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Progression in Multiple Representations

Supporting students' learning with multiple representations in a dynamic simulation-based learning environment

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Abstract

Relating multiple representations and translating between them is important to acquire deeper knowledge about a domain. To relate representations, learners have to 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 presenting representations may improve or hinder 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 120 students from secondary vocational education (aged 15 to 21). Overall, we found the subjects learned from working in the learning environment; the post-test scores on the domain and understanding items were significantly better than the pre-test scores. This was true for both the subjects with and without prior knowledge on the domain. Moreover, the subjects with prior knowledge scored significantly better on both the pre-test and the post-test compared to the subjects without prior knowledge. 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.

Keywords: Multiple representations; Instructional technology; Scientific discovery learning; Simulation-based learning environment

1 Introduction

By using multiple representations in simulation-based learning environments, learners are assumed to acquire deeper knowledge about 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

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representation to anticipate on correspondences in the second (Petre, Blackwell, & Green, 1998). This is believed to lead to a deeper level of cognitive processing and may expose glitches that might otherwise have been missed. A familiar representation can support understanding, and reasoning with, unfamiliar ones (the constraining function; Ainsworth (1999)). In addition, representations can complement each other by containing complementary information or by supporting different complementary processes (the complementing function; Ainsworth (1999)).

In a multi-representational learning environment, learners can choose those representations that fit their prior knowledge and preference (Ainsworth, 1999). However, to be able 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, that is, interpret similarities and differences of corresponding features of two or more representations (van der Meij & de Jong, in press). Several studies (e.g., Kozma, 2003; e.g., Tabachneck, Leonardo, & Simon, 1994) have shown the last two abilities – 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 offered improve or hinder the cognitive processes of relating and translating?

1.1 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, in press) are of proven value. However, both also have their limitations and drawbacks.

1.1.1 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 to learning with non-integrated representations (Ainsworth & Peevers, 2003; Bodemer, Ploetzner, Feuerlein, & Spada, 2004; Chandler & Sweller, 1991; Mayer & Moreno, 1998; Tabbers, Martens, & Van Merriënboer, 2000). However, integration does not always lead to better learning outcomes. Bodemer et al. (2004) found that learners working with integrated representations only learned more compared to learners 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 learners 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.

1.1.2 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 to control their cognitive load (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 to construct the required understanding. Despite the potential problems, dynamic linking seems to be a promising approach to support learning with multiple representations.

1.1.3 Integrating plus dynamic linking

In a study comparing three simulation-based learning environments, van der Meij and de Jong (in press) extended known research on integration by examining its role using dynamic representations instead of static representations. 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, they examined the role of the complexity of the domain and the learning environment. The learning environment was divided into parts of low complexity and high complexity. They found better learning results on domain knowledge when the representations were both integrated and dynamically linked. However, they did not find learning progress on transfer knowledge, whereas transfer is an important argument for using the type of learning environments evaluated in their study. The learning environments they used can be characterized as guided discovery learning environments (e.g., Mayer, 2004; van Joolingen & de Jong, 2003). In discovery 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 discovery process if it is adequately guided by, for example, assignments and explanations.

1.2 Representation progression

Another way to support learners in simulation-based learning environments, is providing model progression (White & Frederiksen, 1990). Model progression sequences the learning environment 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 iteratively. As a result, the number of relations and possible translations increased likewise. Starting with a few relations and possible translations and then introduce 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.

1.3 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 discovery simulation-based learning environment called Moments. Subjects studied the physics topic 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).

2 Method

The experiment was conducted with subjects who already had and who had no prior knowledge about the domain.

2.1 Subjects

2.1.1 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 orienting for following the course and of one student the post-test results were lost, resulting in analyses done with 32 subjects.

2.1.2 Subjects without prior knowledge in the domain

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 3 and 6) or architecture (classes 4 and 5). 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 already participated in a subjects with prior knowledge session, 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 1 shows how the subjects were distributed across the conditions and the schools.

Table 1. Distribution of subjects over 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)
3	1	11	(11/0)	12	(12/0)	23	(23/0)
4	2	14	13/1)	10	(10/0)	24	(23/1)
5	2	13	(13/0)	13	(13/0)	26	(26/0)
6	2	7	(7/0)	8	(8/0)	15	(15/0)
Total		60	(58/2)	60	(59/1)	120	(117/3)

m = male, f = female

2.2 *Materials*

2.2.1 *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 moments in the context of mechanical engineering. The topic is important for these students, since it forms the basis for static mechanics. The learning environment is based on guided discovery learning (de Jong & van Joolingen, 1998). The learner has to engage in discovery activities in order to learn about the properties of the simulation model and is guided in the discovery 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 to ‘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.

Supported by assignments (right screen in Figure 1), the learner can perform experiments in the simulation interface (left screen in Figure 1). The learner can manipulate the force and length input variables and can observe the moment output variable. The assignments stimulate learners to explore both the relation between the variables in the simulation model and the relation between the representations given. 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 2 gives an overview of the instructional support with corresponding representations. Only the variables in representation 2 are introduced explicitly in assignments 2, 3, 4, 5, 7 and 8. The assignments are the same for both experimental conditions.

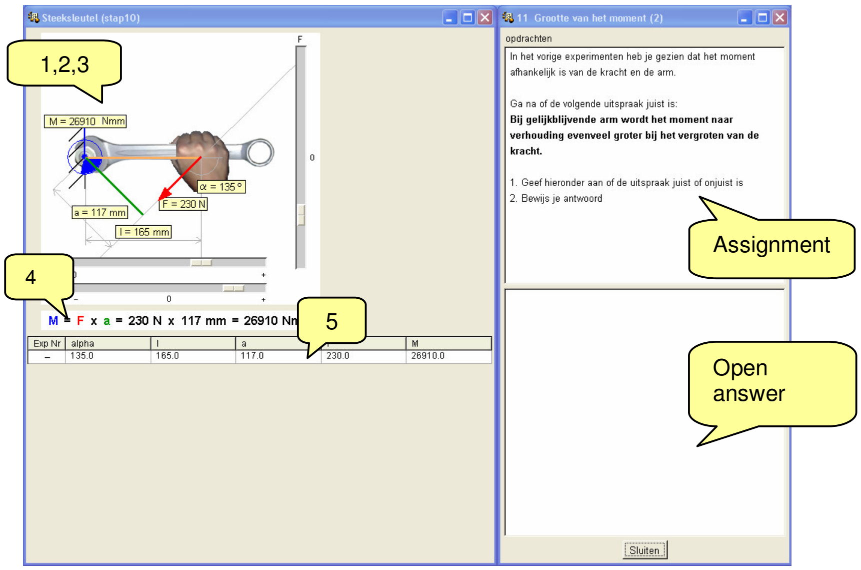


Figure 1. Assignment with simulation interface showing all representation types

Representations 1, 2 and 3 are representations usually found in textbooks. These representations are the basic types presented to learners in this domain. They support learners to get insight in 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 of the other two representations. The concrete representation (1) provides the learner with a context of the simulated task. This representation links the learning material to a real-life experience. The choice for an open-end spanner in this learning environment was made because most of the learners in the target group have experiences in using this tool. 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. 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.

Table 2. Instructional support with corresponding representations

Instructional support (text)	Representations	
	R-Step condition	R-Once condition
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)

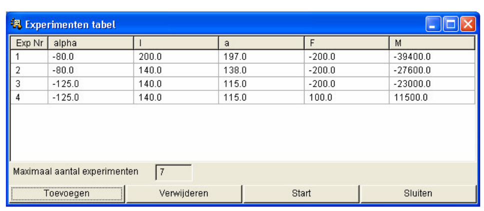


Figure 2. Experiment table

In addition to the table, an experiment table is introduced in assignment 12 (see Figure 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.

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 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 shows the first step; Figure 1 shows the final step).

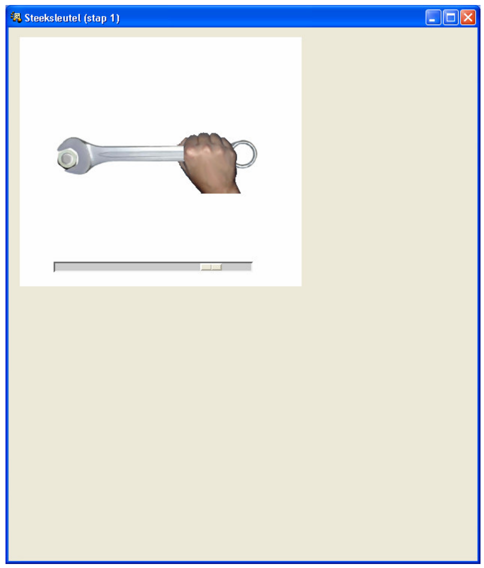


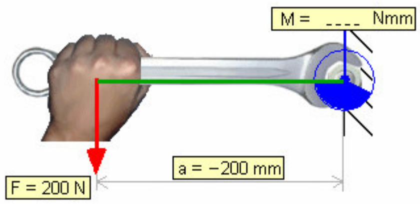
Figure 3. First representation progression step (experimental condition)

2.2.2 *Tests and questionnaires*

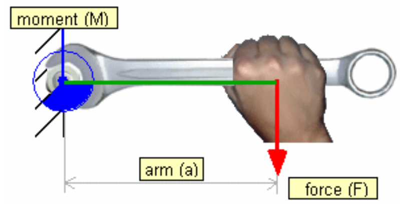
Subjects' prior domain knowledge was assessed using an online pre-test. This was administered directly before working with the learning environment. An online post-test was administered directly after working with the learning environment. The pre-test consisted of 20 items, both multiple-choice and open answer items; 10 items testing domain knowledge and 10 items testing understanding of the domain. The post-test consisted of 40 items, both multiple-choice and open answer items; 10 items testing pure domain knowledge, 10 items testing understanding of the domain, 10 testing the ability to relate representations and 10 items testing the ability to translate between representations. The domain and understanding items corresponded with the post-test items. The post-test items differed slightly from the pre-test by differing 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. Figure 4 shows examples of one test item from each category.

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

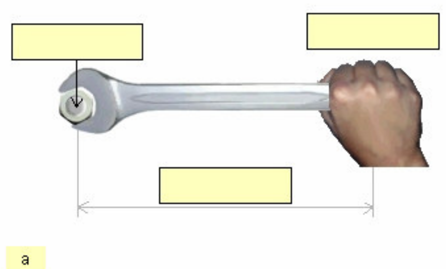


- - 40000 Nmm
- 0 Nmm
- 400 Nmm
- 40000 Nmm

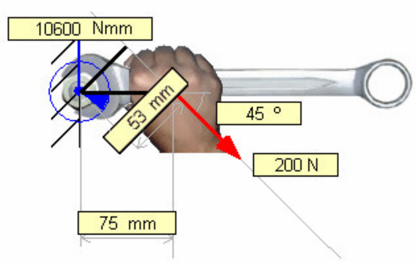


(2) If the force increases four times, then the moment [ ] [ ] times.

(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 4. Example of a (1) domain, (2) understanding, (3) relate and (4) translate item

The *domain items* tested whether the subjects were able to reproduce the content they were explicitly asked to explore in the learning environment. The *understanding items* tested whether the subjects had insight in the domain. To answer these items correctly, the subjects needed to apply their acquired knowledge in new situations. These were new contexts and 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 students were able to relate different representations. These items asked students 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.

An electronic questionnaire based on Swaak's S.O.S. scale (Swaak, 1998) was used to assess the subjects' opinions on 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. The possible answers: easy, average, or difficult.

2.3 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 on 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 thirty minutes to fill in the pre-test.

The learning environment session took place proximally 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 in 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 they 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 forty-five 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.

3 Results

3.1 Pre-test and post-test

3.1.1 Subjects with prior knowledge in the domain

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 understanding items was 13.31

out of 20 test items (*SD* = 2.81). Table 3 shows the means and standard deviations of the scores on the item categories in the pre-test and post-test.

Table 3. 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
Understanding 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 the overall combined domain and understanding post-test score of the 32 subjects was significantly better than the overall pre-test scores ($F(1,31) = 9.07$, $p < .01$). 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 understanding items were significantly better than pre-test scores on these item types ($F(1,31) = 7.52$, $p < .05$). Table 4 shows the means and standard deviations of the pre-test and post-test scores for the four item categories for each condition.

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

	R-Step		R-Once	
Pre-test	Mean	(SD)	Mean	(SD)
Domain items (max. 10)	7.33	(1.63)	6.65	(1.37)
Understanding items (max. 10)	5.53	(1.51)	4.88	(2.26)
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)
Understanding 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)
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 understanding scores ($F(1,30) = 1.68$, $p = .21$; $F(1,30) = .90$, $p = .35$). 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, understanding scores, relate scores and translate scores ($F(1,30) =.02$, $p = .90$; $F(1,30) = .04$, $p = .84$; $F(1,30) = .01$, $p = .92$; $F(1,30) = .02$, $p = .90$).

3.1.2 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 little prior knowledge in the domain. The overall mean score on the post-test domain plus understanding items was 11.64 out of 20 test items (*SD* = 3.10). Table 5 shows the means and standard deviations of the scores on the item categories in the pre-test and post-test.

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

	Pre-test			Post-test		
	Mean	(SD)	%	Mean	(SD)	%
Domain items (max. 10)	5.70	(1.62)	57	6.99	(1.68)	70
Understanding items (max. 10)	3.96	(1.78)	40	4.65	(1.91)	47
Total (max. 20)	9.65	(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 the overall combined domain and understanding post-test score of the 88 subjects was significantly better than the overall pre-test scores ($F(1,87) = 60.68$, $p < .01$). Repeated measures ANOVAs for each item category showed that the post-test scores on domain and understanding items were significantly better than the pre-test scores on these item types ($F(1,87) = 67.51$, $p < .01$ and $F(1,87) = 15.54$, $p < .01$). Table 6 shows the means and standard deviations of the pre-test and post-test scores for the four item categories for each condition.

Table 6. Means (standard deviations) of pre-test and post-test scores per condition

	R-Step		R-Once	
Pre-test	Mean	(SD)	Mean	(SD)
Domain items (max. 10)	5.93	(1.76)	5.44	(1.44)
Understanding items (max. 10)	3.91	(1.73)	4.00	(1.85)
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)
Understanding 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)
Total (max. 40)	22.16	(4.01)	22.67	(5.29)

n = 88

One-way ANOVAs showed no significant differences between the experimental conditions on pre-test domain scores and understanding scores ($F(1,86) = 2.05$, $p = .16$; $F(1,86) = .05$, $p = .82$). 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, understanding scores, relate scores and translate scores ($F(1,86) = .33$, $p = .57$; $F(1,86) = .64$, $p = .43$; $F(1,86) = .94$, $p = .33$; $F(1,86) = .09$, $p = .77$).

3.1.3 Subjects with and without prior knowledge in the domain taken together

The overall mean score on the pre-test was 10.32 out of 20 test items ($SD = 3.10$). These data indicate the subjects had some prior knowledge in the domain. The overall mean score on the post-test domain plus understanding items was 12.08 out of 20 test items ($SD = 3.10$). Table 7 shows the means and standard deviations of the scores on the item categories in the pre-test and post-test.

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

	Pre-test			Post-test		
	Mean	(SD)	%	Mean	(SD)	%
Domain items (max. 10)	6.03	(1.69)	60	7.13	(1.63)	71
Understanding items (max. 10)	4.28	(1.90)	43	4.96	(2.01)	50
Total (max. 20)	10.32	(3.10)	52	12.08	(3.10)	60
Relate items (max. 10)				8.03	(1.47)	80
Translate items (max. 10)				3.18	(1.60)	32

n = 120

A repeated measures ANOVA showed the overall combined domain and understanding post-test score of the 120 subjects was significantly better than the overall pre-test scores ($F(1,119) = 67.38$ $p < .01$). Repeated measures ANOVAs for each item category showed the post-test scores on domain and understanding items were significantly better than the pre-test scores on these item types ($F(1,119) = 61.66$, $p < .01$ and $F(1,119) = 22.57$, $p < .01$). Table 8 shows the means and standard deviations of the pre-test and post-test scores for the four item categories for each condition.

Table 8. Means (standard deviations) of pre-test and post-test scores per condition

	R-Step		R-Once	
Pre-test	Mean	SD	Mean	SD
Domain items (max. 10)	6.28	(1.82)	5.78	(1.51)
Understanding items (max. 10)	4.32	(1.81)	4.25	(2.00)
Total (max. 20)	10.60	(3.17)	10.03	(3.03)
Post-test				
Domain items (max. 10)	7.20	(1.55)	7.05	(1.71)
Understanding items (max. 10)	4.80	(1.75)	5.12	(2.24)
Relate items (max. 10)	7.90	(1.49)	8.17	(1.48)
Translate items (max. 10)	3.12	(1.61)	3.23	(1.61)
Total (max. 40)	23.02	(4.34)	23.57	(5.60)

n = 120

One-way ANOVAs showed no significant differences between the experimental conditions on pre-test domain scores and understanding scores ($F(1,118) = 2.68$, $p = .10$; $F(1,118) = .04$, $p = .85$). 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, understanding scores, relate scores and translate scores ($F(1,118) =.25$, $p = .62$; $F(1,118) = .74$, $p = .39$; $F(1,118) = .99$, $p = .32$; $F(1,118) = .16$, $p = .69$).

3.1.4 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 ($F(1,118) = 17.49$, $p < .01$). The same effect was found for the post-test ($F(1,118) = 11.17$, $p < .01$).

3.2 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 neither subjects with prior knowledge and subjects without prior knowledge.

3.3 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 neither subjects with prior knowledge and subjects without prior knowledge.

4 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 understanding items were significantly better than pre-test scores. In contrast with our expectations, no differences where 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? Do we have to adapt our theory? In search of an answer to these questions we analysed the log files to get insight in the way learners worked through the learning environments. The data suggest that an intervening variable played an important role: the instructional support consisting of assignments and explanations. The instructional support had a great impact on how learners worked with the learning environment. It was the same for both conditions, but was organised according to the steps in the experimental condition where we sequenced the representations. The assignments and explanations directed the subjects' attention to the newly introduced representations and variables. It looks like the instructions supported the subjects in the progression of the learning material; sequencing the material from simple to complex. Thus, it may have affected the subjects processing of the representations.

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 their given answers, the log files showed that learners did not explore the simulation for other features than 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 subject did not focus on relating representations and translating between them. Therefore, the expected support from representational progression was not found in this study.

Despite of 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 are going to 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 that. We believe that sequencing the representations are of additional support here. They avoid overloading learners by directing their attention only to the representations they are asked to relate and translate between. Step-by-step learners are guided to relate more representations and translate between them.

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