructional support was the same for both conditions and focused only on relations between the domain variables. As a result, the subjects seem not to have focused on relating representations and translating between them.

For successful inquiry learning, instructional support in the form of assignments and explanations is crucial (Mayer, 2004; Swaak, van Joolingen, & de Jong, 1998; van Berkum & de Jong, 1991). Instructional support helps learners to find their way through the learning environment and guides them to the aspects of the learning environment that are most important. Until now instructional support has mainly focused on the characteristics of the (simulated) domain.

In simulation based learning environments, for example, the assignments and explanations focus on the relations between the variables of the simulation model, as was the case in our studies cited above (van der Meij & de Jong, 2006a, 2006b). Since we found that instructional support has great impact on how the subjects worked with our multi-representational simulation-based learning environments, using the instructional support not only for domain-guidance, but also for giving hints and prompts to relate and translate between representations might be a good way to support learners.

In a study on economics principles of supply and demand using multiple representations, Tabachneck-Schijf and Simon (1998) found that rather than using multiple representations and benefiting from this, participants tended to reason with only one representation at a time. Students did not seem to realize that the representations should be mentally connected. Explicitly asking learners to relate or translate two or more representations may solve this problem. Moreover, prompting learners in this way may also result in (prompted) self-regulation (Azevedo, 2005; Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Chi, Deleeuw, Chiu, & Lavancher, 1994) in the sense that they have to think about the connections between representations and have to formulate an answer to the question(s) asked. Many authors agree that learning from multiple representations "… is not a passive process, but requires that the students actively engage in the processing of the representations." (Van Meter, Firetto, & Higley, 2007, p. 7). Explicitly prompting learners to process the information from different representations may help.

Research questions

The goal of the current study was to determine if sequencing dynamic representations, combined with explicit instruction to relate representations and translate between them, has an effect on learning outcomes. Two versions of the same simulation-based inquiry learning environment on the physics topic of moments were compared: a learning environment providing the representations step-by-step, where the instructional support focused on relations between the variables in the domain as well as relations between the representations (experimental condition – R-Step) and a learning environment providing all representations at once, where the instructional support focused solely on relations between the variables in the domain (control condition – R-Once). Assignments in both conditions covered the same amount of domain information. The only difference was that students in the R-Step conditions were prompted to include two or more representations in their answers (we give an example in the Materials section on page 84). We expected students to learn the domain in both the R-Step and R-Once learning environment. Therefore, we expected higher post-test scores compared with pre-test scores. We expected the R-Step condition to lead to better learning outcomes on domain knowledge, transfer knowledge and on the ability to relate representations and translate between them.

Method

Subjects

Subjects were 86 students from secondary vocational education (aged 15 to 21) and 125 students from pre-university education (aged 13 to 15). Students in the first group were in their first year of either a course in mechanical engineering or architecture. Students in the second group were in their third year. Subjects came from four schools; two secondary vocational schools (school 1 and 2) and two secondary schools (school 3 and 4). A between subjects design was used, in which participants were randomly assigned to one of the two experimental conditions. Table 4-1 shows how the subjects were distributed across the conditions.

Table 4-1 Distribution of subjects across conditions

Class	School	Condition R-Step (m/f)	Condition R-Once (m/f)	Total (m/f)
1	1	12 (12/0)	10 (10/0)	22 (22/0)
2	1	8 (8/0)	8 (8/0)	16 (16/0)
3	2	13 (13/0)	12 (12/0)	25 (25/0)
4	2	13 (13/0)	10 (10/0)	23 (23/0)
5	3	10 (4/6)	11 (7/4)	21 (11/10)
6	3	12 (3/9)	12 (9/3)	24 (12/12)
7	3	9 (4/5)	8 (6/2)	17 (10/7)
8	4	12 (2/10)	11 (4/7)	23 (6/17)
9	4	11 (9/2)	10 (4/6)	21 (13/8)
10	4	10 (4/6)	9 (9/0)	19 (13/6)
Total		110 (72/38)	101 (79/22)	211 (151/60)

m = male, f = female

Materials

Learning environment

Subjects worked with a simulation-based learning environment on the physics topic of moments, built in the SimQuest authoring environment (de Jong, van Joolingen, Veermans, & van der Meij, 2005; van Joolingen & de Jong, 2003). The topic is compulsory for students in this study. The learning environment is based on guided inquiry learning (de Jong & van Joolingen, 1998). The learner has to engage in inquiry activities in order to learn about the properties of the simulation model and is guided in the inquiry process by a selection of 'cognitive tools' such as hypothesis scratchpads, monitoring facilities, model progression, assignments and explanations. Learners explore the simulation model by manipulating values of the input variables and observing the behaviour of output variables.

The learning environment as used in this study consists of an introduction and several assignments. The introduction, which was the same for both conditions, gives an overview of 'moments' by presenting everyday examples in which moments play a role. After this introduction, learners explore specific aspects of the domain by choosing an assignment from the menu. When opening an assignment, a corresponding simulation interface opens. The assignments are numbered, so that learners are invited to work through the learning environment in a specific order.

Supported by the assignments (right screen in Figure 4-1), which differed between conditions, the learner can perform experiments in the simulation interface (left screen in Figure 4-1). The learner can manipulate the force, length and angle input variables and can observe the moment output variable. The types of representations available are: (1) a concrete representation (animation of a tackle, an open-end spanner or car crane), (2) a diagrammatic representation (an abstract representation of the variables playing a role in the concrete situation), (3) a numerical representation (showing the values of the variables involved), (4) a dynamically changing equation, (5) a moment-arm graph, (6) a moment-force graph and (7) a dynamically changing table (showing one row that is dynamically updated when variables are manipulated by the learner).

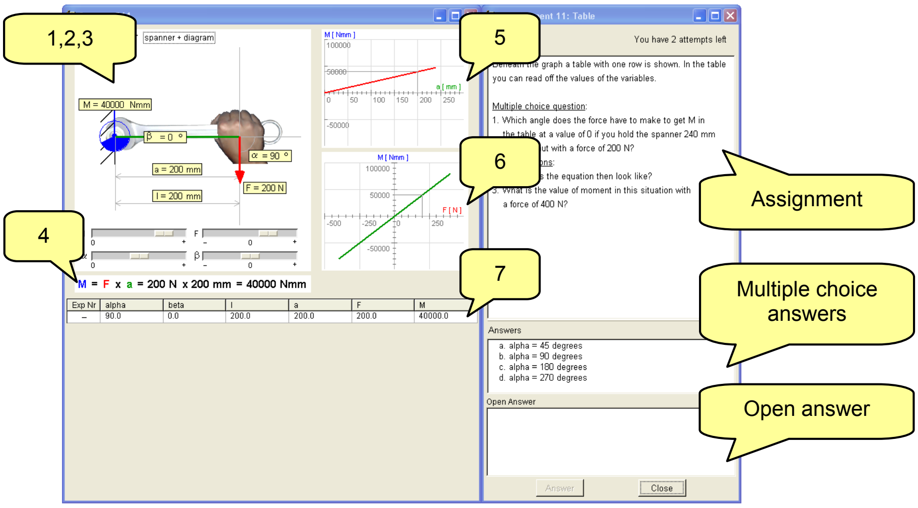
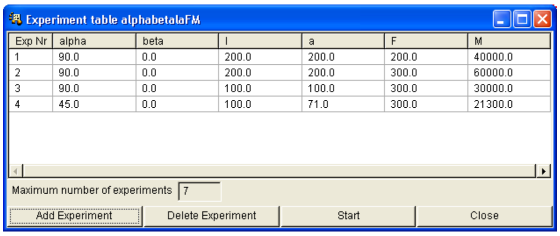


Figure 4-1 Assignment with simulation interface showing all representation types

Representations 1, 2 and 3 are usually found in textbooks. These representations are the basic types presented to learners in this domain. They support learners in getting insight into the domain from different perspectives. The concrete representation (1) provides the learner with a context for the simulated task. This representation links the learning material to a real-life experience. The diagrammatic representation (2) helps learners to go beyond the concrete situation to a more abstract understanding of the relation between the variables involved. By providing this type of representation, it is expected that learners can use their acquired understanding in new situations. Both the concrete and diagrammatic representations present the domain in a qualitative way. The numerical representation (3) gives a quantitative view of the variables involved. The contribution of this representation is showing the values of the variables to support the numerical relations between the variables. The dynamically changing equation (4) represents the domain as a formula with dynamically changing numerical values. It shows the actual values of the variables together with their relations in a direct way. Learning (to use) the equation is very important: it has to be used to calculate moment. The graphs (5 and 6) are provided to help learners to predict relationships between the variables. In the graphs, any 'pictorial' similarity to the represented domain has disappeared; therefore, graphs represent the domain in a more abstract way than do the concrete and diagrammatic representations (Bernsen, 1994). In addition, the graphs give the learner more direct information about the relations between the variables than do representations 1 to 3. The dynamically changing table (7) also supports the understanding of numerical relations. It contains one row representing the actual values of all variables involved. To support learners in relating representations, we chose to dynamically link all the representations. We were able to integrate representations 1, 2 and 3 because of their formats. The concrete and diagrammatic representations could easily be integrated because they share the same spatial properties. The numerical representations could be placed near the objects in the other two representations.

In addition to the dynamically changing table, an experiment table is introduced when learners come to assignment 7 (R-Once condition) or assignment 13 (R-Step condition). The experiment table is shown in Figure 4-2. This table has the same format as representation number 7 (the dynamically changing table), except that learners can save, compare, structure, replay and delete their experiments. Experiments are saved by clicking a save button; this adds a row to the table showing the variables' values in a static fashion. Learners can replay an experiment by selecting a table row and clicking a start button. All representations then represent the values of the table row.



Exp Nr	alpha	beta	l	a	F	M
1	90.0	0.0	200.0	200.0	200.0	40000.0
2	90.0	0.0	200.0	200.0	300.0	60000.0
3	90.0	0.0	100.0	100.0	300.0	30000.0
4	45.0	0.0	100.0	71.0	300.0	21300.0

Figure 4-2 Experiment table

In the simulation interface, learners can manipulate the input variables by using the provided sliders. If a learner manipulates a slider, the corresponding changes are shown in the representations in real time. So, if a learner moves the force-slider, the element representing force is updated continuously and immediately, as is the change in moment. Learners can compare situations by moving the slider back and forth between different states of the simulation. They can also compare situations when they have access to the experiment table (see Figure 4-2).

In the R-step condition, the representations are introduced one by one: starting with the concrete representation, followed by the diagrammatic representation, the numerical representation, the equation, the graphs and ending with the table (Figure 4-3 shows the first step; Figure 4-1 showed the final step).

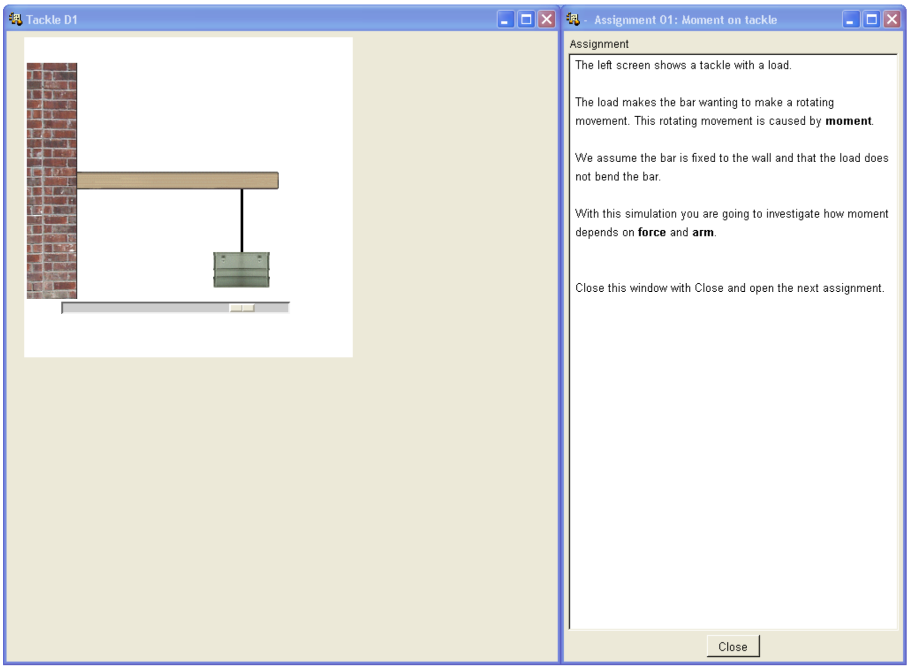


Figure 4-3 First representation progression step (R-Step condition)

Both experimental conditions cover the same amount of domain information. The assignments stimulate learners to explore the relations between the variables in the simulation model. In addition, in the R-Step condition learners are asked to relate and/or translate between the representations explicitly; learners have to find corresponding variables, describe the relation between two representations or have to translate between them. Each assignment starts with a short description of an aspect of the domain, asks the learner to explore this aspect and asks the learner to answer a question about it. In most assignments three or four questions are asked. In these assignments learners have to observe a specific situation, manipulate a variable, answer a multiple choice question and provide an explanation in their own words. For open answers, in the R-Step condition learners are explicitly asked to provide an answer including two or more representations. Figure 4-4 shows an example of a characteristic R-Step assignment.

Because the representations are presented one by one in the R-Step condition and additional hints and prompts for relating and translating are given, more assignments were needed to cover the same domain information compared to the R-Once condition. This resulted in 18 assignments for the R-Step condition and 12 assignments for the R-Once condition.

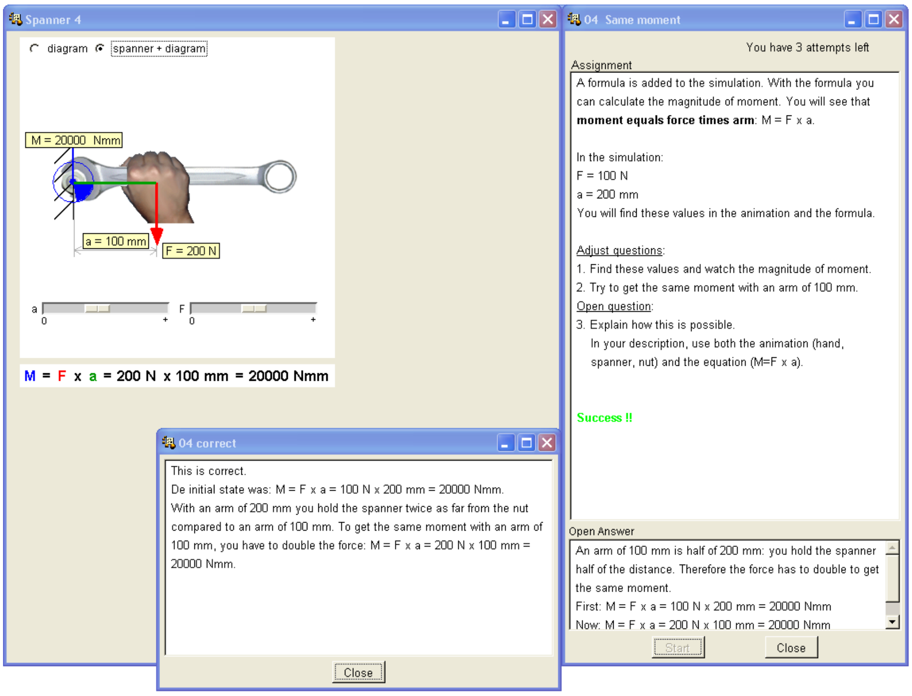


Figure 4-4 Example of a characteristic R-Step assignment

Tests and questionnaire
Subjects' prior domain knowledge was assessed using an online pre-test. The pre-test consisted of 20 items, both multiple-choice and open answer items: 10 items testing domain knowledge and 10 items testing transfer knowledge.The post-test consisted of 40 items, both multiple-choice and open answer items; 10 domain items, 10 transfer items, 10 items testing the ability to relate representations and 10 items testing the ability to translate between representations. See Figure 3-4 on page 71 in chapter 3 for examples of one test item from each category.

The post-test domain and transfer items corresponded to the post-test domain and transfer items. The post-test items differed slightly from the pre-test by changing the item and alternative answer orders. Since subjects did not know which items had been changed, they could not rely on a memory strategy. Compared with the study reported in chapter 3, the pre-test and post-test were slightly adapted because the learning environment in the current study contained graphs, whereas the learning environment used in the previous study did not. As a consequence, one domain item, two transfer items, three relate items and three translate items were different.

For each pre-test and post-test item, a subject received a score of 1 if the answer was correct or a score of 0 if the answer was incorrect. The maximum scores for the pre-test and post-test were 20 and 40 respectively.

To control for the influence of differences in cognitive load (Paas, Renkl, & Sweller, 2003, 2004), we asked the subjects to rate their cognitive load four times during working with the learning environment with an electronic questionnaire. The questionnaire consisted of 6 questions measuring extraneous load (EL), germane load (GL), intrinsic load (IL) and overall load (OL) (see Table 4-2). The questionnaire used a 7-point very easy to very difficult scale.

Table 4-2 Cognitive load measures

Question type	Question
EL1	At this moment I find working with the simulation …
EL2	At this moment I find separating important from unimportant information …
EL3	At this moment I find collecting all information I need in the simulation …
GL	At this moment I understand the simulation …
IL	At this moment I find the topic moments …
OL	At this moment I follow the simulation …

Procedure

The experiments were held at the participating schools and consisted of two experimental sessions of 100 minutes each. These sessions were held on two different days with a week time between the sessions in most cases. The first session consisted of an introduction, pre-test and working with the learning environment. The second session consisted of working with the learning environment and a post-test. Subjects were randomly assigned to one of the two conditions using their seating placement.

In session 1, participants were informed about the experiment and were told that the test measured their prior knowledge of force, arm and moment. As an introduction, two participants were asked to come in front of the class to lift one of two similar chairs. One participant had to lift the chair close to his or her body and the other had to lift the chair with straight arms, as far from his or her body as possible. The class was then asked in which case the chair would feel most heavy. After this, the experimenter gave a brief description of moment, force and arm.

Participants were asked to fill in all pre-test items, even if they were unsure about the right answer. Subjects had a maximum of 40 minutes to fill in the pre-test. The learning environment session took place after all participants had completed the pre-test. After a five minute introduction by the experimenter on how to start and operate the learning environment, subjects could work at their own pace for approximately 40 minutes. They worked on their own and could question the teacher or experiment leader on operating the learning environment. Subjects were asked to do all assignments.

In session 2, participants could continue working with the learning environment. After logging in, the learning environment would continue at the point where participants ended it in session 1. All answers given to assignments in session 1 were available in session 2.

After 45 minutes the participants were asked to close the learning environment and do the post-test. They could work a maximum of 45 minutes on this test.

Results

Pre-test and post-test

The overall mean score on the 20 pre-test items was 10.04 ($SD = 3.00$). The overall mean score on the 20 post-test items corresponding to the pre-test items was 14.27 ($SD = 2.85$). A repeated measures ANOVA showed that the post-test score on corresponding items was significantly better than the pre-test score ($F(1,210) = 387.98$, $p < 0.01$). Repeated measures ANOVAs for each item category showed that the post-test scores on domain and transfer items were significantly better than the pre-test scores on these item types ($F(1,210) = 292.23$, $p < 0.01$ and $F(1,210) = 208.53$, $p < 0.01$).

The overall post-test mean scores on the 10 relate items and 10 translate items were 7.14 ($SD = 1.51$) and 3.22 ($SD = 1.62$) respectively. The overall mean score on the complete post-test was 24.64 ($SD = 4.41$). Table 4-3 shows the means and standard deviations of the pre-test and post-test scores for the different item types per condition.

One-way ANOVAs showed significant differences between the experimental conditions on pre-test domain item scores and pre-test transfer item scores ($F(1,210) = 10.08$, $p < 0.01$ and $F(1,210) = 4.19$, $p < 0.05$) in favour of the R-Once condition. This means that the experimental conditions differed in prior knowledge. Therefore, for analysis on post-test results, the pre-test scores were used as covariate. A one way ANOVA showed no significant difference between overall pre-test scores and school type ($F(1,210) = 1.03$, $p = 0.31$). Therefore, no distinction was made between the two school types. Moreover, a one way ANOVA showed no significant difference between overall pre-test scores and class ($F(1,210) = 0.98$, $p = 0.45$).

One-way ANCOVAs on the post-test scores with pre-test scores as covariate showed the following results. A significant difference was found between experimental conditions on all 40 post-test item scores ($F(1,209) = 5.25$, $p < 0.05$) in favour of the R-Step condition. A significant difference was found between experimental conditions on the 10 domain item scores ($F(1,209) = 4.55$, $p < 0.05$) in favour of the R-Step condition. A trend was found on relate item scores ($F(1,209) = 3.46$, $p = 0.06$) in favour of the R-Step condition. No differences were found on transfer items scores and translate item scores ($F(1,209) = 0.65$, $p = 0.42$ and $F(1,209) = 0.60$, $p = 0.44$).

Table 4-3 Means and standard deviations of pre-test and post-test scores per condition

	R-Step		R-Once	
	Mean	(SD)	Mean	(SD)
Pre-test				
Domain items (max. 10)	5.17	(1.79)	5.95	(1.76)
Transfer items (max. 10)	4.28	(1.63)	4.73	(1.57)
Pre-test total (max. 20)	9.45	(2.98)	10.68	(2.89)
Post-test				
Domain items (max. 10)	7.87	(1.57)	7.07	(1.53)
Transfer items (max. 10)	6.48	(1.77)	6.48	(2.00)
Relate items (max. 10)	7.26	(1.65)	7.01	(1.33)
Translate items (max. 10)	3.22	(1.73)	3.23	(1.51)
Post-test total (max. 40)	24.84	(4.55)	24.42	(4.25)

n = 211

Electronic questionnaire

The different types of cognitive load measures were combined into one cognitive load measure because correlations between the items were high, indicating that subjects did not differentiate between the measures. Reliability analysis showed that the questionnaires were highly reliable (see Table 4-4).

Table 4-4 Reliability of the questionnaire

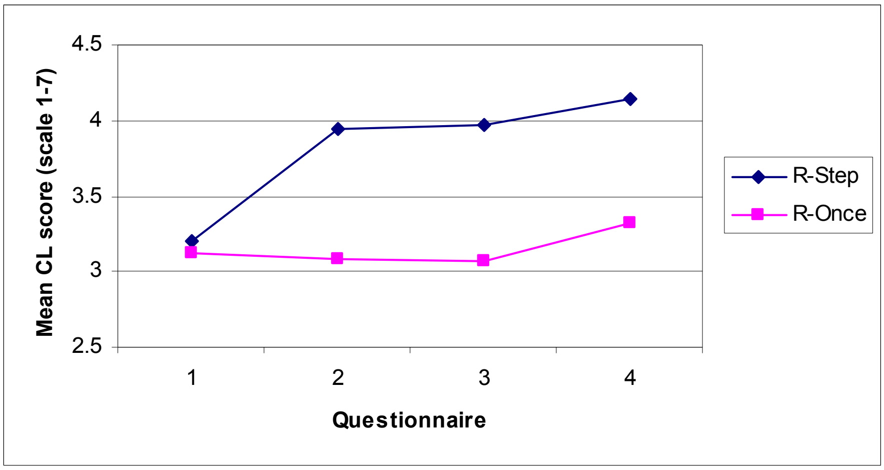
Appearance	N	Cronbach's Alpha
1	193	0.94
2	182	0.96
3	147	0.98
4	119	0.98

Note: The number of subjects (N) filling in the questionnaire decreased dramatically from appearance 1 to 4. This does not mean that they did not work through the complete learning environment. Most subjects completed all assignments. However, many subjects closed questionnaires without answering it.

A repeated measures ANCOVA with pre-test scores as covariate showed an interaction effect between questionnaire appearance and condition ($F(1,100) = 5.83$, $p < 0.01$). Therefore, ANCOVAs per questionnaire appearance were done showing the following results. No differences were found between experimental conditions on first appearance of the questionnaire ($F(1,204) = 0.50$, $p = 0.61$). Significant difference were found between experimental conditions on questionnaire appearance 2, 3 and 4 ($F(1,187) = 10.95$, $p < 0.01$; $F(1,147) = 7.47$, $p < 0.01$; $F(1,120) = 4.29$, $p < 0.05$), with higher cognitive load reports for the R-Step condition.

Figure 4-5 shows the development of cognitive load over the four questionnaire appearances, where higher scores indicate higher cognitive load. Since the number of subjects filling in the questionnaire differed per appearance, the graph only shows the subjects that filled in the questionnaire. A graph per questionnaire appearance including all subjects filling in that particular questionnaire showed the same pattern.

Figure 4-5 Development of cognitive load over the four questionnaire appearances where higher scores indicate higher cognitive load



n = 102

Discussion

The aim of this study was to examine if sequencing multiple dynamic representations combined with explicit instruction to relate and translate between representations (R-Step condition) would lead to better learning results than providing all representations at once with instruction focusing solely on relations between domain variables (R-Once condition).

Overall, we found that subjects learned from working with the learning environment. Post-test scores were significantly better than pre-test scores. Subjects in the R-Step condition improved from an average of 47% correct answers to an average of 72% correct answers on the 20 test items. Subjects in the R-Once condition improved from an average of 53% correct answers to an average of 71% correct answers. Compared to the pre-test scores, the knowledge gain for both conditions was good, indicating that both learning environments were well designed for their purpose. Taking a closer look on the pre-test items, scores on 9 of the 20 items were low in both experimental conditions and in both conditions these were the same items: 4 domain items and 5 transfer items. These items were answered correctly by 3% to 37% of the subjects in the R-Step condition and 3% to 44% of the subjects in the R-Once condition.

Although most subjects scored well on the post-test items, there were two transfer items that most of the subjects were unable to answer correctly. Both items presented situations that differed significantly from the ones offered in the learning environments. The low scores on these items indicate that the subjects did not acquire deep understanding of the domain.

As expected, we found that sequencing representations combined with instructional support focusing on relating and translating representations did lead to better learning outcomes. However, this was found only for the domain test items. A trend in favour of the R-Step condition was found on relate items and no differences were found on transfer items and translate items. Scores on the translate items were low, indicating that subjects had difficulties with these items. These scores were comparable with the low scores found in the study reported in chapter 3.

Subjects did not discriminate between cognitive load types. As a consequence, we were not able to identify what type of load caused higher cognitive load of the R-Step condition. A reason for reporting higher cognitive load by subjects in the R-Step condition could be their lower prior knowledge. As a consequence, they could have experienced the topic and/or the learning environment as more difficult than subjects in the R-Once condition. Whether this is due to the intrinsic load caused by the subject matter content or the extraneous load caused by the learning environment, we cannot say. On the positive side, it could be that subjects in the R-Step condition experienced the prompts for relating and translating between representations as more demanding, which would mean that the learning environment resulted in higher germane load for subjects who were able to relate and translate.

Our results indicate that the subjects gained enough knowledge in the domain to be able to relate the representations. However, this was not the case for all 10 post-test items. Subjects in both experimental conditions had difficulties with three test-items: relating an M-F graph to an M-a graph was difficult, as was indicating arm in two test items where the force was at an angle and where either concrete and diagrammatic representations were shown or only a diagrammatic representation was shown. To be able to answer these test items correctly the subjects needed to have a thorough understanding of arm. They could not rely on surface features such as corresponding colours or values to relate the representations.

Sufficient domain knowledge and being able to relate representations are prerequisites for a successful translation between representations. Since the post-test scores on both domain and relate items are moderate (domain) and high (relate), one could expect subjects in both conditions to have successful results on the translate items. Why is it then that they largely fail to answer these items correctly? At this point every answer to this question is speculative. It could have been the case that subjects were *just* able to master the domain and therefore they were able to answer most of the domain and translate items correctly, but mastering the translate items was one step too many. Since the subjects were unfamiliar with the translate item types, a likely explanation could be that they needed more practice in answering these types of questions. Subjects in the R-Step condition were prompted to translate between representations in the learning environment, but analysis of the answers given showed that the subjects gave very brief answers and that these answers did not go beyond *relating* representations. Looking back at the hints and prompts we can find a possible explanation for this. It appears that most questions could be answered on a 'relate level' so subjects were not 'forced' to translate between representations. Furthermore, having hints and prompts provided was new for our subjects; they were not used to this kind of question. Because of this, it could well be the case that the subjects did not answer the hints and prompts as expected.

We claim that future research on learning with multiple representations needs to focus on encouraging learners to actively translate between representations. The results of this study indicate that using hints and prompts might be a good way to support this. At this moment we do not have an answer to the question of what kinds of hints and prompts give the best support. In addition to research on hints, prompts, the step-by-step introduction of representations also needs more research. In both our previous work and this study we followed a sequence from concrete to abstract when introducing the representations. One could ask if this is the most optimal sequence. At this moment we are unable to answer this question. We followed a sequence that is widely used in textbooks. Whether this is the right sequence for learning with multiple representations is not known. It might be a good idea to set up experiments in which different sequences are studied. Also, the step size needs more attention. In this study we introduced every new representation as a whole, whereas in our former study we introduced some of the representations (diagrammatic and numerical) per domain variable. We have not yet studied the effects of the step size, but it would be interesting to see if the step size makes a difference.

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5

Conclusion and discussion

Two assumptions formed the bases for the studies reported in this thesis. The first was the belief that learning with multiple representations has several advantages over learning with a single representation. The second was that learning with multiple representations also introduces new problems and poses new challenges for students. Therefore specific support was seen as necessary for learners to successfully profit from the advantages of multi-representational learning environments. In our studies, the following research questions were addressed:

Does integrating and/or linking dynamic multiple representations have an effect on learning outcomes?

Does sequencing dynamic representations have an effect on learning outcomes?

Does sequencing dynamic representations combined with explicit instruction to relate and translate between representations have a positive effect on learning outcomes?

In this chapter the results and conclusions of the three studies are summarised, followed by a comparison of the three studies, limitations of our studies and overall conclusions.

Answering the research questions

Does integrating and/or linking dynamic multiple representations have an effect on learning outcomes?

In study one, the role of dynamic linking and integration of representations was examined. Results showed that presenting representations in an integrated plus dynamically linked format yielded the best learning results. We found significant differences on domain item scores, which indicated that the subjects learned the domain better if the representations were integrated plus dynamically linked. To understand the domain, the subjects had to (mentally) integrate the representations. Providing a pre-integrated format where possible, together with dynamic linking, best supported this. This is in accordance with the finding by Chandler and Sweller (1991) that integrated representations lead to better learning results than separate representations when individual units cannot be understood separately. A trend in favour of the integrated plus dynamic linking condition was found on the representation items. Our expectation that supporting learners with a combination of integration and dynamic linking would lead to better transfer to new situations was not confirmed by the results. Results on transfer items, which we defined as “new contexts and relations between variables that were not asked for in the learning environment but could be derived from the domain knowledge”, showed no difference between conditions. This was disappointing, since the support was expected to lead to a deeper understanding of the domain. This can be explained by the short average learning time of 38 minutes and the possibility that the subjects related the domain too much to the contexts provided.

We found no differences in learning results for test items corresponding to the low complexity part of the learning environment. This did not surprise us, since these test items could be answered with limited knowledge about the domain. To be able to answer these items, it was not necessary to combine or integrate information from different representations. For the high complexity part of the learning environment, combining and integrating representations played a greater role. Scores on the domain items corresponding with the high complexity part of the learning environment showed the best learning results for the integrated plus dynamic linking condition. Since the presentation of the domain was more complex in this part, the interaction between the representational support and domain complexity caused the differences between the experimental conditions.

Does sequencing dynamic representations have an effect on learning outcomes?

In study two, a step-by-step introduction of representations was compared with an introduction of all representations at once. Contrary to our expectations, we found no difference between the experimental conditions. We explained this result by the fact that both conditions received the same assignments and that these assignments guided learners through the learning environment step-by-step. The assignments directed the subjects’ attention to the newly introduced representations and variables but did not explicitly focus on relating or translating between the representations. The result was that the subjects did not seem to relate the representations and/or translate between them.

In this study, learning results on translate test items were low. We believe that the ultimate goal of learning with multiple representations is to gain deeper understanding of a domain by being able to translate between the representations, but we obviously did not succeed in supporting this. In both study one and two, the type of support implemented in the learning environments was so-called surface feature level support (see Seufert, 2003; Seufert & Brünken, 2006; Seufert, Jänen, & Brünken, 2007). This type supports learners in finding relations between representations but does not necessarily encourage them to try to translate between them. That is why we focused on encouraging learners to translate between representations in study three.

Does sequencing dynamic representations combined with explicit instruction to relate and translate between representations have a positive effect on learning outcomes?

In study three, we took the findings of study two as our starting point. We compared a learning environment providing the representations step-by-step, where the instructional support focused on relations between the variables in the domain as well as on relating and translating between the representations, with a learning environment providing all representations at once, where the instructional support focused solely on relations between the variables in the domain. The results showed that step-by-step introduction combined with instructional support focussing on both domain knowledge and relating representations led to better learning results on domain test items. Although this study produced the expected results, scores on translate items were again low.

Comparing the three studies

Comparing the learning environments

Although the learning environments in all three studies covered part of the physics domain of moments, the specific part of the domain that was covered differed between studies, as did the number and type of representations and the number and type of assignments.

Part of the domain covered

The part of the domain covered differed between the three studies. Table 5-1 shows which variables were addressed in the studies.

Table 5-1 Variables addressed in the three studies

	Study		
	1	2	3
Moment (M)	v	v	v
Arm (a)	v	v	v
Force (F)	v	v	v
Second arm (a2)	v		
Second force (F2)	v		
Resultant arm (ar)	v		
Resultant force (Fr)	v		
Angle of force (α)		v	v
Length (l)		v	v
Angle of spanner / crane (β)			v

The choice of leaving out a second arm and force in studies two and three was based on conversations with teachers. According to the teachers, their students had the most difficulty with angled forces. Many students think that the distance from a point of application to a clamp determines moment, whereas the shortest distance from a force to a clamp does. Since many learners confuse angled force with a complete angled system and the subjects had more time to work with the learning environment in study three, we included both. Changing the part of the domain covered influenced the information the representations contained as well as the content of the assignments.

Number and type of representations

The number of representations used differed between the three studies. In studies one and two we offered the subjects five representations. In study three the number of representations presented was seven. Although the number of representations in studies one and two were the same, these were not the same types of representations.

A concrete representation in all studies was a learner-controlled animation that provided the subjects with a context for the simulated task. In study one this was either an open-end spanner or a hoisting crane. In study two this was only an open-end spanner. In study three this was either a tackle, open-end spanner or a car crane. We chose different contexts within studies one and three because we wanted to stimulate transfer. The reason for only using one context in study two was because the learning environment used in study one was too extensive. We needed too many assignments to support the subjects in learning the domain with the result that the subjects spent too little time per assignment. This led to a superficial exploration of the domain. Looking back, only providing one context was not a good choice. Providing different contexts in the learning phase is necessary for transfer to new situations. Providing only one situation may lead to student belief that the rules only apply in that specific situation. This is why we re-introduced different contexts in study three. This, however, made the learning environment once again more extensive. That is why we changed our procedure in study three. Subjects now had 90 minutes to work with the learning material instead of a maximum of 60 minutes in studies one and two.

All studies contained a diagrammatic representation. The diagrammatic representation showed the variables and relations between them in an abstract way. We see the diagrammatic representations as intermediate representations between concrete representation(s) and an equation. In study one the diagrammatic representation was presented directly from the start. In studies two and three this depended on the experimental condition. The step-by-step introduction of the diagrammatic representation differed between studies two and three. In study two the diagrammatic representation was introduced variable-by-variable, whereas in study three the three base variables (moment, force and arm) were shown at once. This was done to make the learning environment more consistent: the other representations were also introduced as wholes. Whether representations can better be introduced variable by variable or at once needs further research.

All three studies started by introducing the variables first qualitatively (showing the names) and thereafter quantitatively (showing the symbol, value and unit). This was done to give the subjects the opportunity to get acquainted with the variables and their qualitative relations before going into more detail.

In study one and three we used graphs, whereas in study two we did not. The reason for not using graphs in study two was that we wanted to make the learning environment less extensive. Since graphs are important representations in the moments domain, we re-introduced them in study three. We were able to do this because we increased the learning time.

In the first study, one of the assignments asked the subjects to find the equation for moment (M = F x a) themselves. Since this equation is of great importance and we wanted students to relate the equation to the other representations, in studies two and three we introduced the equation as one of the representations.

The last representation, the dynamically changing table, was only used in studies two and three. We introduced this table because it is expected to support the understanding of numerical relations. By introducing the table, we could also use the experiment table in which subjects could save, compare, structure and replay their experiments.

We based our choices on the types of representations most used in teaching the topic of moments. However, we did not investigate if these were the 'best' representations for learning the domain. Moreover, it does not necessarily follow that combining these representations in a multi-representational learning environment leads to the best mental model of the domain. Research on which combination of representations leads to the best learning outcomes is necessary. The problem is, however, that the best combination largely depends on the domain and learning task.

A good starting point for choice of representations is the analysis by Lohse, Biolsi, Walker and Rueter (1994). In their view, visual representations are data structures for expressing knowledge. They developed a structural classification of representations by analysing the way in which different representations were perceived. This resulted in 11 categories, each with its own characteristics: graphs, numerical tables, graphical tables, time charts, networks, structure diagrams, process diagrams, maps, cartograms, icons and pictures. It might be useful to investigate whether the characteristics identified by Lohse et al. also apply when different representations are combined and how making use of these characteristics can help designers choose the representations best suitable for specific domains and learning tasks. However, it is not enough to use only the classifications developed by Lohse et al. (1994). They categorised only static representations, whereas in our simulation-based learning environments the representations all dynamically changed if learners manipulated a variable. The dynamic representations we used often have different characteristics compared to their static equivalents. Bernsen (1994), in his taxonomy of representational types, identified 28 different types of representations. Of these 28 types, the following are important for the design of simulation-based learning environments: static diagrammatic pictures, static non-diagrammatic real-world pictures, static graphs, animated diagrammatic pictures, dynamic real-world pictures, dynamic graphs, arbitrary static diagrammatic forms, animated arbitrary diagrammatic forms, static graphic structures and dynamic graphic structures.

The representation types are not the only consideration when designing a simulation-based learning environment with multiple representations. We agree with Ainsworth (2006) that the number of representations, the way that the information is distributed over representations and the sequence of the representations are also necessary design decisions.

Number and type of assignments

The number of assignments used in the three studies differed considerably. The learning environment used in study one contained 31 assignments. As reported in the results section of study one, the subjects only spent an average of 77 seconds per assignment. This could be explained by the fact that we asked them to do all assignments. However, since the subjects in study one only spent an average of 29 minutes working with the learning environment, we believed that the assignment types were responsible for the short duration. The assignments asked very specific questions about the relations between the variables in the domain that the subjects could answer either by selecting answer alternatives or by adjusting variable values. Two introductory assignments, in contrast, asked the subjects to formulate their own answer. In these assignments we asked the subjects to describe what they noticed given a specific situation. No feedback was given on these two assignments.

In study two we changed both the number and type of assignments to try to overcome the problem that the subjects only did what was explicitly asked for in the assignments. Although we used the same assignment types, the questions asked in the 16 assignments differed from study one. We encouraged the subjects to reflect on their answers and actions by asking them to justify their answers with their experiment activities and to provide an explanation for their given answers. After answering the question, the subjects received feedback in the form of the right answer with an explanation. As reported in the discussion, however, the log files showed that learners did not explore the simulation for other features than those explicitly indicated in the assignments and their reflections were very brief. Moreover, where almost all reflections contained relations between variables in the domain, only a few reflections contained relations of representations or translations between them.

The number and type of assignments in study three depended on the experimental conditions. The learning environment used in the R-Step condition contained 18 whereas the learning environment used in the R-Once condition contained 12 assignments. The differences is due to the fact that in the R-Step condition, the representations were presented step-by-step and additional hints and prompts for relating and translating were given; therefore more assignments were needed to cover the same domain information compared to the R-Once condition. The assignments stimulated learners to explore the relations between the variables in the simulation model. In addition, in the R-Step condition subjects were asked to relate and/or translate between the representations explicitly; subjects had to find corresponding variables, describe the relation between two representations or had to translate between them. Each assignment started with a short description of an aspect of the domain, asked the subject to explore this aspect and answer a question about it. In most assignments three or four questions were asked. In these assignments the subjects had to observe a specific situation, manipulate a variable, answer a multiple choice question and had to provide an explanation in their own words. In the case of open answers, in the R-Step condition subjects were explicitly asked to provide an answer including two or more representations.

Although research has shown that providing instructional support is needed for successful inquiry learning (de Jong & van Joolingen, 1998; Mayer, 2004; Swaak, van Joolingen, & de Jong, 1998), not much is known about the types of assignments and explanations to provide. Although our research did not primarily focus on the types of assignments and explanations to offer, it has largely influenced our findings. More research is needed to be able to identify how different types of assignments and explanations support learners when learning with simulation-based inquiry learning environments.

Comparing the tests

Both the pre-tests and post-tests differed between the three studies. The pre-test and post-test for study one contained 7 domain test items and 17 transfer items, whereas there were 10 of each in studies two and three. Apart from the number of items, the items themselves differed slightly. These differences were dictated by the differences in the learning environments. The tests in study one contained only multiple choice questions. In studies two and three we used a combination of multiple choice and open answer questions.

In studies two and three we made a distinction between relate and translate representation items; this was not the case in study one, where the post-test representation items were a combination of both. To determine whether the subjects were better at relating or translating between representations we re-analysed the representation items from study one. Of the 14 representation items, 5 could be classified as relate items and 6 as translate items. Table 5-2 shows the means and standard deviations of the relate and translate items from study one. Although the remaining three items contained a question in text with a multiple choice answer of four diagrams, these items could not be categorised as either relate or translate items by the definitions we use for relating and translating. These items gave diagrammatic representations of two forces and asked the subjects to calculate the resultant force, asked them to indicate which representation showed the resultant force in the right place and asked them when the given resultant force was equal to force one.

A one way ANOVA showed a marginally significant difference between the experimental conditions on relate item scores ($F(2,69) = 2.95$, $p = 0.06$). Tukey HSD post hoc analyses showed that subjects in the I-DL condition scored marginally better than subjects in the S-NL condition ($p = 0.08$). No difference was found between conditions on translate item scores ($F(2,69) = 0.94$, $p = 0.40$).

Table 5-2 Means (standard deviations) of relate and translate items study 1 per condition

	Condition					
	S-NL		S-DL		I-DL	
Relate items (max. 5)	3.13	(1.08)	3.21	(1.47)	3.92	(1.14)
Translate items (max. 6)	3.04	(1.20)	3.29	(1.33)	3.54	(1.25)
Total (max. 11)*	6.17	(1.88)	6.50	(2.34)	7.46	(1.82)

n = 72

* Three items could not be categorised as relate or translate items

In study one, both the pre-test and post-test contained specific relate and translate items, whereas in studies two and three, we only included these items in the post-test. The reason for not including these items in the pre-test in studies two and three was that we assumed the subjects had no or low prior knowledge about the domain and that we believe prior knowledge is necessary to be able to relate and translate between multiple representations.

Limitations of our studies

The consequence of our choice to support learning with multiple representations in simulation-based learning environments based on inquiry learning was that the environments were very complex. The subjects had several different tasks to perform in a short period of time. It may well be the case that the inquiry tasks they had to perform interacted with the support we gave them to learn with multiple representations. As found in study two, the type of assignments most probably had impact on the way the subjects processed the representations. Our studies cannot answer the question of what exactly caused what. In all three studies it was the combination of inquiry support and representational support that led to the results found.

Our learning environments contained five (studies one and two) or seven (study three) different representations. This may have been too many to evaluate the effects of the representational support we provided. However, fewer representations cannot cover all aspects of the domain. Despite this problem, it may be worthwhile to start off with fewer representations to see more specifically what the effects of the support measures are.

Our choice to perform the experiments in the participating schools as part of the curriculum can be seen as either an advantage or disadvantage. The advantage is that our studies were implemented in the course curricula. Instead of using standard materials, the students worked with our simulations to learn the topic. Because of this, the ecological validity of our experiments was high. A disadvantage was the lack of experimental control apparent when conducting research in schools as opposed to lab experimentation. In our studies we had to cope with classrooms that were double booked, a complete group that did not turn up because the teacher was away, computer malfunctions, uninstalled software and no Internet access in one of the classrooms. Although, most of these problems were overcome, in study three they resulted in missing values for a complete group with the result that this group had to be excluded from the study. Another disadvantage was that not all subjects were motivated to participate in our studies. Pre-university students especially did not always see the point of learning the topic.

Ideally, we would like learners to become experts in using multiple representations over a very short period of time. In our studies learners had a maximum of one and a half hours to work with the learning materials. Experts in a domain, however, became experts over a very long period of time. They learn to switch between representations to solve a particular problem through experience. Our expectation that learners would be able to translate between representations after a learning phase of 90 minutes maximum was perhaps too optimistic. In a recent study, Dean and Kuhn (2007) found that students need longer time to learn with inquiry learning environments for knowledge consolidation. Since our learning environments were based on inquiry learning, it would be interesting and valuable to carry out studies in which learners could learn with multiple representations over a longer period of time.

Since we wanted to investigate the role of support measures within our learning environments we gave the teachers involved a very small role. They were not allowed to explain relations between representations. However, we believe that teachers can play a very important role in stimulating learners to relate and translate between representations. Moreover, teachers can give learners just in time support when they do not understand a specific representation, among other learning difficulties inherent with complex science topics. We argue that the role of the teacher is crucial, even if the learning material is designed for self-study.

Overall conclusions

From study one we can conclude that dynamic linking combined with integration of representations is preferable in learning with multiple dynamically changing representations in simulation-based learning environments. This was found to yield the best learning results. Although one could conclude on the basis of the results found in study two that introducing representations step-by-step is not necessary, we argue that a step-by-step introduction is preferred. Sequencing multiple representations has two advantages. First, the step-by-step introduction of representations gives learners the opportunity to get acquainted with one representation before moving on to the next. Second, as was the case in study two, it supports instructional designers in structuring the instructional support. Without a step-by-step introduction of representations the instructional support would most likely be structured differently, as was the case in study one. Our rationale for sequencing multiple representations, domain and task permitting, was confirmed in study three. In this study the R-Step condition showed the best learning outcomes. Since the R-Step condition was a combination of step-by-step introduction of representations and providing hints and prompts, we cannot say whether it was the combination of both or one of the support types that led to this result. Future research might investigate specific effects of different support types.

Working with the learning environments resulted in good scores on domain items and relate items but not on transfer and translate items. Working with the learning environments used in study three led to the best learning results on transfer items. Subjects in the R-Step condition in study three answered 65% of the transfer items correctly, whereas in study one subjects in the I-DL answered 45% of the transfer items correctly and in study two 47% of the transfer items were answered correctly. Since we found no differences on transfer scores between experimental conditions in study three and the post-test transfer items in studies two and three were the same, it seems that the combination of a longer learning phase and providing more contexts led to better transfer. However, although transfer scores in study three were better than the scores in studies one and two, they were still relatively low. In all three studies the scores on translate items were even lower. One reason for low scores on both the transfer and translate items could be that learners had to perform too many new tasks. Almost everything in our learning environments was new for the subjects. They did not have any experience with simulation-based learning environments or the types of questions asked, nor were they used to inquiry learning (apart from doing physics and science lab experiments with real objects). Furthermore, they were not used to learning from multiple dynamically changing representations. This may also have led to their 'normal' behaviour of doing only what they were explicitly asked for in the assignments. For these subjects this may have been the only thing that looked familiar.

4 tasks in 4 steps

The starting point for the support examined in our studies was that learners need to be able to perform four tasks when learning with multiple representations. First, they have to understand the syntax of each representation. Understanding the syntax means that learners understand the format (e.g., labels, axes and line shapes) and operators (e.g., plus, minus and divide) of the representation. Second, they have to understand which parts of the domain are represented. Third, they have to be able to relate the representations to each other if the representations are (partially) redundant. This means that learners have to search for similarities and differences. Fourth, they have to be able to translate between the representations. This means that learners need to interpret the effects that changes in one representation have on corresponding representations. Translating between multiple representations is the ultimate goal of using them. By translating, learners are expected to gain deeper understanding of the domain by articulating what happens to a second representation when a first is manipulated and/or by reflecting upon the similarities and differences between the representations. Learners must perform these tasks in sequential order to be able to learn from multiple representations.

Step one: understanding the syntax

We cannot expect learners to learn from learning environments containing multiple representations if they are unfamiliar with the syntax of the representations. If learners are unfamiliar with the *format and operators* of a representation, the learning environment must provide support for this. The kind of support the learning environment should give depends on the domain, the prior knowledge of the learner and the complexity of the representation(s). In addition, a familiar representation can support learners in learning successfully the format and operators of an unfamiliar one. In this case the relations between the familiar and unfamiliar representations should be made explicit somehow (see the section on Step three: relating representations, page 107).

Although it is imperative for learning with multiple representations, we did not explicitly support learners in understanding the syntax of the representations. We assumed that learners would be able to relate possibly unfamiliar representations to familiar ones. All learning environments started with concrete examples and representations that had the function of constraining interpretation of the other representations. However, we did not study whether the constraining representations could fulfil this role. Moreover, we did not support learning all syntaxes nor did we test to see if students were already familiar with the ones presented.

Examining whether learners understand the syntax of the representations provided in multi-representational learning environments should be a theme in future research. Formative tests during the learning phase can possibly be implemented to determine if the syntax is understood. Moreover, if learners are unfamiliar with a type of representation, the relations between a familiar and the unfamiliar representation not only needs to be shown but must also be explained.

Step two: understanding which parts of the domain are represented

The second step in learning with multiple representations is understanding which parts of the domain are represented. For this, learners need to have some prior knowledge about the domain. The minimum requirement for the learners is to know which variables are involved. If learners are new to the domain, these variables should be introduced explicitly.

Our learning environments were expected to support learners in understanding which parts of the domain were represented. All introductions gave an overview of both the domain and learning environment followed by real life examples and problems. Moreover, the assignments guided learners in learning the domain through an inquiry approach. However, we did not examine whether learners knew which representations represented which parts of the domain.

Step three: relating representations

Steps three and four are important exclusively for learning with multiple representations, where relating representations is a prerequisite for translating between them. Relating representations can be supported in various ways. In chapter one, we gave several examples of this. In study one we found that dynamic linking combined with integrating representations led to better learning outcomes. Therefore, we also included this support types in studies two and three.

Although dynamic linking and integration showed positive effects in our learning environments, it is necessary to study their effects more. From the results of our studies, for example, we cannot tell the conditions under which integration does or doesn't work. For this, we suggest experiments focussing exclusively on the role of integration of representations. The same applies for dynamically linking multiple representations.

Step four: translating between representations

The ultimate goal of learning with multiple representations is to gain deeper understanding of a domain by translating between the representations. Translating between representations is expected to lead to a mental model of the domain consisting of different representations with meaningful links between them. This mental model should be organised in such a way that learners can take advantage of the properties of several (mental) representations to solve domain problems. Therefore, they must be able to switch between different representations. Kozma and Russel (1997) found that this distinguishes experts from novices. Kozma (2003) wrote: "Scientists coordinate features within and across multiple representations to reason about their research and negotiate shared understanding based on underlying entities and processes." (p. 205). Learning to translate between representations is expected to lead to this expert behaviour. Multi-representational learning environments have the potential to give learners a repertoire of representations to choose from to solve a particular problem. For example, given a concrete situation, the learner must be able to (mentally) project a diagram of the situation to be able to use the variables and relations that play a role.

Our assumption in studies one and two was that integration and dynamic linking would support both relating and translating between representations. However, this was not the case. We see translating between representations as an active process to be carried out by the learner. Support must provoke this active behaviour. The results of study three showed that providing hints and prompts to encourage learners to actively translate between representations results in better learning outcomes. But, because we could not separate the effects of the step-by-step introduction of representations and providing hints and prompts, we cannot say what led to higher domain knowledge. Moreover, the provided support did not lead to better scores on the translate items. Besides our speculative conclusion that the subjects could only have been able to *just* master the domain in the short learning time and that the type of questions asked were new for them, the type of hints and prompts we gave may not have been sufficient to encourage the subjects to translate between the representations. Future research has to focus on encouraging learners to translate between representations. Since we found that the instructional support given in the assignments and explanations had great impact on how learners work through the learning environment, we argue that support mechanisms of this type can play an important role. Therefore, future research needs to address the role of assignments and explanations.

In our research we were not able to detect what (combinations of) representations learners used. However, it is important to know what representations learners use to solve particular problems in order to study the effects of different representations. Recently, eye tracking studies have been carried out (see e.g., Schwonke, Renkl, & Berthold, 2007) in order to observe how learners use multiple representations,. At the moment most studies using eye tracking are exploratory. We consider the use of eye tracking for answering specific research questions, such as observing how learners react on specific assignments asking them to relate two representations, to be necessary and promising. However, eye tracking information does not provide information on *why* learners look at certain representations. Because it is important to study learners' reasoning processes, eye tracking needs to be combined with other techniques like cued retrospective reporting and structured interviews (van Gog, Paas, van Merriënboer, & Witte, 2005).

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Summary

Many learning materials offer multiple representations. Textbooks, for example, use photographic images to illustrate and explain parts of the text. In modern, computer-based learning environments many additional representation types are available, including: audio, video, animations and dynamically changing graphs and tables. This thesis bundles three studies on supporting learning with multiple representations in simulation-based learning environments.

Simulation-based learning environments offer learners the opportunity to perform experiments in controlled settings. They contain an executable model of a (natural) system and simulate the behaviour of the modelled system. Learners explore the simulation model by manipulating values of input variables and observing the behaviour of output variables. By understanding the relations between the variables, it is expected that learners acquire a deeper understanding of the domain and are able to transfer this knowledge to similar 'problems' in other (real) situations. The representations in simulation-based learning environments are often dynamic, meaning that the information they hold changes based on manipulations in the learning environment. Most simulation-based learning environments contain multiple representations.

The basic idea of using multiple representations is that learners can benefit from the properties of each representation. If learners are capable of mentally coordinating the information from several representations, they have a more complete picture of the represented domain compared with learning the domain with only one representation. It is expected that this will lead to a deeper understanding of the subject being taught. However, to learn from multiple representations learners have to: (1) understand the syntax of each representation, (2) understand which parts of the domain are represented, (3) relate the representations to each other if the representations are (partially) redundant and (4) translate between the representations.

In order to *understand the syntax* of each representation, learners must learn the format and operators of the representations. Moreover, operations on a representation must be coordinated with the format of the representation. So, the learner must understand which operations to carry out on particular representations.

To learn from a representation, learners have to *understand which parts of the domain are being represented*. This could be either a complete domain with all its variables and relations or only a specific part of the domain.

To *relate representations*, learners must mentally search for similarities and differences. In a simulation about a car in motion, for example, the learner has to relate the slope of the line in a speed-time graph to the right property of the moving car.

To *translate between representations*, learners need to interpret the effects that changes in one representation have on corresponding representations. Learners are supposed to gain deeper understanding of the domain by articulating what happens

to a second representation when a first is manipulated and/or by reflecting upon the similarities and differences between the representations.

When learning with multiple representations, learners must be supported in the aforementioned tasks. In this thesis we focused on support for both relating and translating between representations. It reports three studies in which we examined different ways to support learners in relating representations and to encourage them to translate between representations.

Does integrating and/or linking dynamic multiple representations have an effect on learning outcomes?

The goal of the first study was to determine whether integrating and/or linking dynamic multiple representations has an effect on learning outcomes. Multiple representations, when integrated, appear to be one representation showing different aspects of the domain. Through physical integration, relations between the representations are directly shown to the learner. With dynamically linked representations, actions performed on one representation are automatically shown in all other representations. If a learner changes the value of a force in a numerical representation, for example, the corresponding representation of the force in an animation is updated automatically.

The same learning environment, that of the physics topic of moments, was presented in three experimental conditions, with separate, non-linked representations (S-NL condition), with separate, dynamically linked representations (S-DL condition) and with integrated, dynamically linked representations (I-DL condition). The learning environment was divided into a low complexity part and a high complexity part.

Subjects were 72 students from middle vocational training (aged 16 to 18). They worked with the learning environment, Moment, built in the authoring environment SimQuest. The learning environment was based on guided inquiry learning. The simulation interface contained five representations: (1) concrete representation (animation of an open-end spanner or hoisting crane), (2) diagrammatic representation (an abstract representation of the variables playing a role in the concrete situation), (3) numerical representation (showing the values of the variables involved) and (4, 5) two graphs (moment-force and moment-arm or moment-force and moment-height).

Prior knowledge and learning results were measured with a pre-test and post-test containing three different item types. *Domain items* tested the subjects' domain knowledge. The content of the items was analogous to the content of the learning environment. *Transfer items* tested the ability of the subjects to apply their acquired knowledge in new situations: new contexts and relations between variables that were not asked for in the learning environment but could be derived from the domain knowledge. *Representation items* tested the subjects' ability to relate and translate between different representational formats. A questionnaire, assessing the subjects' opinions of the learning environment and the domain, appeared five times as they worked with the learning environment.

Overall, the I-DL condition showed the best learning performance. Subjects in the I-DL condition, compared to the S-NL condition, showed better learning results on post-test items measuring domain knowledge. A trend in favour of the I-DL condition compared with the S-NL condition was found on the post-test representation items. A subjective measure of experienced difficulty showed that subjects in the I-DL condition experienced the learning environment as easiest to work with. The complexity of the learning environment and domain interacted with the effects of the experimental conditions. Differences between conditions were found only on the test items that corresponded to the high complexity part of the learning environment.

Does sequencing dynamic representations have an effect on learning outcomes?

In the second study, described in chapter three, we used the findings of study one as our starting point and examined whether sequencing dynamic representations has an effect on learning outcomes. In this study, sequencing of representations was done on the basis of model progression from simple to complex. Based on the model progression used, we increased the number of representations iteratively. As a result, the number of relations and possible translations increased likewise. Starting with a few relations and possible translations and then introducing more relations and possible translations step-by-step might support learners in relating the representations and translating between them.

Two versions of the same simulation-based learning environment covering the physics topic of moments were compared: a learning environment providing the representations step-by-step (R-Step condition) and a learning environment providing all representations at once (R-Once condition).

Subjects were 88 students at the start of their first year of secondary vocational education. They were between 15 and 21 years old and took a course in either mechanical engineering or architecture. They worked with the Moments learning environment that was built in the SimQuest authoring environment. The simulation interface contained five representations: (1) a concrete representation (animation of an open-end spanner), (2) a diagrammatic representation (an abstract representation of the variables playing a role in the concrete situation), (3) a numerical representation (showing the values of the variables involved), (4) a dynamically changing equation and (5) a dynamically changing table (showing one row that was dynamically updated when variables were manipulated by the subjects).

Prior knowledge was measured with a pre-test containing domain items and transfer items. Learning results were measured with a post-test containing domain items, transfer items, relate items and translate items. The *domain items* tested whether the subjects were able to reproduce the content they were explicitly asked to explore in the learning environment. The *transfer items* tested the ability of the subjects to apply their acquired knowledge in new situations. The *relate items* asked students to relate similar variables from representations with different representational codes. To be able to answer *translate items* correctly, the subjects had to make a mental translation from manipulations on one representation to the effects in another representation. A questionnaire, assessing the subjects' opinions on the learning environment and the domain, appeared three times as they worked with the learning environment.

Overall, we found that the subjects learned from working in the learning environment; the post-test scores on the domain items and transfer items were significantly better than the pre-test scores. Despite our expectations, no differences were found between the two experimental conditions. The subjects learned equally well regardless of the way in which the representations were presented. Also, the extent to which the subjects experienced complexity of both the topic and the learning environment did not differ between the experimental conditions.

Does sequencing dynamic representations combined with explicit instruction to relate and translate between representations have a positive effect on learning outcomes?

While study one and two focused on surface level support, in study three we examined the effect of providing hints and prompts to encourage the subjects to translate between representations. This study is described in chapter four.

Two versions of the same simulation-based inquiry learning environment on the physics topic of moments were compared. One learning environment provided all representations at once and instructional support focused solely on relations between the domain variables (R-Once condition). The second learning environment provided the subjects with representations step-by-step and with instructional support that focused additionally on relating representations and translating between them (R-Step condition). The learning environments in both conditions made use of dynamic linking and integration.

Subjects were 86 students from secondary vocational education (aged 15 to 21) and 125 students from pre-university education (aged 13 to 15). Students in the first group were in their first year of a course in either mechanical engineering or architecture. Students in the second group were in their third year. Subjects came from four schools: two secondary vocational schools and two secondary schools. They worked with a simulation-based inquiry learning environment on the physics topic of moments, built in the SimQuest authoring environment. The simulation interface contained seven representations: (1) a concrete representation (animation of a tackle, an open-end spanner or car crane), (2) a diagrammatic representation, (3) a numerical representation, (4) a dynamically changing equation, (5) a moment-arm graph, (6) a moment-force graph and (7) a dynamically changing table.

Prior knowledge was measured with a pre-test containing domain items and transfer items. Learning results were measured with a post-test containing domain items, transfer items, relate items and translate items. To control for the influence of differences in cognitive load, we used an electronic questionnaire to ask subjects to rate their cognitive load four times as they worked with the learning environment.

Overall, we found that subjects learned from working with the learning environment. Post-test scores were significantly better than pre-test scores. As expected, we found that sequencing representations combined with instructional support focusing on relating and translating representations did lead to better learning outcomes. However, this was only found for the domain test items. A trend, in favour of the R-Step condition, was found on relate items. No differences were found on transfer items and translate items. Subjects in the R-Step condition reported higher cognitive load scores. Subjects did not, however, discriminate between cognitive load types. As a consequence, we were not able to identify what type of load caused the higher cognitive load of the R-Step condition.

From study one we can conclude that dynamic linking combined with integration of representations is preferable in learning with multiple dynamically changing representations in simulation-based learning environments. This was found to give the best learning results. Although one could conclude on the basis of the results found in study two that introducing representations step-by-step is not necessary, we argue that a step-by-step introduction is preferred. Sequencing multiple representations has two advantages. First, the step-by-step introduction of representations gives learners the opportunity to get acquainted with one representation before moving on to the next. Second, as was the case in study two, it supports instructional designers in structuring the instructional support. Without a step-by-step introduction of representations the instructional support would most likely be structured differently, as was the case in study one. Our rationale for sequencing multiple representations, domain and task permitting, was confirmed in study three. In this study the R-Step condition showed the best learning outcomes. Since the R-Step condition was a combination of step-by-step introduction of representations and providing hints and prompts, we cannot say whether it was the combination of both or one of the support types that led to this result. Future research might investigate specific effects of different support types.

Samenvatting

In lesmateriaal wordt veel gebruik gemaakt van multipele representaties. In boeken bijvoorbeeld, worden afbeeldingen gebruikt om delen van teksten te illustreren of betekenis te geven. In moderne computer leeromgevingen is een grote verscheidenheid aan additionele representaties voorhanden zoals: geluid, video, animaties en dynamische grafieken en tabellen. Dit proefschrift bundelt drie studies naar het ondersteunen van leren met multipele representaties in simulatie-leeromgevingen.

Simulatie-leeromgevingen bieden leerlingen de mogelijkheid om experimenten uit te voeren in een gecontroleerde omgeving. Ze bevatten een model van een (natuurlijk) systeem en simuleren het gedrag van dit gemodelleerde systeem. Leerlingen onderzoeken het simulatiemodel door het manipuleren van invoer variabelen en het observeren van het gedrag van uitvoer variabelen. De verwachting is dat leerlingen door begrip van de relaties tussen de variabelen diepere domeinkennis verwerven en daarmee in staat zijn hun kennis toe te passen in andere (werkelijke) situaties. De representaties in simulatie-leeromgevingen zijn vaak dynamisch. Dit betekent dat deze representaties veranderen door manipulaties in de leeromgeving. De meeste simulatie-leeromgevingen bevatten multipele representaties.

De gedachte achter het gebruik van multipele representaties is dat leerlingen kunnen profiteren van de unieke eigenschappen van elke representatie. Daarnaast kunnen leerlingen, vergeleken met leren met een enkele representatie, een completer beeld van het gerepresenteerde domein ontwikkelen als ze in staat zijn de informatie van verschillende representaties mentaal te combineren De verwachting is dat het combineren tot dieper begrip van onderwerp leidt. Om te leren van multiple representaties moeten leerlingen echter in staat zijn om: (1) de syntaxis van elke representatie begrijpen, (2) begrijpen welke delen van het domein worden gerepresenteerd, (3) de representaties aan elkaar relateren als ze (gedeeltelijk) overlappende informatie bevatten en (4) een vertaling tussen de representaties maken.

Om de *syntaxis* van elke representatie te *begrijpen* moeten leerlingen de structuur en de mogelijke acties op de representaties leren. Bovendien moeten de acties op een representatie overeenstemmen met de structuur. Leerlingen moeten dus begrijpen welke acties ze kunnen uitvoeren op bepaalde representaties.

Om te leren van een representatie moeten leerlingen *begrijpen welke delen van het domein worden gerepresenteerd*. Dit kan een compleet domein zijn met alle variabelen en relaties of een bepaald deel van het domein.

Voor het *relateren van representaties* moeten leerlingen mentaal naar overeenkomsten en verschillen zoeken. In een simulatie van een bewegende auto bijvoorbeeld, moet de leerling de helling van een lijn in een snelheid-tijd diagram relateren aan de juiste eigenschap van de auto.

Voor het *vertalen tussen representaties* moeten leerlingen interpreteren wat de effecten van een verandering in één representatie zijn op overeenkomstige representaties. De verwachting is dat leerlingen dieper begrip van het domein krijgen door uit te drukken wat er gebeurt in een tweede representatie als de eerste wordt gemanipuleerd en/of door te reflecteren op de overeenkomsten en verschillen tussen representaties.

Leerlingen moeten bij het leren met multipele representaties in bovengenoemde taken ondersteund worden. In dit proefschrift richten we ons op de ondersteuning van het relateren en vertalen tussen representaties. Het proefschrift beschrijft drie studies waarin we verschillende manieren hebben onderzocht om leerlingen te ondersteunen bij het relateren van representaties en waarin we ze hebben aangemoedigd te vertalen tussen representaties.

Heeft het integreren en/of linken van dynamische multipele representaties invloed op leeruitkomsten?

Het doel van deze studie was vast te stellen of het integreren en/of linken van dynamische multipele representaties invloed heeft op leeruitkomsten. Door het integreren van multiple representaties zien ze er uit als één representatie die de verschillende eigenschappen van het domein weergeeft. Het fysiek integreren van representaties maakt de relaties tussen de representaties direct zichtbaar voor de leerling. Door het dynamisch linken van representaties worden acties uitgevoerd in één representatie automatisch getoond in andere representaties. Als een leerling bijvoorbeeld de waarde van een kracht in een numerieke representatie verandert, zal de overeenkomstige representatie van deze kracht in een animatie automatisch mee veranderen.

In drie experimentele condities is de momentenstelling weergegeven in een leeromgeving met aparte, niet gelinkte representaties (S-NL conditie), in een leeromgeving met aparte, dynamisch gelinkte representaties (S-DL conditie) en in een leeromgeving met geïntegreerde, dynamisch gelinkte representaties (I-DL conditie). De leeromgeving was verdeeld in een laag en hoog complex deel.

De proefpersonen waren 72 studenten uit het middelbaar beroepsonderwijs (leeftijd 16 tot en met 18 jaar). Ze werkten met de leeromgeving Momentenstelling gemaakt met de auteursomgeving SimQuest. De leeromgeving was gebaseerd op onderzoekend leren. De simulatie interface bevatte vijf representaties: (1) een concrete representatie (animatie van een steeksleutel of hijskraan), (2) een abstracte representatie, (3) een numerieke representatie en (4, 5) twee grafieken (moment-kracht en moment-arm of moment-kracht en moment-hoogte).

Voorkennis en leerresultaten werden gemeten met een voor- en natoets met drie verschillende typen vragen. De domeinkennis van de proefpersonen werd gemeten met *domeinvragen*. De inhoud van deze vragen was analoog aan de inhoud van de leeromgeving. Met *transfervragen* werd gemeten of de proefpersonen de aangeleerde kennis konden toepassen in nieuwe situaties: vragen met nieuwe contexten en vragen over relaties tussen variabelen waarnaar niet werd gevraagd in de leeromgeving maar die konden worden beantwoord met de aangeleerde domeinkennis. Met *representatievragen* werd gemeten of de proefpersonen verschillende representaties konden relateren of tussen verschillende representaties konden vertalen. Tijdens het werken in de leeromgeving verscheen vijf keer een vragenlijst waarin de proefpersonen werd gevraagd naar hun mening over de leeromgeving en het domein.

De I-DL conditie liet de beste leerresultaten zien. Proefpersonen uit de I-DL conditie haalden in vergelijk met de S-NL betere leerresultaten op de natoets domeinvragen. Er werd een trend gevonden op de representatievragen in het voordeel van de I-DL conditie vergeleken met de S-NL conditie. Een subjectieve meting naar ervaren complexiteit liet zien dat de proefpersonen in de I-DL conditie het werken met hun leeromgeving het gemakkelijkst vonden. We vonden een interactie tussen de complexiteit van het domein en de experimentele condities. De verschillen tussen de condities werden alleen gevonden op de toetsvragen die correspondeerden met het complexe deel van de leeromgeving.

Heeft het sequentieel aanbieden van dynamische representaties een effect op leeruitkomsten?

In de tweede studie, beschreven in hoofdstuk 2, hebben we de bevindingen uit studie één als startpunt genomen en onderzocht of het sequentieel aanbieden van dynamische representaties invloed heeft op leeruitkomsten. In deze studie is het sequentieel aanbieden van representaties gebaseerd op een modelprogressie van simpel naar complex. Gebaseerd op de gebruikte modelprogressie hebben we het aantal representaties iteratief verhoogd. Hiermee verhoogde eveneens het aantal relaties en mogelijke vertalingen. Beginnen met een paar relaties en mogelijke vertalingen en vervolgens stap voor stap introduceren van meer relaties en mogelijke vertalingen zou leerlingen kunnen ondersteunen in het relateren van representaties en het vertalen ertussen.

Twee versies van dezelfde simulatie-leeromgeving over het onderwerp momentenstelling zijn vergeleken: een leeromgeving waarin de representaties stap voor stap werden aangeboden (R-Step conditie) en een leeromgeving waarin alle representaties ineens werden aangeboden (R-Once conditie).

De proefpersonen waren 88 eerstejaars studenten uit het middelbaar beroepsonderwijs. Ze waren 15 tot en met 21 jaar oud en volgden de opleiding werktuigbouwkunde of bouwkunde. Ze werkten met de leeromgeving Momentenstelling gemaakt met de auteursomgeving SimQuest. De simulatie interface bevatte vijf representaties: (1) een concrete representatie (animatie van een steeksleutel), (2) een abstracte representatie (representatie van de variabelen die een rol spelen in de concrete situatie), (3) een numerieke representatie (weergave van de waarden van de variabelen), (4) een dynamisch veranderende vergelijking en (5) een dynamisch veranderende tabel (weergave van één rij variabelen waarvan de waarde automatisch werd bijgewerkt wanneer ze werden gemanipuleerd in andere representaties).

Voorkennis werd gemeten met een voortoets met domeinvragen en transfervragen. Leerresultaten werden gemeten met een natoets met domeinvragen, transfervragen, relateervragen en vertaalvragen. Met de *domeinvragen* werd gemeten of de proefpersonen in staat waren de leerinhoud te reproduceren die ze in de leeromgeving expliciet werd gevraagd te onderzoeken. Met de *transfervragen* werd gemeten of de proefpersonen de opgedane kennis konden toepassen in nieuwe situaties. De *relateervragen* vroegen de proefpersonen dezelfde variabelen te relateren in twee representaties met een verschillende structuur. Om de *vertaalvragen* goed te beantwoorden moesten de proefpersonen een mentale vertaling maken van manipulaties in één representatie op de effecten in een andere representatie. Tijdens het werken in de leeromgeving verscheen drie keer een vragenlijst waarin de proefpersonen werd gevraagd naar hun mening over de leeromgeving en het domein.

We vonden dat de proefpersonen leerden van het werken met de leeromgeving. De natoets scores op de domeinvragen en transfervragen waren significant beter dan de voortoets scores. In tegenstelling tot onze verwachtingen vonden we geen verschillen tussen de experimentele condities. Onafhankelijk van de wijze waarop de representaties werden aangeboden behaalden de proefpersonen dezelfde resultaten. Ook de mate waarin de proefpersonen de complexiteit van de leeromgeving en het domein ervoeren verschilde niet tussen de experimentele condities.

Heeft het sequentieel aanbieden van dynamische representaties, gecombineerd met expliciete instructie om te relateren en vertalen tussen representaties een effect op leeruitkomsten?

Terwijl de ondersteuning in studie één en twee gericht was op het zichtbaar maken van relaties tussen representaties, hebben we ons in studie drie gericht op het ondersteunen van begrip. Door het aanbieden van hints en prompts hebben we de proefpersonen aangemoedigd de representaties betekenisvol te relateren en een vertaling tussen de representaties te maken. Dit is beschreven in hoofdstuk vier.

We hebben twee versies van dezelfde simulatie-leeromgeving over het onderwerp momentenstelling vergeleken. In de eerste leeromgeving werden alle representaties in een keer aangeboden waarbij de instructionele ondersteuning was gericht op de relaties tussen de variabelen in het domein (R-Once conditie). In de tweede leeromgeving werden de representaties stap voor stap aangeboden waarbij de instructionele ondersteuning zich aanvullend richtte op het relateren en vertalen tussen de representaties. Beide leeromgevingen maakten gebruik van dynamisch linken en integratie van representaties.

Proefpersonen waren 68 studenten uit het middelbaar beroepsonderwijs (leeftijd 15 tot en met 21 jaar) en 125 vwo-leerlingen (leeftijd 13 tot en met 15 jaar). De studenten uit de eerste groep waren eerstejaars werktuigbouwkunde of eerstejaars bouwkunde studenten. De studenten uit de tweede groep zaten in hun derde jaar. De proefpersonen kwamen van vier verschillende scholen; twee ROC’s en twee scholen voor voortgezet onderwijs. Ze werkten met de leeromgeving Momentenstelling gemaakt met de auteursomgeving SimQuest. De simulatie interface bevatte zeven representaties: (1) een concrete representatie (animatie van een hijsbalk, een steeksleutel of een autokraan), (2) een abstracte representatie, (3) een numerieke representatie, (4) een dynamisch veranderende vergelijking, (5) een moment-arm grafiek, (6) een moment-kracht grafiek en (7) een dynamisch veranderende tabel.

Voorkennis werd gemeten met een voortoets met domeinvragen en transfervragen. Leerresultaten werden gemeten met een natoets met domeinvragen, transfervragen, relateervragen en vertaalvragen. Een eventueel verschil in cognitieve belasting werd gemeten met een vragenlijst die vier keer verscheen tijdens het werken met de leeromgeving.

We vonden dat de proefpersonen leerden van het werken met de leeromgeving. De natoets scores op de domeinvragen en transfervragen waren significant beter dan de voortoets scores. Zoals verwacht vonden we dat het sequentieel aanbieden van representaties gecombineerd met instructie gericht op het relateren en vertalen tussen representaties leidde tot betere leeruitkomsten. Dit gold echter alleen voor de domeinvragen. We vonden een trend op de relatievragen in het voordeel van de R-Step conditie. We vonden geen verschillen op de transfervragen en vertaalvragen. De proefpersonen in de R-Step conditie rapporteerden een hogere cognitieve belasting. De proefpersonen maakten echter geen onderscheid in typen cognitieve belasting waardoor we konden vaststellen welk type cognitieve belasting tot de hogere cognitieve belasting in de R-Step conditie heeft geleid.

Uit de drie studies kunnen we een aantal conclusies trekken. Op basis van studie één kan geconcludeerd worden dat dynamisch linken gecombineerd met integratie van representaties is aan te bevelen in het leren met multipele dynamisch veranderende representaties in simulatie-leeromgevingen. In studie één leidde dit tot de beste leerresultaten. Hoewel op basis van studie twee geconcludeerd zou kunnen worden dat het stap voor stap aanbieden van representaties niet zinvol is, zijn er twee redenen dit wel te doen. Ten eerste geeft het stap voor stap aanbieden van representaties leerlingen de gelegenheid vertrouwd te raken met een representatie voor ze een volgende representatie krijgen aangeboden. Ten tweede ondersteunt het ontwerpers in het structuren van de instructionele ondersteuning. De instructionele ondersteuning had er in studie twee heel anders uitgezien als het was gebaseerd op het ineens aanbieden van de representaties. De instructie zou dan veel meer op die van studie één hebben geleken. Ons pleidooi voor het sequentieel aanbieden van representaties wordt ondersteund door de resultaten van studie drie. In deze studie leidde een combinatie van het sequentieel aanbieden van representaties en het geven van hints en prompts tot de beste leeruitkomsten. Of het deze combinatie was of één van de typen ondersteuning dat leidde tot dit resultaat uitkomst is onderwerp voor toekomstig onderzoek.