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The influence of student characteristics on the use of adaptive e-learning material

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ABSTRACT

Adaptive e-learning materials can help teachers to educate heterogeneous student groups. This study provides empirical data about the way academic students differ in their learning when using adaptive e-learning materials. Ninety-four students participated in the study. We determined characteristics in a heterogeneous student group by collecting demographic data and measuring motivation and prior knowledge. We also measured the learning paths students followed and learning strategies they used when working with adaptive e-learning material in a molecular biology course. We then combined these data to study if and how student characteristics relate to the learning paths and strategies they used. We observed that students did follow different learning paths. Gender did not have an effect, but (mainly Dutch) BSc students differed from (international) MSc students in the intrinsic motivation they had and the learning paths and strategies they followed when using the adaptive e-learning material.

1. Introduction

The variety in prior knowledge within student groups has increased since the Bachelor/Master system was introduced at European universities in order to increase student mobility within the EU. Students enrolling in Master's programmes come from different universities and their knowledge on specific topics varies. These varying backgrounds mean that university staff must provide the students with intensive tutoring. Time-consuming tutoring can be supported by adaptive e-learning material. Adaptive e-learning is suitable for teaching heterogeneous student populations in higher education (Schiaffino, Garcia, & Amandi, 2008), as it addresses the variety in the prior knowledge of students who enrol in a course. This gives students the opportunity to follow individual learning paths and meet their specific training needs (Brusilovsky, Eklund, & Schwarz, 1998).

Although several studies report on the benefits of adaptive e-learning (see for example Armani, 2005; Melis et al., 2001; Virvou & Tsiriga, 2001), there is little to no empirical evidence that students do follow individual learning paths associated with their differences in prior knowledge. It is also unknown whether other student characteristics such as gender or intrinsic motivation influence their learning paths. Since the development costs of computer-based learning environments (CBLEs) are high, it is important to know under what circumstances and for which student groups adaptive e-learning is effective. This study provides empirical evidence to support educators' decisions. As such, it links up with questions raised by, for instance, Narciss, Proske, and Koerndle (2007) at the end of their manuscript: 'To date there has been little research into how individual differences in problem-solving strategies and styles, students' goals and motivational orientations and students' meta-cognitive skills contribute to differences in studying in web-based learning environments. … An… issue for future research and practice is the question how individual variables may determine the way students learn with web-based learning environments'. (p. 1141)

In addition to these practical aims, research into computer-based learning can provide more insight into the ways students self-regulate their learning. As Winne (2010) has pointed out: 'widespread use of CBLEs is vital to significantly accelerating the science of learning, particularly regarding self-regulated learning (SRL), and applying its findings in education.' (p.267) Azevedo, Moos, Johnson, and Chauncey (2010) claim that learning in hypermedia environments involves the use of numerous self-regulatory processes, such as planning, knowledge activation, metacognitive monitoring and regulation, and reflection. We think that this claim can be extended to other CBLEs and

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that adaptive e-learning material is a good tool to investigate SRL. This study therefore paid special attention to the SRL strategies that students adopt when using adaptive e-learning material.

1.1. Adaptive e-learning

E-learning is defined by Shute and Towle (2003) as 'learning that takes place in front of a computer that is connected to the Internet' (p. 106). Adaptive e-learning is generally perceived from the instruction point of view and comprises CBLEs that can interact with a student to provide the most appropriate instruction. Thus, it is not students' learning that adapts, but the instruction provided by the system. Adaptive e-learning is currently applied to improve the instruction given to heterogeneous student groups (Brusilovsky et al., 1998; Van Seters, Ossevoort, Goedhart, & Tramper, 2011).

Adaptive e-learning material has been investigated by multiple disciplines, including educational psychology and computer science, and each discipline uses its own terminology to label similar concepts. Adaptive e-learning systems consist of multiple components that together enable instruction that is tailored to the needs of the individual students. The names of the components, according to the terms used in educational psychology (with those from computer science given between brackets), are: the content model (domain model), the learner model (user model), the instruction model (interface model) and the adaptive engine (Brusilovsky, 1996; Shute & Towle, 2003).

The *content model* contains the concepts that a student should master. In educational research, the concepts are usually described as learning objectives, which combine the concepts with the actions that students should be capable of doing, such as remember, understand, apply, etc.

The *learner model* contains information about the individual student, such as preferences for textual or visual information, demographic data such as gender or age, and information about the knowledge of a specific topic. The information in the learner model can be obtained before commencement of the learning activity and does not change during the interaction with the system (static), or it can be updated during the interaction (dynamic) (Brusilovsky, 2001).

The *instruction model* monitors the learner model in relation to the content model in order to ascertain the student's mastery of concepts. As such, the instruction model determines how close a student is to the target competence level after carrying out a learning activity.

The *adaptive engine* is an algorithm that integrates information from the preceding models in order to select appropriate learning content to present to the student.

1.2. Self-regulated learning

Being able to regulate one's own learning is viewed by educational psychologists and policy makers as the key to successful learning at school and beyond. SRL refers to learning situations in which students set their own learning objectives. Students plan, conduct, regulate and evaluate the learning process individually to achieve their objectives. Monitoring and evaluating the learning progress are essential for successful SRL (Narciss et al., 2007). To allow students to reflect on their own learning, they should have control over their learning process. A way to provide self-control is by offering choices (Winne, 1995; Winne & Perry, 2000).

A well-known driving force for SRL is intrinsic motivation. Students who are eager to study a subject and appreciate the learning environment engage more in SRL. In addition, the familiarity that students already have with the subject and the learning environment influences their use of SRL (Winne, 1996). Other factors that influence self-regulated learning are, for instance, demographic characteristics such as culture or gender. Women are reported to score higher than men on help-seeking strategies, utility value and performance anxiety (Virtanen & Nevgi, 2010). Cultural differences have also been reported to influence SRL (Biemans & Van Mil, 2008). In this study, Chinese students are less likely to self-regulate their learning than Dutch students, since the former adopt a reproduction-directed learning style.

In a recent article, Winne (2010) points out the problem of measuring SRL. Commonly used methods are inventories and think-aloud protocols, but these methods have some disadvantages. Inventories gather data after an intervention, relying on the memory of students. Think-aloud protocols alter the learning environment and natural behavior of the student. CBLEs offer an alternative way to measure SRL by logging the student interactions with the system, resulting in reliable data for educational research (Winne, 2010). These 'traces' are gathered during interventions, on the fly and do not intervene with a student's natural behavior.

1.3. Feedback

Feedback is defined as any message that is generated in response to a student's action (Mason & Bruning, 2001). Feedback usually indicates the student's performance in comparison with the expected one (Johnson & Johnson, 1993). By doing so, feedback helps students to identify errors and become aware of misconceptions. Feedback also provides clues about the best approaches to correcting errors (Mason & Bruning, 2001). Good feedback might strengthen the students' capacity to self-regulate their own performance (Nicol & Macfarlane-Dick, 2006) and is therefore an important aspect to take into account when investigating SRL.

Feedback is most effective when it is tailored to individual students and helps them to proceed (Brookhart, 2008). Many types and classifications of feedback have been reported, as has the effectiveness of each type. Feedback can be about the task (FT), the processing of the task (FP), self-regulation (FR) or the self as a person (FS). FT is the most common and is often called corrective feedback or knowledge of results. FT tells a student whether the answer he or she provided is correct or incorrect, such as: 'Your answer is correct, but you have to include more arguments to support your conclusion'. FP is more specific to the learning steps that are needed to perform tasks, such as: 'The order of the calculation steps you made was correct.' FR concerns the feedback students create for themselves. Self-regulation feedback is initiated by the student rather than by the teacher and can prompt the student to look for more information on a certain topic, without specific directions. FS typically expresses positive evaluations, such as 'Well done' or 'Great effort', although it can be negative. It usually contains little task-related information and is rarely converted into more engagement, commitment to the learning goals, enhanced self-efficacy or understanding of the task (Hattie & Timperley, 2007). Feedback on the processing of the task (FP) has been applied to intelligent e-learning by Narciss et al. (2007), which they call informative tutoring feedback. Informative tutoring feedback provides strategically useful information that guides the student step by step towards successful task completion, thereby assisting multiple solution attempts.

Informative tutoring feedback delivers instructions to solve the task successfully, by guiding and tutoring the learning process, rather than offering the correct solution (Narciss & Huth, 2004). Furthermore, students have to act in order to receive these instructions: they have to work on a task and, if they make a mistake, receive the informative feedback (Narciss et al., 2007).

Computer-based feedback can be used to support teachers by taking over the labour-intensive task of providing explanations to common mistakes (Vasilyeva, Puuronen, Pechenizkiy, & Rasanen, 2007). The biggest advantage of using computers is their ability to repeatedly provide immediate feedback on individual responses (Mason & Bruning, 2001). Computer-based feedback can be provided as local or global feedback. Local feedback is a specific response to student activities and is aimed at correcting errors and guiding students in solving the problem. Global feedback provides coaching for several aspects of the entire learning process (Melis & Ullrich, 2003). Web-based feedback can provide tailored instructions by varying its content according to the individual characteristics and performance of the student, independent of the local computer that is used (Vasilyeva et al., 2007). This type of feedback is called adaptive feedback and is often included in adaptive e-learning or intelligent tutoring systems.

Many best practices for the design of effective feedback have been reported in the literature. According to Kulhavy and Stock (1989), effective feedback provides the student with two types of information: verification and elaboration. Verification is the simple judgement of whether an answer is correct or incorrect, while elaboration is the informational component that provides relevant cues to guide the student towards a correct answer (Mason & Bruning, 2001). Good practices regarding feedback in general are also well described by Hattie and Timperley (2007). These researchers report that feedback is most effective when it addresses faulty interpretations, not a total lack of understanding; provides cues or reinforcement to students; is in the form of video-, audio- or computer-assisted instructional feedback; and/or relates to goals. Feedback is more effective when it provides information about correct rather than incorrect responses. It is also effective when it consists of information about progress and/or about how to proceed. Good practices regarding computer-based feedback describe that response-specific feedback enhances student achievement more than other, general forms of feedback (Mason & Bruning, 2001). The types of feedback that are most effective depend on the level of the task. Delayed and knowledge-of-correct-response feedback may be more beneficial for lower-level learning, and answer-until-correct feedback may be more effective for higher-level learning (Morrison, Ross, Gopalakrishnan, & Casey, 1995).

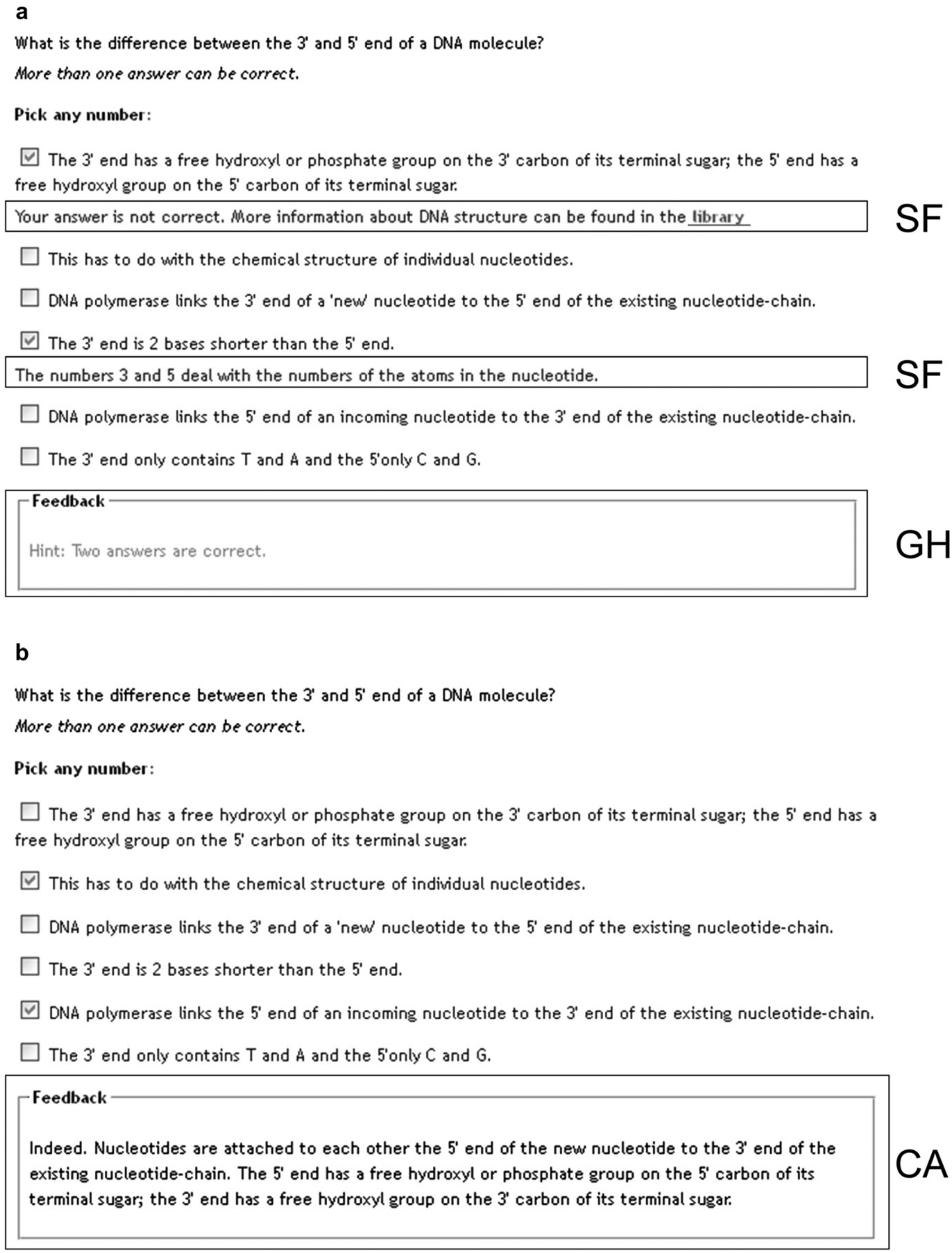
Practices that should be avoided are also described in the literature. Feedback should not take too much time or provide too much irrelevant information (Winne, 2010). FT about the task should not be mixed with FS, since the mix is reported to be less effective than FT on its own (Hattie & Timperley, 2007). In addition, it is useless to present feedback to students who have no initial domain knowledge or completely lack the skills that are to be learned. In these situations, instruction is more useful than feedback. Feedback can only build on something; it is of little use when there is no initial learning or surface information (Hattie & Timperley, 2007).

The adaptive e-learning system that was investigated in this research provides immediate feedback on both correct and incorrect answers (Fig. 1). The feedback consists of general hints and specific feedback. General hints are presented upon the submission of any incorrect answer. This type of feedback incorporates aspects from feedback about self-regulation (FR). It for instance suggests to look for information, but does not provide detailed instruction about where to find this information. In addition, general hints can provide global feedback such as information about notation of the answer. Specific feedback directs students to specific information sources in case they have no knowledge to build on yet. As mentioned, instruction is more useful than feedback if the student's prior knowledge is too limited. The specific feedback helps the student to identify and understand the specific error that was made and guides him or her towards the correct answer. The feedback that is provided by the system used in this study, Proteus, is adaptive. The content of the feedback varies according to the individual performance of students. This performance consists of the type of mistake that was made, but also of the number of incorrect answers a student has already submitted. After many tries, more extensive feedback is given to help the student as is the case with informative feedback as described above.

1.4. The adaptive e-learning system

The adaptive e-learning system investigated in this research is called Proteus. It was developed by Sessink, Beeftink, Tramper, and Hartog (2007) and used by Van Seters et al. (2011). This computer-based system offers 'task or question modules to evaluate the learning process', which is a common approach according to Narciss et al. (2007). Adaptive e-learning systems are characterized based on *what*, *where, why* and *how* the systems can adapt (Knutov, De Bra, & Pechenizkiy, 2009). Proteus adapts the amount of training and the content of feedback students receive (Van Seters et al., 2011) (*what*). The adaptation of the amount of training and the feedback takes place during students' interaction with the e-learning system (*where*). The amount of training is adapted to fulfil the needs of students who have little prior knowledge, but without imposing too much repetition on students who have more prior knowledge. The content of the feedback is adapted to target specific mistakes that students make (*why*). The system varies the number of exercises according to the answers students submit to exercises related to the same learning objective. In addition, to establish the second mode of personalization (*how*), the system lets learners choose the next exercise according to three levels of complexity. These three levels of complexity are based on the first three levels of the Taxonomy of Educational Objectives which was initially described by Bloom, Engelhart, Furst, Hill, and Krathwohl (1956) and revised by Krathwohl (2002). These three levels are: remember, understand and apply. Remembering is defined by Krathwohl as "retrieving relevant knowledge from long-term memory" (p. 215) and includes recognition and recall of information. Understanding concerns "determination of the meaning of instructional messages" (p. 215) and includes student activities such as interpreting, exemplifying, classifying, summarizing, inferring, comparing and explaining. Application refers to "carrying out or using a procedure in a given situation" (p. 215) and includes activities such as executing a task or implementing a plan.

The system offers a mixed form of regulation according to Boekaerts (1999), in that 'students and teachers (in this case, the adaptive e-learning material functions as teacher) share the regulatory functions' (p. 450). The system selects appropriate exercises with regard to the current knowledge level of the student (the learner model), as described in the literature on computerized adaptive tests (Van der Linden & Glas, 2000). To select appropriate exercises, the system compares the learner model to the content model. Based on the gap between these models, the system selects exercises that will fill this gap. The regulatory function directed by the students is the step size they select before doing an exercise. Students choose between a small, medium or big step for the next exercise. The step size relates to the progress students may make towards the target level: a big step may lead to significant progress, while a small step may only lead to limited progress. Before



a

What is the difference between the 3' and 5' end of a DNA molecule?

More than one answer can be correct.

Pick any number:

- [x] The 3' end has a free hydroxyl or phosphate group on the 3' carbon of its terminal sugar; the 5' end has a free hydroxyl group on the 5' carbon of its terminal sugar.

Your answer is not correct. More information about DNA structure can be found in the library — SF

- [ ] This has to do with the chemical structure of individual nucleotides.
- [ ] DNA polymerase links the 3' end of a 'new' nucleotide to the 5' end of the existing nucleotide-chain.
- [x] The 3' end is 2 bases shorter than the 5' end.

The numbers 3 and 5 deal with the numbers of the atoms in the nucleotide. — SF

- [ ] DNA polymerase links the 5' end of an incoming nucleotide to the 3' end of the existing nucleotide-chain.
- [ ] The 3' end only contains T and A and the 5'only C and G.

Feedback

Hint: Two answers are correct. — GH

b

What is the difference between the 3' and 5' end of a DNA molecule?

More than one answer can be correct.

Pick any number:

- [ ] The 3' end has a free hydroxyl or phosphate group on the 3' carbon of its terminal sugar; the 5' end has a free hydroxyl group on the 5' carbon of its terminal sugar.
- [x] This has to do with the chemical structure of individual nucleotides.
- [ ] DNA polymerase links the 3' end of a 'new' nucleotide to the 5' end of the existing nucleotide-chain.
- [ ] The 3' end is 2 bases shorter than the 5' end.
- [x] DNA polymerase links the 5' end of an incoming nucleotide to the 3' end of the existing nucleotide-chain.
- [ ] The 3' end only contains T and A and the 5'only C and G.

Feedback

Indeed. Nucleotides are attached to each other the 5' end of the new nucleotide to the 3' end of the existing nucleotide-chain. The 5' end has a free hydroxyl or phosphate group on the 5' carbon of its terminal sugar; the 3' end has a free hydroxyl group on the 3' carbon of its terminal sugar. — CA

Fig. 1. Screenshot of an exercise with (a) specific feedback (in blue) and a general hint (in red) and (b) the feedback to the correct answer, shown at the bottom of the exercise. (For interpretation of color in this figure legend the reader is referred to web version of the article.)

each exercise, students may adapt the step size, allowing them to reflect on their learning. This way of stimulating self-reflection is known as embedded direct intervention (Narciss et al., 2007). The exercises contain adaptive feedback as described above.

Students tend to adopt a 'trial and error' behavior in e-learning environments (Narciss et al., 2007). In our system, this will not help students. Exercises have multiple answer options, making it harder for students to guess the correct answer. In addition, students have to complete more exercises if they give many incorrect answers. This feature has two advantages: it gives students who have not mastered the content a lot of practice and it prevents guessing.

1.5. Research aim

The aim of this study was to investigate how individual student characteristics influence the learning paths they follow and the learning strategies they use when working with adaptive e-learning material. By learning path we mean the way students go through the adaptive e-learning material. The path is characterized by the exercises that students do and the subsequent progress they make towards achieving the learning goal(s). The variables we measured to determine the learning path of students are: average step size chosen, average number of tries needed to complete an exercise, number of exercises to complete and time needed to finish the module.

The learning strategies we determined are the students' approach to do exercises and their use of information sources, and the degree to which they regulate their learning by varying the step sizes. The approach to do exercises comprises the steps students undertake to answer the questions asked in the exercises.

The student characteristics we considered were selected based on the likelihood that they have an influence on learning paths and strategies. The characteristics we selected are: prior knowledge, study level, gender and intrinsic motivation. Students' prior knowledge is reported to have an influence on the way they self-regulate their learning (Moos & Azevedo, 2008) and on their approach to solving problems (Liu, Andre, & Greenbowe, 2008). Students' study level is related to their prior knowledge. We expected to find, for example, that postgraduate students work more independently than undergraduates and look for information sources themselves. Gender was selected as a characteristic because it is reported to influence SRL (Virtanen & Nevgi, 2010) and the use of e-learning material (Sullivan, 2001), as mentioned above. The intrinsic motivation of students is reported to have a large influence on SRL (Winne, 1995). Students with high intrinsic motivation are assumed to be more eager to understand the concepts taught rather than to just find the right answer.

The aim of the study was to find out whether there is a relation between student characteristics and the way students use adaptive e-learning material. The following research questions were formulated:

1. Does the adaptivity of the e-learning material work by letting students follow different learning paths?
2. What is the influence of students' prior knowledge, study level, gender and intrinsic motivation on their learning paths?
3. What is the influence of students' prior knowledge, study level, gender and intrinsic motivation on the learning strategies they use?

2. Methods

2.1. Research design

Students worked with adaptive e-learning material about the design of PCR primers, which is an important molecular biology technique required for gene technology. The students first attended a lecture on the applications of cloning techniques in molecular biology research. The following day, they worked with the material during a two-hour session. The instructor and several assistants were available to help them with the material. Student prior knowledge was measured by taking a pre-test. After the intervention, students' intrinsic motivation and demographic data were measured by a questionnaire. Learning paths and strategies were measured with self-report items in the questionnaire and obtained from traces from students' interactions with the learning material. The classroom procedure comprised three steps:

1. The participants took the pre-test individually. They were not allowed to use external information from textbooks, peers or the teacher.
2. The participants used the adaptive learning material by doing the exercises that were presented to them. They were allowed to use all the information sources they needed to do the exercises, such as textbooks, their peers and the teacher. The participants had to complete as many exercises as necessary to finish the task.
3. The participants filled out the questionnaire individually.

2.2. Participants

The participants were Wageningen University students who followed the Gene Technology course in May 2011. Of the 94 students, 86 (91%) completed the pre-test (step 1), all 94 (100%) finished the adaptive e-learning material (step 2) and 80 (85%) completed the questionnaire (step 3).

Of the 80 participants who completed the questionnaire, 55% were male and 45% were female. Most (76%) of the students were following a BSc programme and almost all the others (23%) an MSc programme. Although the students who completed the questionnaire represented 12 nationalities, the majority (75%) were Dutch. The ratio Dutch to international students differs between BSc and MSc. The majority of BSc students (90%), but a minority of the MSc students (22%) were Dutch. Most (88%) students were between 18 and 25 years old; the other (12%) students were older than 25 years.

2.3. Instruments

Various instruments were used to measure the variables. Those that describe the learning paths were measured by logging student interactions with the adaptive e-learning to yield traces. The variables describing the strategies the students used were measured with self-reports (for approach to do the exercises, information sources used and chosen step size) and traces (for chosen step size in relation to the number of tries that were needed). The student characteristics were measured with a pre-test (for prior knowledge) and a questionnaire (for study level, gender and intrinsic motivation).

2.3.1. Traces

The system used in this study was adapted to enable tracing, as proposed by Winne (2010). The step sizes the students selected, the exercises provided by the system, the answers that students submitted to the exercises and the subsequent update of the learner model were logged. The average step size that students chose was calculated from the traces by:

$$AVGStep = \frac{(1 \cdot \Sigma S + 2 \cdot \Sigma M + 3 \cdot \Sigma B)}{\Sigma E}$$

where AVGStep = Average step size, S = Number of small step sizes that were chosen, M = Number of medium step sizes that were chosen, B = Number of big step sizes that were chosen, $\#E$ = Total number of exercises that were done = the number of step sizes that were chosen.

The average number of tries was calculated by dividing the total number of answers that students submitted by the total number of exercises. The answers students submitted after finding the correct answer (some students do this in order to be able to read all the feedback) were not taken into account. The total number of exercises was deducted by counting the number of exercises that students made in order to finish the material. For example, a student who only chose big steps will have an average step size of 3. A student who only chose small steps will have an average step size of 1. A student who chose five small steps, two medium steps and one big step will have an average step size of 1.5. The time students needed to finish the material was measured as the time between they submitted the pre-test and they finished the adaptive e-learning material.

We considered the variation in step sizes as the degree to which students regulate their learning. This was determined from the combined number of tries and chosen step size. These look like: B6 S1 M3. This code indicates that a student first chose the big step and needed six tries to complete the exercise. He or she then chose a small step and found the correct answer in one try. The student then chose a medium step and needed three tries to complete the exercise. Students were categorized into those who varied the step size and those who did not.

2.3.2. Pre-test

The students' prior knowledge was measured with a pre-test that consisted of one open question. This question was a complex exercise to design PCR primers, which was also the learning goal for the adaptive e-learning material on PCR design, called the PCR Tutor. The students' answers were scored by the first author using a scoring model that has previously been reported to be valid (Van Seters, Wellink, Tramper, Goedhart, & Ossevoort, 2011). In short, the students could acquire one to six points, and those who obtained five or six points had achieved the learning goal.

2.3.3. Intrinsic motivation inventory

Information about the intrinsic motivation of the students was collected with a questionnaire. Intrinsic motivation was measured in three subscales: appreciation of material, appreciation of computer-based education and usefulness of the subject. Items from the subscales are based on items from the Intrinsic Motivation Inventory (McAuley, Duncan, & Tammen, 1989), which has also been described and used in an educational setting (Vos, van der Meijden, & Denessen, 2011). We extended the inventory with specific items for our study to measure the appreciation of the material separate from the appreciation of using computer-based education in general. Students participating in a pilot were interviewed by the first author to identify their interpretation of the items, since small changes in the wording of items can be very important (Karabenick et al., 2007). Ambiguous items were revised. The reliability of the subscales, calculated as Cronbach's alpha, was measured (Table 1). An alpha value above 0.7 is generally adopted as sufficient reliability, so all three scales are reliable. The corrected item-total correlations represent the correlations between each item and the total score from the scale. Items with a correlation above .3 correlate enough with the total score. All items correlated well, so deletion of items was not necessary.

Correlations between the three intrinsic motivation subscales were calculated. Spearman's correlations revealed that all scales correlated significantly at the .01 level (Table 2). This indicates that the three intrinsic motivation subscales are related. The intrinsic motivation was thus calculated by averaging the score for the three subscales.

2.3.4. Self-reports

Student self-reports about SRL strategies were used to support the results from the traced SRL. Self-reports were collected in three categories: approach to doing exercises, step size choice and use of information sources.

Spearman's correlation coefficients, r_s, for the traced data and the self-report data were calculated to investigate the reliability of self-reporting by students. The time students reported to have spent on the material correlates very well with the logged time, $r_s = .59$, $p < .01$. The average step size correlates negatively with the self-report item 'I chose small steps', $r_s = -.70$, $p < .01$, and positively with 'I chose big steps', $r_s = .72$, $p < .01$. These strong correlations suggest a good reliability of student self-reports in this study. The self-report data were therefore used to measure the variables 'approach to doing exercises' and 'use of information sources'. These variables were not traced. The average step size that students chose is called 'step size choice' in further analysis.

2.4. Data analysis

We performed Mann–Whitney analyses and Spearman's correlations to study the influence of student characteristics on their learning paths and learning strategies. A level of .05 was adopted to test for significance. Mann–Whitney analyses were used for dichotomous data. This was the case with gender (man or woman), traced self-regulation (yes or no) and level of study (undergraduate or graduate). Effect sizes, r, for the results were calculated by:

Table 1
The items and internal consistency of the three motivation scales from the questionnaire.

Scale	Items	Corrected item-total correlation
Appreciation material	I enjoyed this module.[a]	.72
	This module was boring.[a]	.53
	This module was challenging.	.65
	This module motivated me to think about the subject.	.60
	This module made learning about the subject more interesting.	.71
	I preferred this module on the subject to traditional learning material.	.33
	Reliability (Cronbach's α)	*.82*
Appreciation computer-based education	Using computer-based modules is a nicer way of studying the theory than completing assignments on paper.	.77
	I should like to do modules like this on a range of subjects and topics.	.72
	In general, I prefer using computer-based learning material to other types of learning material.	.72
	I like working with computers as part of my studies.	.59
	Reliability (Cronbach's α)	*.85*
Usefulness	I find the subject an interesting one.	.56
	I think having a good understanding of the subject is important for my studies.[a]	.75
	Learning about the subject is useful.[a]	.71
	Understanding the subject is important for my future career.[a]	.62
	Reliability (Cronbach's α)	*.82*

[a] Based on item from the Intrinsic Motivation Inventory.

$$r = \frac{Z}{\sqrt{N}}$$

where z = the z-score from the Mann–Whitney analysis, N = the number of respondents.

We adopted the general boundaries to denote the magnitude of the effect size: $0.10 < r < 0.30$ for a small effect, $0.30 < r < 0.50$ for a medium effect and $r > 0.50$ for a large effect.

Spearman's correlation coefficients, r_s, were calculated for scaled variables, such as prior knowledge (scale 1–6) and intrinsic motivation (scale 1–5). Calculation of effect sizes is not needed for these correlations, since the correlation coefficients *are* effect sizes.

3. Results

3.1. Student characteristics

The results of the pre-test ranged from 1 to 5, with a mean (M) of 2.93 and a standard deviation (SD) of 1.28. These results indicate that the prior knowledge of the students varies. They also show that the students on average did not master the learning goal beforehand, since the average score is far below 5. Students achieve the learning goal with a score of 5 or 6. In this study, none of the students obtained a score of 6 for the pre-test. There were no significant differences between the pre-test scores of male and female students, and between BSc and MSc students.

The intrinsic motivation of the students was measured by averaging three subscales. Students had a relatively high intrinsic motivation ($M = 3.74$). There were no significant differences between men and women in their intrinsic motivation, $U = 682.50$, $p > 0.05$. The intrinsic motivation of students in the MSc phase (*Median* (*Mdn*) = 4.08) was higher than of those in the BSc phase ($Mdn = 3.71$), $U = 306.00$, $p < 0.05$, $r = -.032$. No relation was found between students' prior knowledge and their intrinsic motivation, $r = .07$, $p > .05$

3.2. Strategies

The self-reported learning strategies are presented in Table 3. Generally, students reported reading the text of the exercise carefully before selecting the best answer ($M = 4.36$). Guessing the answer without reading the text was rarely done ($M = 1.06$). The feedback on incorrect answers is often read ($M = 4.63$), the feedback on correct answers is moderately often read ($M = 3.50$). The other information sources, including the online library, are used less often (3 questions, mean range 1.54–2.26).

The self-reports show that 23 (29%) students did not choose the step size consciously, while 55 (71%) did.

Table 2
Spearman's correlations between intrinsic motivation subscales.

	Appreciation of material	Appreciation of computer-based education	Usefulness
Appreciation of material	–		
Appreciation of computer-based education	.631[a]	–	
Usefulness	.370[a]	.319[a]	–

[a] Significant at .01 level

Table 3
Descriptive statistics for self-report items on learning strategies on a 5-point scale (1 = never, 2 = seldom, 3 = sometimes, 4 = often, 5 = always).

	n	Mean (SD)
Approach to doing exercises		
I studied relevant theory on the exercise before working on it. I then selected the best answer.	79	2.56 (1.22)
I read the exercise carefully and selected the best answer.	80	4.36 (.72)
I read the exercise and took a guess at first. Then I read the feedback and tried to select the right answer.	79	2.13 (1.03)
I didn't read the exercise and guessed the answer.	78	1.06 (.30)
I discussed with my fellow students what the best answer would be, and then chose that answer.	79	1.77 (1.09)
I asked the teacher to explain the exercise before submitting an answer.	79	1.24 (.60)
Information sources		
I read the feedback on incorrect answers.	80	4.63 (.75)
I read the feedback on correct answers.	80	3.50 (1.36)
I used the information in the online library.	80	2.26 (1.26)
I used the information sources when the feedback directed me there.	80	2.11 (1.27)
I used the Internet to find additional information.	80	1.54 (1.03)

3.3. Learning paths

The learning path a student follows is determined by average step size chosen, average number of tries, total number of exercises and time needed to finish.

We illustrate the variation in learning path followed by presenting the number of credit points that fourteen randomly chosen students earned as a function of the number of exercises they completed (Fig. 2). The indicated learning paths are determined by the chosen step sizes, the exercises that the system selected for the student to do and the number of tries a student needed to complete the exercise. Time is not taken into account in this figure. Note that students sometimes loose credit points (for one case indicated by arrow).

The average step size chosen during the working with the material varied within the range of 1–3 ($M = 2.04$, $SD = .59$). The average number of tries per exercise ranged from 1.0 to 3.5 ($M = 2.0$, $SD = .51$). The time students spent on the material ranged from 10 to 156 minutes ($M = 37$, $SD = 22$). The number of exercises students needed to finish ranged from 1 to 29 ($M = 11.7$, $SD = 7.45$).

Correlations between the four variables that were measured to determine the learning paths were calculated (Table 4). The logged step size choice correlates with the number of exercises that were needed ($p < 0.01$) but not with the number of tries ($p > 0.05$). The step size choice correlates negatively with the time spent on the material, so students who chose bigger steps needed less time.

3.4. Student characteristics and learning paths

No difference was found between men and women in their learning path variables. BSc students needed on average fewer exercises to finish ($Mdn = 10.5$, $M = 11.2$) than MSc students ($Mdn = 16.5$, $M = 15.7$), $U = 333.5$, $p < 0.05$, $r = -.28$. The average number of tries per exercise did not differ for BSc and MSc students. The average step size did differ, however: BSc students chose bigger steps ($Mdn = 2.09$, $M = 2.14$) than MSc students ($Mdn = 1.74$, $M = 1.61$), $U = 270.0$, $p < 0.05$, $r = -.36$. BSc students ($Mdn = 28.0$, $M = 29.6$) needed less time to finish than MSc students ($Mdn = 54.0$, $M = 60.4$), $U = 78.5$, $p < 0.05$, $r = -.53$. These effects are all medium to large with an effect size (r) around 0.30–0.50.

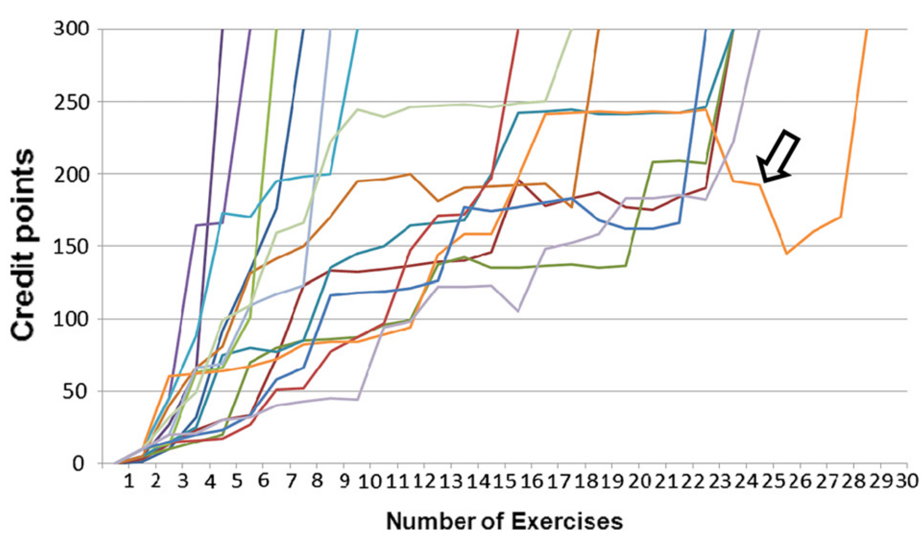


Fig. 2. The learning paths of 14 randomly chosen students are shown. The number of credit points gained is plotted against the number of exercises completed. Both parameters were collected by traces. The threshold level to finish the material is 300 credit points.

Table 4
Spearman correlations of the variables that determine the learning path.

	Number of exercises	Number of tries	Step size choice	Time spent
Number of exercises	–			
Number of tries	−.06	–		
Step size choice	−.80[a]	.13	–	
Time spent	−.41[a]	.08	−.41[a]	–

[a] Significant at .01 level.

Spearman's correlation coefficients, r_s, of prior knowledge and intrinsic motivation with the learning paths are shown in Table 5. The intrinsic motivation of students correlates negatively with the average step size they chose, meaning that students who have a higher level of intrinsic motivation chose smaller step sizes. The intrinsic motivation also correlates negatively with the number of tries that students needed, but we did not find a relation between prior knowledge and the number of tries that were needed. Intrinsic motivation correlates with the time students spent on the material, meaning that students with higher motivation needed more time.

3.5. Student characteristics and learning strategies

The results of the self-reported learning strategies are presented in Table 3. There are no differences between men and women in the self-reported strategies. MSc students ($Mdn = 4$, $M = 3.24$) more often studied relevant theory before doing an exercise than BSc students ($Mdn = 2$, $M = 2.38$), $U = 315.50$, $p < 0.05$, $r = -.29$. MSc students ($Mdn = 3$, $M = 2.71$) also more often guessed at first and then used the feedback to find the correct answer than BSc students ($Mdn = 2$, $M = 1.97$), $U = 345.50$, $p < 0.05$, $r = -0.25$. MSc students ($Mdn = 1$, $M = 1.59$) more often asked the teacher to explain the exercise than BSc students ($Mdn = 1$, $M = 1.15$), $U = 383.50$, $p < 0.05$, $r = -0.30$. These effects are all small to medium with an effect size (r) of between 0.25 and 0.30.

The self-reported learning strategies were correlated with the prior knowledge and intrinsic motivation of students (Table 6). Students who had a higher level of prior knowledge less often discussed with their fellow students to find the correct answer and chose the step size more consciously. Students with higher intrinsic also chose the step size more consciously and used the information sources more. The correlations that were found are not very strong, with an effect size around 0.3.

The traces provide information about the degree to which students changed their step size selection when working on the material. Thirty-one students did not change the step size they selected, while 46 students did change it. Men and women did not differ in their variation of step sizes, nor did BSc and MSc students. There is no relation between the intrinsic motivation of students and their step size variation, $U = 692.5$, $p > .05$. Students who did not vary the step sizes had a higher level of prior knowledge ($Mdn = 3$, $M = 3.4$) than students who varied the step sizes ($Mdn = 3$, $M = 2.6$), $U = 561.0$, $p < .05$, $r = -.30$. Of the 31 students who did not change their step sizes, most of them (22) made a conscious choice not to change them. Of the 46 students who varied their step sizes, 32 did so consciously.

4. Discussion and conclusions

The aim of this study was to investigate whether students follow different learning paths when using adaptive e-learning, and whether learning paths and strategies relate to student characteristics. The results show that students do indeed follow individual learning paths. They need a varying number of exercises to finish the task; the number is determined mainly by the step size they select to master the set learning objectives. As answer to the first research question, we therefore state that the adaptivity of the system works and that the option to choose step sizes is an essential factor in the system's adaptivity. In addition, students who chose bigger steps needed less time, indicating that students were well able to predict their own capacities.

The findings of this study indicate that some student characteristics are related to their learning paths. Gender and prior knowledge did not have an effect. BSc students needed less exercises and less time to finish than MSc students. This difference relates to the observation that BSc students chose bigger steps than MSc students. These findings are likely caused by the different compositions of the BSc and MSc student groups. Most of the BSc students were Dutch (90%) while the MSc students represented a large variety of nationalities with only 22% Dutch. This means that the nationality of students confounds with the study level and that more research is needed to attribute the reported differences between BSc and MSc students to the correct characteristics. Intrinsic motivation unexpectedly had a bigger influence on the learning path than students' prior knowledge. This can be explained by the desire of highly intrinsically motivated students to really understand the subject: they chose small steps in order to get more practice. These highly motivated students then need more time but also fewer tries to complete the exercises with the small steps, which is expected because they do not have less prior knowledge. Thus, the answer to the second research question is that intrinsic motivation has an influence on students' learning paths, and this is caused by the average step sizes they choose.

Table 5
Spearman correlations of student characteristics and learning path variables.

	Prior knowledge	Intrinsic motivation
Number of exercises	−.14	.16
Number of tries	−.14	−.26[a]
Step size choice	.09	−.25[a]
Time spent	−.16	.26[a]

[a] Significant at .05 level.

Table 6
Spearman correlation coefficients for prior knowledge and intrinsic motivation and self-report items on three learning strategies.

	Prior knowledge	Intrinsic motivation
Approach to doing exercises		
I studied the relevant theory before doing the exercise. I then selected the best answer.	.00	.14
I read the exercise carefully and selected the best answer.	.13	−.22
I read the exercise and took a guess at first. Then I read the feedback and tried to select the right answer.	−.16	−.07
I didn't read the exercise and guessed the answer.	.23	−.13
I discussed with my fellow students what the best answer would be, and then chose that answer.	−.28[b]	−.09
I asked the teacher to explain the exercise before submitting an answer.	−.08	.13
Regulation of step sizes		
I consciously chose the step size.	.24[b]	.26[b]
Information sources		
I read the feedback on incorrect answers.	.00	.31[a]
I read the feedback on correct answers.	−.04	.33[a]
I used the information in the online library.	−.21	.20
I used the information sources when the feedback directed me there.	−.11	.30[a]
I used the Internet to find additional information	−.18	−.03

[a] Significant at .01 level
[b] Significant at .05 level

We also investigated the relation between student characteristics and the strategies they used when working with the adaptive e-learning material. The gender of students did not affect their learning strategies. Men and women did not differ in their intrinsic motivation, which is in line with the results from the study by Shashaani and Khalili (2001). Students who had a higher level of prior knowledge less often discussed with their fellow students to find the correct answer and chose the step size more consciously. The relation between prior knowledge and self-regulated learning is in line with the recent study from Greene, Costa, Robertson, Pan, and Deekens (2010). Compared to BSc students, MSc students more often studied relevant theory before doing an exercise, guessed at first and then used the feedback to find the correct answer, and asked the teacher to explain the exercise. Students with higher intrinsic motivation chose the step size more consciously and used the information sources more. The effect size of these relations was not very high. Thus, the answer to the third research question is that although intrinsic motivation, study level and prior knowledge do relate to the strategies that students adopt, these relations are not very strong.

This study presents insights into the ways students use adaptive e-learning. However, some limitations should be mentioned. An important one concerns the content of the adaptive e-learning material that was used in this study. Students could achieve the learning objective by completing only one exercise or a small number of them. The students who finished with very few exercises found it hard to complete the questionnaire, since they could not use many different learning strategies. In this study, 13 students needed three exercises or less to finish. As mentioned in the introduction, cultural background may have an influence on the learning strategies that students adopt. The students in this study differed in their cultural backgrounds: they came from the Netherlands, China, Ecuador, Ethiopia, Germany, Greece, Indonesia, Iran, Italy, Malaysia, Nepal and Vietnam. The variety in cultures was so great and student numbers per culture so small that it was not possible to compare groups with similar characteristics. The cultural background was therefore not taken into account in this study.

This study contributes to the educational research on SRL with CBLEs. We support the importance of using traces with CBLEs to gain more information about student SRL. Because adaptive e-learning gives the student some control, self-regulated learning strategies can well be studied. This study explored the possible influence of student characteristics on their learning paths and learning strategies, and investigated some strategies that can be seen as self-regulated learning. Our study contributes to the spectrum of available literature on the influence of student characteristics for elementary schools (Park, Lee, & Kim, 2009) and secondary schools (Lowrie & Jorgensen, 2011) by providing empirical data for tertiary level.

For further research, we suggest using existing models (Pintrich, 2003) to describe SRL in order to obtain better identification of the self-regulated learning strategies. The adaptive e-learning system that was used to create the adaptive e-learning material in this study has also been used to create learning material for other courses. Thus, some students may have already been familiar with this type of adaptive e-learning material. It has been reported that novices interact differently with e-learning material than more experienced students (Winne, 1995). Unfortunately, we did not collect data in our study about the experience of students with this type of adaptive e-learning material. It is interesting to measure the experience students already have with the specific learning environment, e.g. by adding an item to the questionnaire, and relate this characteristic to the learning path followed and strategies used.

This study provides empirical data to support the hypothesis that adaptive e-learning material provides personalized instruction to heterogeneous groups of students. We therefore recommend teachers to consider using adaptive e-learning material when faced with a heterogeneous student group, especially if it is a mixed group of BSc and international MSc students.

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