Computers in Human Behavior 27 (2011) 82–88

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Effectiveness of cognitive-load based adaptive instruction in genetics education

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A R T I C L E I N F O

Article history:
Available online 16 June 2010

Keywords:
Cognitive load
Adaptive instruction
Learner control
Non-adaptive program control
Learning efficiency
Problem selection algorithm

A B S T R A C T

Research addressing the issue of instructional control in computer-assisted instruction has revealed mixed results. Prior knowledge level seems to play a mediating role in the student's ability to effectively use given instructional control. This study examined the effects of three types of instructional control (non-adaptive program control, learner control, adaptive program control) and prior knowledge (high school, 1st year and 2nd year college students) on effectiveness and efficiency of learning in a genetics training program. The results revealed that adaptive program control led to highest training performance but not to superior post-test or far-transfer performance. Furthermore, adaptive program control proved to be more efficient in terms of learning outcomes of the test phase than the other two instructional control types. College students outperformed the high school students on all aspects of the study thereby strengthening the importance of prior knowledge in learning effectiveness and efficiency. Lastly, the interaction effects showed that for each prior knowledge level different levels of support were beneficial to learning.

1. Introduction

Although substantial research has been conducted on the locus of instructional control in computer-assisted instruction, the findings vary and are contradictory (e.g., Kopcha & Sullivan, 2007); while some results suggest that students learn more when given control over their learning (e.g., Gray, 1987); other results indicate that students making their own decisions do not learn as much as those who follow a predetermined path (e.g., Steinberg, 1989). A meta-analysis by Kraiger and Jerden (2007) concluded that learner control leads to the equal or slightly better learning results than program control, although the impact is small.

A possible explanation for the contradictory finding that not all students get the same learning benefits from control over their instruction can be found in students' prior knowledge (Kopcha & Sullivan, 2007). Overall, the findings indicate that learner control can be detrimental for low prior knowledge students (Ross & Rakow, 1981), but beneficial for high prior knowledge students (Shyu & Brown, 1992). It seems that the acquired meta-cognitive skills necessary for making appropriate task selections enable high prior knowledge students to identify their instructional needs and performance strategies (Lee & Lee, 1991), which guide their learning.

These findings correspond well with Cognitive Load Theory (CLT) which states that for novices (i.e., students with low prior knowledge) the acquisition of complex skills is constrained by the limited processing capacity of their working memory and as a consequence, their cognitive system might become overloaded by the high amount of interacting elements of information that has to be processed (e.g., Paas, Renkl, & Sweller, 2003). Therefore, in the absence of relevant knowledge, dealing with many new and complex elements of information might easily overload novices working memory capacity. Additionally, the expertise reversal effect (e.g., Kalyuga, 2007) states that initial levels of support that are beneficial for novices become detrimental for more advanced students. Whereas novices require considerable external support to build new knowledge structures in a relatively efficient manner, experts (i.e., students with high prior knowledge) may better use their available knowledge structures for handling tasks without any additional support. Once learners have acquired and automated certain knowledge structures, all elements in those knowledge structures can be handled as one chunk of information, and consequently require less working memory capacity. Because, working memory capacity is needed to deal with given learner control, it can be argued that only when students have gained a certain amount of knowledge, this working memory capacity will be available (Lee & Lee, 1991).

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doi:10.1016/j.chb.2010.05.027

A promising way to manage both novice and advanced students' cognitive load and to improve learning is to adapt instruction to the individual student's progress (Kalyuga & Sweller, 2005; Salden, Paas, & Van Merriënboer, 2006). In order to prevent a possible cognitive overload, the difficulty and support level of each new problem can be adapted to the students' expertise. When all students are prescribed a standard instructional sequence, as in the non-adaptive program control condition, mismatches between individual needs and instructional prescriptions might occur and hamper learning. Research using such adaptive program control has shown to lead to a more efficient training (i.e., higher performance combined with lower mental effort) and higher transfer performance compared to non-adaptive program control (e.g., Corbalan, Kester, & Van Merriënboer, 2006).

Extending these studies, the purpose of the current study was to assess the effectiveness (i.e., training and test performance) and learning efficiency (i.e., test performance, its associated test mental effort and training time) of non-adaptive program control, learner control and adaptive program control in learning genetics using students of different prior knowledge levels. The main research question entails what effects do these three types of instructional control, students' prior knowledge (i.e., high school, first year and second year college students), and the interaction between both factors have on learning outcomes and learning efficiency. It was hypothesized that the adaptive program control would yield higher performance and be more efficient than the other two conditions. Whereas the non-adaptive program instruction was expected to be insensitive to individual students' learning needs, the learner-controlled instruction might overload the students.

With regard to students' prior knowledge it was hypothesized that higher prior knowledge students (i.e., college students) would achieve higher performance and be more efficient than students with a low prior knowledge (i.e., high school students). Furthermore, it was expected that higher prior knowledge level students perceive their current learning state and instructional needs more accurately, and thus would be better able to manage their own instruction. Additionally, it was expected that the high prior knowledge students would spend more time-on-task due to engaging in deeper cognitive engagement and self-reflecting (see Chi, 2006) than the low prior knowledge students.

2. Method

2.1. Participants

Two-hundred-and-one students (M = 18.66 years, SD = 3.76; 32 males and 169 females) participated in this study. The high school students (n = 74; age M = 15.24 years, SD = 0.52) were novices while the first year college students (n = 86; age M = 20.52 years, SD = 3.96) and second year college students (n = 41; age M = 20.90 years, SD = 1.59) were intermediate students since they had been educated on the genetics domain in high school. All participants were randomly assigned to a non-adaptive program control condition (n = 65; 25 high school and 40 college students), a learner control condition (n = 70; 25 high school and 45 college students), or an adaptive program control condition (n = 66; 24 high school and 42 college students). They volunteered to participate in this study and were not paid for their participation.

2.2. Materials

2.2.1. Electronic learning environment

The learning environment developed for this study was a Web application written in PHP scripting language. A MySQL database connected to the learning environment contained the learning material and registered student actions: performance and mental effort scores, problem selection choices, and time-on-task. Furthermore, this database contained a basic introduction to genetics, a pre-test and post-test, a far-transfer test, and a glossary with the main genetics concepts. The learning environment was pilot tested with 22 high school and college students for functionality and usability assessment. The results indicated that the program promotes learning and the provided content is suitable for target population. The content of the instructional program was part of the regular biology curriculum for high school students and Neuropsychology curriculum for first year college students from Psychology.

2.2.2. Introduction

The introduction included the main genetics concepts required for solving problems concerning dominant and recessive genes, genotype, phenotype, homozygous and heterozygous gene pairs.

2.2.3. Pre-test

The pre-test and post-test consisted of the same ten multiple-choice questions on the subject of heredity (i.e., Mendel's Laws). The maximum score was 10 points, one point for each correct answer.

2.2.4. Learning tasks

The participants received genetics problems represented in a database (see Fig. 1; Kostons, Van Gog, & Paas, 2010) as a combination between five difficulty levels (i.e., from low to high), three levels of support (i.e., high, low, and no support) and three problems per support level with different surface features (i.e., aspects of the tasks that are not related to goal attainment such as eye color, hair shape). The difficulty levels were defined in cooperation with two biology professors from Babeş-Bolyai University using several problem characteristics: the number of generations, the number of possible correct solutions, and type of reasoning (deductive and/or inductive). One of the professors was familiar with the biology curriculum for high school and the required standards.

Each difficulty level contained three support levels, differing in the amount of embedded support and diminishing in a "scaffolding" process (Van Merriënboer, 1997). These three levels are: (1) completion problems with high support which provided many, but not all solution steps; (2) completion problems with low support that provided a few solution steps; and (3) conventional problems that did not provide any support.

The selection of problems from the database of the 45 genetics problems (see Fig. 1) differed between the experimental conditions. In the non-adaptive program control condition, participants received 15 problems with three randomly chosen problems of each support level within each of the five difficulty levels. These problems were presented in a predetermined simple to complex sequence, designed according to the 4C/ID model (Van Merriënboer, 1997). In the learner control condition, participants received an overview of all 45 problems with an indication of their difficulty and support level, and they could choose any problem to solve next.

For the adaptive program control condition the performance and invested mental effort scores were used as a variable for dynamic problem selection. Based on these scores a selection algorithm determined the appropriate difficulty and support level of the next problem for each individual learner. More specifically, the difficulty level of the first training problem would always be level 1 and the pre-test performance and associated mental effort scores determined the support level. Overall, most pre-test scores would lead to completion problems with high support (+1), some led to completion problems with low support (+2) and only a few led to conventional problems (+3).

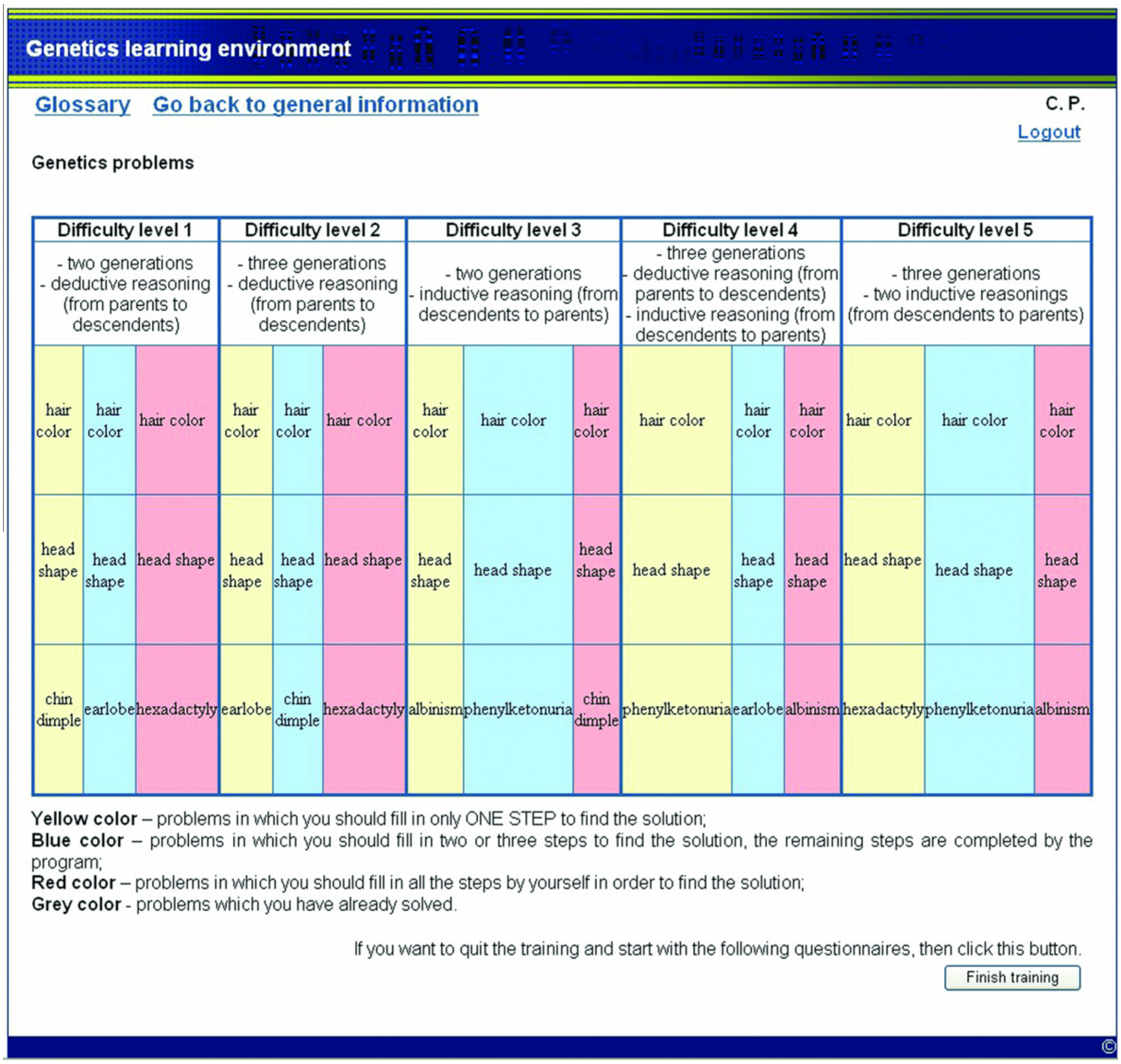

Fig. 1. Overview of problems with the combination of difficulty and support levels and task features.

Once working in the training phase, the selection algorithm determined the difficulty and support level of the next problem considering the support level the participants previously worked in. For instance, if a participant has successfully solved a completion problem with high support in difficulty level 1 by obtaining a performance score of 3 and a mental effort score of 1, s/he must jump 2 steps ahead, meaning that the amount of support decreases two levels. Therefore, the learner will move to a conventional problem at the current difficulty level. For completion problems with high support, the mental effort scores determine changes in the support level within a certain difficulty level, since the performance score is preset to a fixed value (3).

Table 1
Selection table indicating step size for completion problems with low support and conventional problems.

Mental effort	Performance				
	1	2	3	4	5
1	0	0	1	2	3
2	−1	0	0	1	2
3	−1	−1	0	0	1
4	−2	−1	−1	0	0
5	−3	−2	−1	−1	0

Table 1 shows the selection decisions for completion problems with low support and conventional problems. The students receive a similar problem when their performance and corresponding mental effort scores are the same (+0) and they can jump to a higher or lower support level (+/−1 and +/−2) when these scores are different. If a learner solved a completion problem with low support obtaining a mean performance score of 5 and a mental effort score of 1, s/he must jump 3 steps ahead. But since there are less than three support levels available at the current difficulty level, the learner has to advance to a low support level of the next difficulty level. Therefore, only by obtaining the highest performance while investing the lowest mental effort can students jump between difficulty levels (+3). Similarly, participants can also drop to the previous difficulty level when obtaining the lowest performance (1) and the highest mental effort (5).

It should be noted that all students received a maximum of 20 training problems regardless of how far they advanced in difficulty and support levels. This was implemented to avoid overly large differences in time-on-task and avoid students losing motivation.

2.2.5. Far-transfer test

The far-transfer test consisted of five problems which differed structurally from the training problems and measured students' ability to apply the learned procedures to new learning situations. Specifically, participants had to solve problems on dihybrid crossings, problems involving sex-linkage and co-dominant genes (i.e., blood types; see Appendix). The transfer problems had distinctive solution steps, resulting in a maximum total score of 16. The reliability (Cronbach's alpha) of the pre-test, post-test, and far-transfer test was: .52, .69, and .75 respectively.

2.2.6. Mental effort

The perceived mental effort was measured after each problem during each phase of the study (i.e., pre-test, post-test, training, far-transfer test) on a 5-point rating scale adapted from Paas (1992), with values ranging from 1 (very low) to 5 (very high).

2.2.7. Learning efficiency

Learning efficiency was determined using the following formula derived from the original formula proposed by Paas and Van Merriënboer (1993; see also Tuovinen & Paas, 2004):

$$E = \frac{P + TT - ME}{\sqrt{3}}$$

In this formula, E = learning efficiency, P = test performance, TT = total training time, and ME = mental effort during test. To calculate learning efficiency, all variables were standardized before being entered into the formula.

2.3. Procedure

All participants were given a pre-test and a basic introduction before the training phase started. Participants were free to consult this basic introduction during the entire training session. The participants were not allowed to skip any of the sub-steps of a problem and were forced to rate their mental effort before the program would let them advance. Immediately after the training, participants received the post-test and far-transfer test, and mental effort was measured after each solved problem. Overall, the experiment lasted about two hours.

3. Results

All the analyses were done using ANOVAs with between-subjects factors (1) type of instructional control and (2) prior knowledge, and a significance level of .05 was used. Dependent variables were performance, mental effort, time on pre-test, time on training, time on post-test, and time on far-transfer test, total solved problems, total solved problems per difficulty and support level, and learning efficiency.

Table 2 provides an overview of the results during training and test phase for factor (1) and Table 3 provides an overview of the results during training and test phase for factor (2).

3.1. Type of instructional control

3.1.1. Pre-test

No differences were found on performance, invested mental effort (all Fs < 1), and time spent on the pre-test, $F(2, 198) = 2.49$, $MSE = 21.41$, *ns*.

3.1.2. Training phase

Significant differences were found for performance, $F(2, 198) = 3.07$, $MSE = 2834.71$, $p < .05$, $\eta_p^2 = .03$, and training time, $F(2, 198) = 11.25$, $MSE = 219.03$, $p < .0001$, $\eta_p^2 = .10$. Planned comparisons showed that participants in the adaptive program condition attained higher performance, $t(198) = 2.20$, $p < .05$, $d = .36$, and spent more time on training, $t(198) = 3.85$, $p < .0001$, $d = .58$, than the participants in the non-adaptive and learner control conditions.

A main effect was found regarding the number of completed problems: $F(2, 198) = 5.74$, $MSE = 15.55$, $p < .01$, $\eta_p^2 = .06$. Planned comparisons showed that participants in the adaptive program condition solved more problems, $t(198) = 3.38$, $p < .01$, $d = .55$, than the participants in the other two conditions.

Concerning the total solved problems for each difficulty level, significant differences were revealed on total solved problems for difficulty level 1, $F(2, 194) = 23.72$, $MSE = 5.63$, $p < .0001$, $\eta_p^2 = .20$; difficulty level 2, $F(2, 195) = 19.10$, $MSE = 4.68$, $p < .0001$, $\eta_p^2 = .16$; difficulty level 4, $F(2, 152) = 21.53$, $MSE = 1.90$, $p < .0001$, $\eta_p^2 = .22$; and difficulty level 5, $F(2, 137) = 4.01$, $MSE = 1.36$, $p < .05$, $\eta_p^2 = .06$. Overall, participants in the learner control and adaptive program control conditions solved more problems from lower difficulty levels (i.e., difficulty level 1 and 2) and fewer problems from higher difficulty levels (i.e., difficulty level 4 and 5) than participants in the non-adaptive condition.

For the total solved problems for each support level main effects were found on total solved completion problems with high support, $F(2, 195) = 8.12$, $MSE = 6.02$, $p < .0001$, $\eta_p^2 = .08$, and completion problems with low support, $F(2, 194) = 8.85$, $MSE = 3.13$, $p < .0001$, $\eta_p^2 = .08$. Planned comparisons revealed that participants in the learner control condition solved more completion problems with high support, $t(195) = 3.95$, $p < .0001$, $d = .68$, than participants in the non-adaptive program control condition, and participants in the adaptive program control condition solved more completion problems with low support, $t(194) = 4.20$, $p < .0001$, $d = .73$, compared to participants in the other two conditions.

Table 2
Overview of results from the training phase and the test phase for type of instructional control.

Dependent variables	Type of instructional control					
	Non-adaptive program control (n = 65)		Learner control (n = 70)		Adaptive program control (n = 66)	
	M	*SD*	*M*	*SD*	*M*	*SD*
Training phase						
Time (min)	39.38	13.95	32.53	15.76	44.51	14.57
Mental effort (1–5)	2.96	1.05	2.63	1.21	2.92	.83
Performance (0–332)	127.20	37.70	117.26	71.16	139.85	43.13
Post-test phase						
Time (min)	6.20	4.42	7.83	5.38	7.72	6.00
Mental effort (1–5)	2.73	.97	2.63	1.08	2.69	1.11
Performance (1–10)	5.18	2.45	5.14	2.58	5.17	2.48
Far-transfer test phase						
Time (min)	11.75	7.60	12.49	8.13	12.97	8.43
Mental effort (1–5)	4.01	.92	3.83	1.06	3.76	.98
Performance (1–16)	3.95	3.02	3.86	2.90	4.04	3.06

Table 3
Overview of results from the training phase and the test phase for prior knowledge.

Dependent variables	Prior knowledge					
	High school students ($n = 74$)		First year college students ($n = 86$)		Second year college students ($n = 41$)	
	M	*SD*	*M*	*SD*	*M*	*SD*
Training phase						
Time (min)	30.50	1.44	42.62	1.31	45.17	1.87
Mental effort (1–5)	3.13	.10	2.72	.10	2.53	.13
Performance (0–332)	102.99	42.42	137.42	50.04	152.85	62.28
Post-test phase						
Time (min)	3.82	.43	8.85	.39	10.17	.56
Mental effort (1–5)	3.02	.09	2.57	.08	2.32	.12
Performance (1–10)	4.54	.25	5.50	.22	5.60	.33
Far-transfer test phase						
Time (min)	4.78	.61	16.63	.56	17.31	.80
Mental effort (1–5)	3.96	.11	3.86	.10	3.73	.13
Performance (1–16)	1.73	.29	5.23	.25	4.98	.37

3.1.3. Test phase

No significant differences were found on performance, invested mental effort and time spent for the post-test and far-transfer test (Fs < 1).

3.2. Prior knowledge

3.2.1. Pre-test

Significant differences were found on performance, $F(2, 198) = 15.39$, $MSE = 3.82$, $p < .0001$, $\eta_p^2 = .14$; invested mental effort, $F(2, 198) = 22.47$, $MSE = .59$, $p < .0001$, $\eta_p^2 = .19$; and pre-test time, $F(2, 198) = 11.07$, $MSE = 19.74$, $p < .0001$, $\eta_p^2 = .10$. Planned comparisons revealed that first year college students achieved higher performance, $t(198) = 4.26$, $p < .0001$, $d = .71$, than high school students and second year college students achieved higher performance, $t(198) = 3.70$, $p < .0001$, $d = .63$, compared to high school students and first year college students. Additionally, first year college students experienced lower mental effort, $t(198) = -6.68$, $p < .0001$, $d = 1.04$, and spent more time on the pre-test, $t(198) = 4.49$, $p < .0001$, $d = .71$, than high school students. Therefore, ANCOVAs with pre-test performance, time and mental effort were used as covariates in the subsequent analyses and estimated marginal means are presented.

3.2.2. Training phase

Main effects were found on performance, $F(2, 197) = 8.77$, $MSE = 2416.45$, $p < .0001$, $\eta_p^2 = .08$; invested mental effort, $F(2, 197) = 7.12$, $MSE = .72$, $p < .01$, $\eta_p^2 = .07$; and training time, $F(2, 197) = 25.50$, $MSE = 142.34$, $p < .0001$, $\eta_p^2 = .21$. Planned comparisons revealed that first year college students achieved higher performance, $t(197) = 3.33$, $p < .01$, $d = .74$, than high school students, whereas second year college students achieved higher training performance, $t(197) = 2.88$, $p < .01$, $d = .60$, than the other two school levels.

Furthermore, first year college students experienced lower mental effort, $t(197) = -2.74$, $p < .01$, $d = .91$, than high school students, whereas second year college students experienced lower mental effort, $t(197) = -2.65$, $p < .01$, $d = .39$, than the other two school levels. Lastly, first year college students spent more time on training, $t(197) = 6.11$, $p < .0001$, $d = 1.34$, than high school students, whereas second year college students spent more time, $t(197) = 4.10$, $p < .0001$, $d = .71$, than high school students and first year college students.

For total solved problems per difficulty level effects were found for difficulty level 1, $F(2, 194) = 4.11$, $MSE = 6.2$, $p < .05$, $\eta_p^2 = .04$, and difficulty level 2, $F(2, 195) = 8.88$, $MSE = 5.13$, $p < .0001$, $\eta_p^2 = .08$. No significant effects were found for the other difficulty levels (Fs < 1). Overall, first year college students solved less problems, less problems from difficulty levels 1 and 2 than high school students, but there were no significant differences for problems from difficulty levels 4 and 5.

Regarding the solved problems for each support level, a main effect was found for total solved completion problems with high support, $F(2, 195) = 11.17$, $MSE = 5.85$, $p < .0001$, $\eta_p^2 = .10$. Planned comparisons revealed that first year college students solved less completion problems with high support, $t(195) = -3.36$, $p < .01$, $d = .51$, than the high school students, whereas second year college students solved less completion problems with high support, $t(195) = -3.47$, $p < .01$, $d = .65$, than the other two school levels.

3.2.3. Test phase

Significant main effects were found on performance, $F(2, 197) = 4.89$, $MSE = 4.11$, $p < .01$, $\eta_p^2 = .05$; invested mental effort, $F(2, 197) = 12.67$, $MSE = .55$, $p < .0001$, $\eta_p^2 = .11$; and time spent on post-test, $F(2, 197) = 51.47$, $MSE = 12.68$, $p < .0001$, $\eta_p^2 = .34$. Planned comparisons revealed that first year college students achieved higher post-test performance, $t(197) = 2.85$, $p < .01$, $d = .78$, than high school students. Furthermore, first year college students experienced lower mental effort during the post-test, $t(197) = -3.51$, $p < .01$, $d = 1.09$, than high school students, whereas second year college students experienced lower mental effort, $t(197) = -3.68$, $p < .0001$, $d = .50$, than the other two school levels. Finally, first year college students spent more time on the post-test, $t(197) = 8.42$, $p < .0001$, $d = 1.67$, than high school students, whereas second year college students spent more time, $t(197) = 6.10$, $p < .0001$, $d = 1.06$, than high school students and first year college students.

Main effects were found on performance, $F(2, 192) = 43.57$, $MSE = 5.31$, $p < .0001$, $\eta_p^2 = .31$, and time spent on far-transfer, $F(2, 197) = 118.57$, $MSE = 25.93$, $p < .0001$, $\eta_p^2 = .55$, but no effects on invested mental effort, $F < 1$. Planned comparisons revealed that first year college students achieved higher far-transfer performance, $t(192) = 8.98$, $p < .0001$, $d = 1.71$, than high school students, whereas second year college students achieved higher performance, $t(192) = 3.59$, $p < .0001$, $d = .77$, than high school students and first year college students. Additionally, first year college students spent more time during the far-transfer test, $t(197) = 13.99$, $p < .0001$, $d = 2.56$, than high school students, whereas second year college students spent more time, $t(197) = 7.36$, $p < .0001$, $d = 1.28$, than the other two school levels.

3.2.4. Pre-to-post gain

Using paired t-tests a significant gain from pre-to-post-test in performance ($t(200) = 7.08$, $p < .0001$) as well as a significant drop in mental effort, $t(200) = -7.00$, $p < .0001$, were found, indicating that learning did take place across all groups.

3.2.5. Interaction between type of instructional control and prior knowledge

No significant effects were found on performance, invested mental effort and time spent for the pre-test, post-test and far-transfer test (all *F*s < 1). Regarding the training phase, significant main effects were found on total solved problems, $F(4, 192) = 4.81$, $MSE = 13.97$, $p < .01$, $\eta_p^2 = .09$; completion problems with high support, $F(4, 189) = 4.89$, $MSE = 4.94$, $p < .01$, $\eta_p^2 = .09$; and conventional problems, $F(4, 188) = 2.94$, $MSE = 2.73$, $p < .05$, $\eta_p^2 = .06$ (see Fig. 2).

3.3. Learning efficiency

3.3.1. Type of instructional control

No efficiency differences were found on post-test, $F(2, 198) = 1.62$, $MSE = 1.81$, *ns*; and far-transfer, $F(2, 193) = 2.79$, $MSE = 1.69$, *ns*. However, when excluding the zero efficiency value from the non-adaptive condition, a strong trend was found on post-test performance, $t(134) = 1.77$, $p = .05$, $d = .30$, favoring the adaptive program control condition. Furthermore, on far-transfer the adaptive program control condition was more efficient, $t(131) = 2.28$, $p < .05$, $d = .40$, than the learner control condition.

3.3.2. Prior knowledge

Significant efficiency differences were found on post-test, $F(2, 198) = 51.48$, $MSE = 1.21$, $p < .0001$, $\eta_p^2 = .34$; and far-transfer, $F(2, 193) = 66.17$, $MSE = 1.03$, $p < .0001$, $\eta_p^2 = .41$. Planned comparisons for post-test performance showed that first year college students are more efficient, $t(198) = 9.12$, $p < .0001$, $d = 1.49$, than high school students, whereas second year college students are more efficient, $t(198) = 4.86$, $p < .0001$, $d = .82$, than high school students and first year college students. Furthermore, planned comparisons for far-transfer performance revealed that first year college students are more efficient, $t(193) = 4.79$, $p < .0001$, $d = 1.76$, than high school students, whereas second year college students are more efficient, $t(193) = 10.69$, $p < .0001$, $d = .85$, than the other two school levels.

3.3.3. Interaction between type of instructional control and prior knowledge

No efficiency effects were found on post-test ($F < 1$) and far-transfer test, $F(4, 187) = 1.42$, $MSE = .98$, *ns*.

4. Discussion

This study explored the effects of different types of instructional control on performance and learning efficiency of students with differing prior knowledge. Regarding type of instructional control, the first hypothesis of this study stating that adapting the difficulty and support of problems to the students' expertise level would make learning more effective and efficient was only partially confirmed by the data. As predicted, the results show that the adaptive program control condition achieved higher training performance scores compared to the non-adaptive program control and learner control conditions.

Additionally, the adaptive program condition needed more time to complete the training than the other two experimental conditions. This difference in time could be attributed not only to the fact that the adaptive program condition solved significantly more problems, but possibly participants also noticed the relationship between their accuracy in solving the problems and the difficulty plus embedded support of the subsequent problems and consequently spent more time analyzing and self-reflecting.

Although the non-adaptive program control condition attained the same training performance as the learner control condition, the former needed significantly more time to complete the training phase. A possible explanation could be that the learner control condition solved more problems from lower difficulty levels, less problems from higher difficulty levels, and more completion problems with a high support than the non-adaptive program control condition. Not only did the learner control condition solve mostly easier problems, they also received more support in their problem solving than the non-adaptive program control condition.

Unfortunately, the higher training effectiveness of the adaptive program condition is not reflected in superior post-test or far-transfer performance. It should be noted that although we found a significant pre-to-post-gain the overall post-test scores are chance level (around 50%). In addition, the levels of invested mental effort are slightly above average on the post-test and relatively high for far-transfer. As such these levels do not seem indicate an overload of working memory capacity.

A possible explanation for the lack of higher post-test and far-transfer performance could be related to the difficulty levels the participants mostly worked in. The adaptive program control condition mostly worked in lower difficulty levels compared to the non-adaptive program control condition yet did not attain inferior

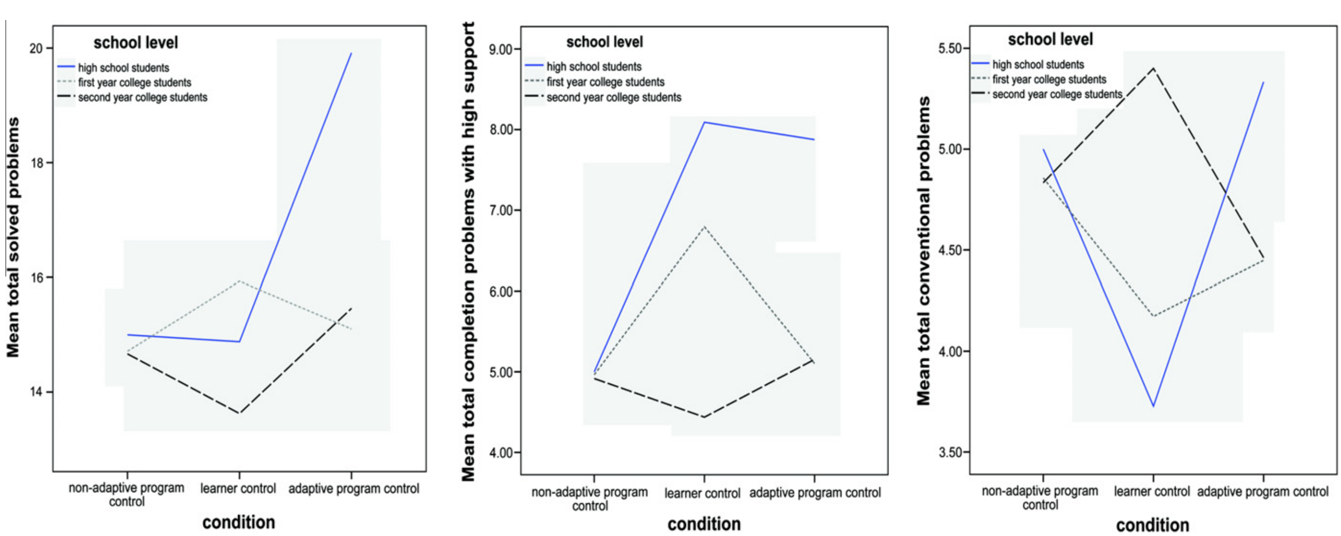

Fig. 2. Graphical representation of the interaction between type of instruction and prior knowledge level on total solved problems, completion problems with high support, and conventional problems.

post-test or far-transfer performance. More precisely, despite the fact that roughly 66% of the participants in the adaptive program control condition did not reach difficulty level 5 they did not do worse in terms of post-training performance. Future research could investigate whether allowing more training time would enable them to reach the highest difficulty level and obtain significantly better post-test and far-transfer performance.

Regarding the students' prior knowledge level, the prediction that the college students would outperform the high school students, spend more time-on-task and experience less mental effort was confirmed. While the same pattern was found for the second year college students over both first year college students and high school students, the differences between first and second year college students were relatively small. Because the high school students solved lower difficulty problems and received more completion problems with high support they spent less time on the training compared to college students whose higher time-on-task is assumed to be related to a deeper cognitive engagement and self-reflecting (see Chi, 2006). As such, the college students invested considerable time in deeper analyzing and self-reflection which led to higher learning outcomes. Consistent with the literature on age differences in cognitive capacity which has found that adolescents demonstrate adult-like levels of maturity by the time they reach 15 or 16 (see Steinberg, Cauffman, Woolard, Graham, & Banich, 2009), it is unlikely that age differences between high school students and college students might affect the results regarding prior knowledge since after these ages cognitive performance does not change.

The interaction effects found in this study show that the students' prior knowledge strongly affects the students learning path in the learner control and the adaptive program control conditions. More specifically, the first year college students in the learner control condition selected more problems than the high schools students while those in the adaptive program control condition received significantly less problems to solve than the high school students. Furthermore, the high schools students solved more completion problems with high support than college students and lastly, while the high school students in the learner control condition selected the least conventional problems, their peers in the adaptive program control condition received the most conventional problems.

In summary, the results of this study partially confirmed the hypothesis that adapting training to the students' individual needs leads to more effective learning outcomes and higher learning efficiency. The students' prior knowledge showed strong learning outcomes differences between high school students and college students and even between first and second year college students. Additionally, the interaction effects revealed that for each prior knowledge level different support levels were beneficial to learning. Future studies need to address the benefits and shortcomings of types of instructional control and how to combine them with support levels more effectively as student's knowledge level increases.

Appendix. Examples of genetics problems from tests

1. Pre- and post-test problem

A parental couple has four children, of which two are healthy and two are affected by hexadactyly. One of the descendants affected by hexadactily gets married with a woman with the same disease and they have three healthy children and one with hexadactyly. Considering *H* the gene which causes hexadactyly, find out the genotype of the parents from the first generation.

2. Far-transfer test problem

A parental couple has four children, a healthy boy, two healthy girls and a haemophilic boy. The boy with haemophilia is getting married with a healthy girl (genotypic homozygous dominant) and they subsequently have two girls. Use *h* for the gene that causes haemophilia and *H* for the normal gene, and find out the phenotype (and the percentage) of the girls from the third generation.

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