DOI 10.1007/s11412-012-9146-z

Computer-Supported Collaborative Learning

1 3 2

4

5

6

# Scripted collaborative learning with the cognitive tutor algebra

Nikol Rummel · Dejana Mullins · Hans Spada

Received: 24 December 2010 / Accepted: 24 April 2012 © International Society of the Learning Sciences, Inc.; Springer Science + Business Media, LLC 2012

8 9

7

Abstract With the aim to promote students' mathematics learning, we extended the 10 Cognitive Tutor Algebra (CTA), a computer-based tutoring system for high school 11 mathematics, to a collaborative setting. Furthermore we developed a collaboration script 12to support students' interactions. In an experimental classroom study, we compared three 13 conditions: scripted collaborative learning, unscripted collaborative learning, and individual 14 learning. After a 2-day learning phase, posttests assessed individual and collaborative 15reproduction of knowledge and skills, and future learning. First, with the collaboration 16script we aimed to improve students' interaction. Second, we assumed that due to an 17improved interaction students would benefit more from the learning opportunities during 18 collaboration and, in consequence, their learning would increase as compared with the other 19conditions. To investigate the first assumption, we compared the interaction of a scripted 20dyad and an unscripted dyad. The in-depth process analyses revealed a positive impact of the 21script on student collaboration and problem solving during scripted interaction and in 22subsequent unscripted interaction. While this effect was mirrored in the learning gains of 23the two dyads, we could not establish a general learning effect in the quantitative between-24condition comparison of student performance. Particularly for students with low prior 25knowledge, the removal of the script in the test phase initially entailed a decline in 26reproduction performance as students had to get used to the unscripted problem-solving 27situation. A notable finding was, however, that the collaborative conditions yielded the same 28outcomes as the individual condition in the individual reproduction test even though 29students had solved fewer problems during the learning phase and had only solved them 30 collaboratively. 31

N. Rummel (🖂)

D. Mullins · H. Spada Institute of Psychology, Albert-Ludwigs-Universität Freiburg, Freiburg im Breisgau, Germany

Institute of Educational Research, RuhrUniversität Bochum, Universitätsstraße 150, 44801 Bochum, Germany e-mail: nikol.rummel@rub.de

**Keywords** Computer-supported collaborative learning · Scripted collaboration · Mathematics learning · Experimental classroom study · Collaboration process analysis

#### Introduction

Interest in developing improved methods for mathematics instruction has increased since 36 TIMSS (Third International Mathematics and Science Study) and PISA (Programme for 37 International Student Assessment). There is broad agreement that the goal of instruction 38 should go beyond improving students' solving of tasks where they can apply well-practiced 39 procedures. Instead, school education should aim to equip students with competencies that 40prepare them for the challenges of their future life (Organisation for Economic Co-operation 41 and Development [OECD] n.d.). According to the OECD, one of the most important 42competencies to be achieved in school is "Mathematical Literacy". In order to improve 43mathematics instruction and to support the development of students' mathematical literacy, 44 different instructional approaches have been investigated (e.g., Dubinsky et al. 1997). One 45approach that is consistent with the curriculum recommendations from the National Council 46 of Teachers of Mathematics (NCTM 2006), and that has proven effective for increasing 47students' learning of mathematics, is learning with cognitive tutors as, for example, 48developed by Anderson and colleagues (Anderson et al. 1995; Koedinger et al. 1997). 49Cognitive tutors present students with real-world tasks and adaptively support their 50problem-solving by providing just-in-time feedback and offering on-demand hints. 51Although cognitive tutors have repeatedly been shown to increase learning outcomes, 52they also have been criticized for facilitating shallow learning strategies (e.g. Aleven 53et al. 2004). For instance, students have been found to abuse hints given in the 54tutoring environment by merely copying the answers, instead of elaborating on the 55hints (Aleven et al. 2004). Also, students have been found to game the system, that 56is, they systematically exploit regularities in the software to perform well and to 57advance faster in the cognitive tutor curriculum (Baker et al. 2004). In consequence of 58such behaviors, a deeper understanding of underlying mathematical concepts and 59robust mathematical skills are not necessarily achieved. Against this background, we 60 propose to extend cognitive tutors with scripted collaboration to promote students' 61elaborative sense-making activities, with the hope to yield better learning results and, 62ultimately, improved mathematical literacy. In the present study we evaluated col-63 laborative extensions to an existing cognitive tutor, the Cognitive Tutor Algebra 64 (© Carnegie Learning Inc.). 65

As research has shown, collaborative problem solving and learning have the potential to 66 promote deeper elaboration of the learning content (Teasley 1995) and can yield improved 67 conceptual understanding. In collaborative learning, the process is of central importance 68 (e.g., Reimann 2007). According to the "interaction paradigm" (Dillenbourg et al. 1996), the 69 interaction among students is the mediating variable that determines whether collaboration 70will yield effects on their learning outcome. Collaborative behaviors that account for the 71beneficial impact of collaboration are, for instance, giving and receiving explanations and 72joint knowledge construction (Hausmann et al. 2004; Rummel and Spada 2005; Meier et al. 732007). These mechanisms can lead to important opportunities for learning in collaborative 74settings, however only if they occur and if students take advantage of them. Unfortunately, 75students often do not show fruitful collaborative behaviors spontaneously, but need support 76(Rummel and Spada 2005). Two aspects that can be regarded as preconditions for a fruitful 77 interaction are the flow of the collaboration and the motivation of the collaborating partners. 78

34

#### Computer-Supported Collaborative Learning

Collaboration flow refers to the degree to which students' actions and utterances build on 79each other and whether they maintain a joint focus on the task they are solving (Rummel et 80 al. 2011). Motivation of the collaborating partners is indicated by students' attitude towards 81 the collaboration and their commitment to the joint task (Meier et al. 2007). For students to 82 benefit from the collaboration, it is crucial that they participate actively in the interaction— 83 be it in a symmetrical relationship, or in complementary roles such as tutor and tutee (e.g., 84 O'Donnell 1999; Slavin 1996). A related problem frequently reported is *unequal contribution* 85 of the collaborating partners to the problem solving process as they do not feel mutually 86 responsible for the collaborative outcome; a phenomenon that most often harms both learning 87 partners (e.g., O'Donnell 1999; Slavin 1996): If the interaction is characterized by one student 88 telling his or her partner what to do, and the other student is following the instructions without 89 understanding why, the latter student will presumably fail to acquire a deeper understanding 90 (Webb et al. 1995). At the same time, this eliminates any possibility for the learning partner to 91profit from the collaborative learning setting through giving or receiving help and joint 92knowledge construction. 93

One approach that has shown to be effective in fostering collaboration, also particularly in 94mathematics, is to provide guidance by means of a collaboration script (e.g., Berg 1993, 951994; King 2007; O'Donnell 1999; for an overview see Kollar et al. 2006). Collaboration 96 scripts guide the learning partners through a sequence of interaction phases with designated 97 activities and roles (O'Donnell 1999) and thus promote particular cognitive, metacognitive 98and social processes conducive to learning (King 2007). For instance, in a jigsaw script 99(Aronson et al. 1978; Dillenbourg and Jermann 2007) knowledge or materials relevant to 100solving the task at hand is distributed between the learning partners. Distributing expertise in 101 this way has been shown to strengthen students' individual accountability for the collaborative 102task, thus leading to better, more engaged interactions, and promoting learning (Dillenbourg 103and Jermann 2007; Slavin 1992). Moreover, it has been demonstrated that scripts can serve as 104 model for future collaborations (Rummel and Spada 2005, 2007). 105

In the current study, we therefore developed a collaboration script with two goals 106(cf. Dillenbourg and Jermann 2007; Rummel and Spada 2007): first, to support student 107interaction while working with the script and thus improve their learning (script as method: 108effects of the script); and, second, to improve students' collaboration skills, yielding fruitful 109collaborative behavior even when script support is no longer available (script as objective; 110effects with the script). The effects with the script should then help students to successfully 111 tackle new tasks in a future collaborative learning situation (cf. Bransford and Schwartz 1121999: preparation for future learning). 113

A potential pitfall of scripting collaboration is to "over-script" students that may already 114have enough collaboration skills (Dillenbourg 2002; Kollar et al. 2007). If the goal is for 115students to internalize the scripted behavior and to apply it even when script support is no 116longer available, then scripting could be ceased after some scripted collaboration 117 (e.g., Rummel and Spada 2005, 2007) or faded out over time (Wecker et al. 2010). However, 118this is still no solution if script support was obsolete from the beginning. Also, it does not 119help in situations where students are "under-scripted" and would need more support than the 120script is providing. A promising idea is therefore to support students' collaboration in an 121adaptive fashion, tailored to their individual and changing needs for support. Intelligent 122tutoring technologies open a new horizon with regard to adaptive tutoring of collaboration. 123As Walker and colleagues (2009a, b, 2010, 2011; see also Diziol et al. 2010) have shown, 124125the technology that is used by cognitive tutors to provide just-in-time adaptive support for domain learning can also be applied to provide just-in-time adaptive support for collaboration, 126that is, to prompt fruitful collaborative behaviors in relevant moments of the interaction. The 127

work presented in the current paper is related to the work by Walker and colleagues as our128collaboration script also built on the Cognitive Tutor Algebra and included some adaptive script129elements.130

#### **Research questions and hypotheses**

In the introduction, we described the risk that students might solve tasks within a cognitive 132tutoring system without acquiring deeper conceptual understanding. We discussed the 133potential of collaborative learning to increase students' elaboration of the learning material 134and yield improved learning outcomes. We argued that support is needed to ensure that 135students tap the potentials of a collaborative learning setting, and introduced collaboration 136scripts as a promising way to promote collaboration. Finally, we discussed the possibility of 137leveraging existing intelligent tutor technology to provide adaptive scripting of 138 collaboration. 139

Against this background we developed collaborative extensions to the Cognitive Tutor 140Algebra (CTA), an established cognitive tutoring system for mathematics instruction at the 141 high school level (e.g., Koedinger et al. 1997), and implemented a collaboration script to 142support students' collaborative learning with the system. To evaluate the effects of our 143collaborative script extensions to the CTA, we conducted an in vivo study, that is, a 144controlled classroom experiment. In the study we compared collaborative learning with 145script support (scripted condition) to collaborative learning without script support (unscripted 146condition) and individual learning (individual condition). All three conditions were 147implemented within the CTA. After a 2 day learning phase we administered three posttests 148assessing individual and collaborative reproduction, and future learning. 149

Which effects did we expect from scripted collaborative learning? With the collaboration 150script we aimed to improve student interaction. As was argued above, it is through the 151interaction with their peers that students' understanding develops in a collaborative setting. 152Thus, we assumed that due to an improved interaction students would benefit more from the 153learning opportunities during collaboration and, in consequence, their learning would be 154increased. To investigate how the script influenced student interaction, we first conducted 155in-depth process analyses of two case studies (one dyad from the unscripted condition and 156one dyad from the scripted condition). More specifically, we looked at how the collaboration 157script influenced the quality of student interaction during the learning phase, that is, during 158scripted problem solving. Furthermore, we investigated how scripted practice during the 159learning phase related to the quality of student interaction during subsequent, unscripted 160problem solving in the test phase. And finally, we checked whether the interaction quality of 161the selected dyads was mirrored in their learning outcomes. In our process analyses we 162assessed the quality of the collaboration analogous to process analyses we had conducted in 163previous studies (Meier et al. 2007; Rummel et al. 2011). As the goal of the current study 164was to promote learning in mathematics, we additionally evaluated students' problem-165166solving during particularly challenging problem-solving steps.

In a second step we statistically compared the *learning outcomes* across all three 167 experimental conditions in order to evaluate how collaboration, and especially scripted 168 collaboration, affected learning. We expected to find the following effects: The mechanisms 169 of collaborative learning were expected to lead to deeper learning particularly in the scripted 170 condition, and thus to yield improved mathematical skill fluency as measured by our 171 reproduction posttests. We furthermore hypothesized that the learning effect would carry 172 over from collaborative to individual performance; that is, we were also expecting better 173

181

185

Computer-Supported Collaborative Learning

performance of the collaborative conditions, and particularly the scripted condition, on the174individual reproduction posttest. This would be an important effect, taking into account that175school assessment is primarily based on the evaluation of individual performance. Finally,176we assumed that scripted students would have learned to take advantage of the collaborative177learning setting, and that this ability would help them to tackle new learning content178consecutively; thus they should perform better than the other conditions on a future learning179posttest assessing their performance on new learning content.180

#### Method

Before we describe the study design and procedure in more detail, we briefly introduce the182cognitive tutoring system that we employed in our study and the curriculum unit that we183used as learning material, and we describe the collaboration script we developed.184

Learning environment and material

The Cognitive Tutor Algebra (CTA) is a tutoring software for high school instruction used in over 2000 schools across the USA. As several studies have shown, learning with the CTA improves student performance by about one standard deviation compared to traditional classroom instruction on measures of algebra understanding (Koedinger et al. 1997, 2000). The CTA comprises 32 different curriculum units that cover the learning content of algebra I. It consists of several tools, and depending on the unit, some or all of them are 191

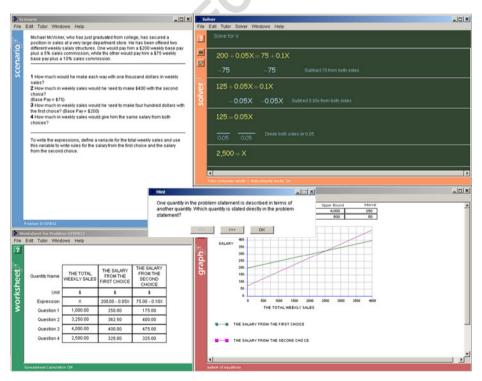


Fig. 1 Screenshot of the Cognitive Tutor Algebra, unit system of equations

displayed. Figure 1 shows a screenshot of the CTA from the unit system of equations (unit19213). This was the unit we used for the learning material in our study. Our participants had not193yet been introduced to the system-of-equations concept in their classroom instruction.194

In unit 13 of the CTA, the *Problem Scenario* (top left corner) shows a story problem with 195several questions. The story problems use concrete, real-world scenarios (for instance, in the 196example shown in Fig. 1, students have to compare two salary structures that were offered to 197Michael McVicker). Students are requested to find the y-values for a given x-value or the 198 x-value corresponding to a given y-value, respectively. For instance, in question 1 of the 199example task, the weekly sales are given, and students have to find the resulting income for 200the two salary structures; in questions 2 and 3, students are told about McVicker's income 201and have to find the weekly sales he must have made. These types of questions are 202structurally similar to the questions in the unit linear equations (unit 7 of the CTA), which 203our participants were already familiar with (in the following, we will therefore refer to these 204questions using the term *simple questions*). One question is new in unit 13 and was thus 205particularly challenging for students participating in the study: the question of how to find 206the *intersection point* (i.e. question 4 in Fig. 1). Prior to answering this question students are 207additionally required to construct a graph of the problem situation. 208

In summary, when solving a system-of-equations problem such as the one in Fig. 1 with 209the CTA, students are required to perform the following steps (see Table 1): First, students 210label the columns of the Worksheet (see Fig. 1 bottom left) according to the entities described 211in the problem, enter the appropriate units and derive the algebraic expressions (step 212deriving expressions). Then they work on solving the questions of the story problem (step 213solving simple questions, step graphing, and step finding intersection point) making use of 214the help facilities of the CTA. The Solver window (see Fig. 1 top right) enables students to 215solve equations. To construct the graph of the problem situation in the Grapher window (see 216Fig. 1 bottom right), students first have to label the axes, set the appropriate bounds and 217intervals so that all points of the Worksheet can be plotted, and finally graph the lines (step 218graphing). The *Hint* window in the middle of the screen in Fig. 1 on top of the other 219windows gives an example for the hint messages the CTA provides on demand and when 220students make errors. In the hint window students can click on the arrow button to receive 221more detailed hints. The final hint tells them the answer to the current problem-solving step. 222

<b>VI</b> 01.1	Table 1 Troblem-solving su	eps (system-or-equation problems)
t1.2	Steps	Students' tasks
t1.3	Deriving expressions	label columns of Worksheet
t1.4		enter units
t1.5		derive algebraic expressions from the story problem and enter in Worksheet
t1.6	Solving simple questions	solve questions 1 through 3 with help of the Solver tool (note: questions are structurally equivalent to questions from a previous CTA unit on linear equations (unit 7))
t1.7		enter solutions in Worksheet
t1.8	Graphing	label axes
t1.9		set bounds and intervals
t1.10		graph the lines
t1.11	Finding intersection point	equate the two expressions in the Solver tool
t1.12		solve the resulting equation for x
t1.13		enter solution in Worksheet

<b>1</b> t1.1	Table 1	Problem-solving	steps (system-of-	equation problems)	

O

Computer-Supported Collaborative Learning

In addition to the hints, the CTA provides just-in-time feedback by marking student errors 223 red. Students insert the answers to the questions of the story problem in the corresponding 224 cells of the worksheet. 225

The school that participated in our study uses the CTA curriculum in their regular 226mathematics instruction. In classroom courses following the CTA curriculum, three of five 227course periods a week are classroom lessons; during the remaining two periods, students 228 work on the CTA in the computer lab (Koedinger 1998, Koedinger et al. 1997). Therefore 229our study participants were well-acquainted with the CTA functionality and were used to 230learning with this software. This is important to note as often initial positive or negative 231effects of computer-based learning environments have to be ascribed to the novelty of the 232environment to students. 233

A collaboration script for solving problems on the cognitive tutor algebra

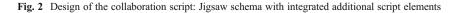
We developed a collaboration script that supported students as they collaboratively learned 235to solve system-of-equations problems using the CTA. The script (see Fig. 2) employed a 236jigsaw schema (Aronson et al. 1978; Dillenbourg and Jermann 2007) as general framework; 237in other words, it distributed the responsibility for the story problem between the learning 238partners: During an *individual phase*, each student solved questions containing one linear 239equation in the CTA; during the following collaborative phase, students joined on a single 240computer to solve questions combining the two linear equations into a system-of-equations 241problem. For the system-of-equations problems, students were prompted to take responsibility 242 for problem steps relating to their individual expertise (e.g., they explained to their partner how 243to derive the equation corresponding to their part of the story problem and were responsible to 244answer the simple questions corresponding to their problem part). Then they were asked to 245jointly solve the step pertaining to the new problem type: finding the intersection point. The 246individual and collaborative phases were repeated for each story problem students solved while 247working on the CTA. The script was directly implemented in the CTA software. 248

The jigsaw framework already provided a setup that has been shown to promote fruitful 249collaboration by increasing learners' individual accountability. In order to further support 250students' individual accountability, the interaction was additionally supported by *fixed script* 251elements that prompted particular collaborative behaviors and allocated roles. Based on the 252task structure, the collaborative problem solving process was divided into several steps. A 253short instruction preceded each step, prompting students to engage in particular collaborative 254behaviors. For instance, at steps where students had to contribute their individual expertise 255the responsibilities were marked by color coding and students were told to alternate between 256

Student A individual problem solving: linear equation A (3 questions) Student B individual problem solving: linear equation B (3 questions)

Collaborative problem-solving:

- Students collaboratively solve system-of-equations problem that combines the individual problems (4 questions)
- Fixed script elements prompt fruitful collaborative behaviors and allocate roles
- Adaptive script elements (error messages and penultimate hint messages) guide students when impasses occur



the roles of explainer and listener. The explainer was prompted to give elaborated257explanations while the listener was prompted to ask for further explanation when having258problems in understanding.259

In the introduction, we have discussed adaptive scripting as one possible solution to avoid 260providing too little support or over-scripting collaboration. Following this argumentation we 261additionally implemented *adaptive elements* in our collaboration script in order to counteract 262problematic student behaviors reported in the literature on learning with cognitive tutors 263(e.g. trial and error, hint abuse, gaming behavior): An error message popped up when dyads 264made an error. It prompted students to learn from the error by mutually reflecting on their 265problem solving process or by requesting a hint from the CTA. The error message aimed at 266reducing gaming behavior and at increasing the amount of expedient help requests. Second, 267when students engaged in hint abuse, that is, when they clicked on the hint widget repeatedly 268in order to receive the bottom-out hint, a *penultimate hint message* appeared (see Fig. 3). It 269prompted students to mutually elaborate on the hints received so far and to try to find the 270answer on their own and thus learn for future problem solving. 271

Study design and procedure

The study took place during five class periods over the course of a week: a single period on day 1, and two block periods on days 2 and 3 (see Table 2). The first minutes at the beginning of each period were used for organizational purposes: on day 1, students received a short introduction to their condition; on day 2 and 3, teachers rearranged dyads if one partner was missing (see explanation in the participants section). 273 274 275 276 277

On days 1 and 2 (*learning phase*), students solved a system-of-equations problem 278 according to their condition working at their own pace. In the *scripted condition* the dyads' 279 interaction was structured by our collaboration script. As described, the script guided 280 students to alternate between individual and collaborative work phases while solving 281

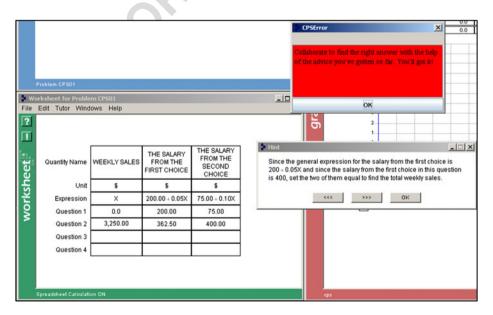


Fig. 3 Screenshot of adaptive hint prompt

Computer-Supported Collaborative Learning

	Scripted collaboration	Unscripted collaboration	Individual learning
Learning phase	Day 1 (single period)		
		Short introduction	
	Scripted collaborative problem- solving on the CTA <sup>a</sup>	Collaborative problem- solving on the CTA	Individual problem- solving on the CTA
	Day 2 (block period)		
	Regrouping of dyads with missing learning partner		
	Scripted collaborative problem- solving on the CTA (students continue with problem from previous day)	Collaborative problem- solving on the CTA (students continue with problem from previous day)	Individual problem- solving on the CTL (students continue with problem from previous day)
Test phase	Day 3 (block period)		
	Regrouping of dyads with missing learning partner	Q`	
	Condition-specific reproduction test: collaborative problem- solving (CTA)	<u>, (</u> )	Condition-specific reproduction test: individual problem solving (CTA)
	Future learning test: collaborative problem-solving (CTA)		Future learning test: individual problem solving (CTA)
	Individual reproduction test: individual problem- solving (CTA)		

<sup>a</sup> CTA cognitive tutor algebra

problems with the CTA and adaptively supported them during their collaboration. During the 282individual work phases students worked on separate computers; for the collaborative phases 283they joined on one computer. In the unscripted condition, two students joined on one 284computer to collaboratively solve problems with the CTA, but did not receive specific 285support for their collaboration. This condition corresponds to the way collaborative learning 286is often implemented in classrooms: students are simply put together in small groups to work 287on certain tasks; however, without support, they might fail to take advantage of the 288collaborative setting. The individual condition served as an ecological control condition 289corresponding to current practice in the CTA curriculum: students individually solved 290problems with the CTA. 291

In all conditions, the problems that students solved consisted of seven questions: six 292introductory linear equations questions (corresponding to the simple questions in Fig. 1 and 293Table 1), followed by one question targeting the system-of-equations concept. This seventh 294and last question asked students to compute the intersection point. Students in the scripted 295condition answered three of the linear equations questions during the individual phase and 296the remaining four questions, including the intersection point question, during the collaborative 297phase. Learning time was kept constant across conditions. Students worked at their own pace, 298solving problems until time was up. Students in all conditions worked on the same problems. 299Their problem-solving was supported by the CTA, which provided immediate feedback and 300 hints in its regular fashion, as described. 301

N. Rummel et al.

On day 3 (*test phase*), three posttests were administered to evaluate the effects of the 302 experimental conditions on the learning outcomes. Students first solved a *condition-specific* 303 *reproduction* test and a test assessing *future learning*. These tests were solved collaboratively 304 in the collaborative conditions and individually in the individual condition. Next, all 305 participants solved an *individual reproduction* test; this test was solved individually in all 306 conditions. All three tests took place on the computer within the CTA. 307

#### Participants

308

342

The current study was conducted as an in vivo *experiment* at one of the LearnLab research 309 facilities of the Pittsburgh Science of Learning Center (PSLC, http://learnlab.org). Five 310 teachers agreed to host the study in their algebra classes (eight classes and 139 students in 311 total). Parents were asked to give informed consent for their children's participation. To 312 guarantee student anonymity, each student received a fictitious name that was used to 313 identify the student throughout the study. These names were used as logins for the CTA.

To prevent internal validity threats such as treatment diffusion, the study was conducted 315in a between-classroom design. The participating eight classes were randomly assigned to 316 conditions, taking into account the following preconditions: classes taught by the same 317teacher were assigned to different conditions, and each condition was supposed to consist of 318a comparable number of students or dyads respectively. In both collaborative conditions, 319teachers assigned students to homogenous dyads based on their math grade, making sure to 320 pair students that got along well. In our statistical analyses we took care to control for 321differences in prior knowledge that may have resulted from the between-classroom design. 322

323 The school that participated in our study is a vocational high school: for half of the day, students attend regular classes in different grades at their home schools; the other half of the 324 day, they attend the vocational school to take part in instructional program courses (e.g., 325carpentry and culinary arts) and "basics" courses, such as mathematics. In a pre study 326 conducted at the same school, we realized that-due to the specific school format-the rate 327 of student absenteeism was quite high (Diziol et al. 2007) In order to decrease the loss of 328 data that would result from excluding both learning partners if one student was missing, 329students were regrouped at the beginning of each day when necessary. Regrouping rules 330 guided teachers' decisions when forming new dyads, ensuring that all teachers dealt with 331 this issue in a similar way. Conditions did not differ in the rate of student attrition ( $\chi^2 = .75$ , 332 p=.69). To ensure a high ecological validity, we included as many students as possible in our 333 data analyses: we included students that remained in the same condition throughout the 334study, that participated in at least 1 day of the learning phase, and that were present on the 335 test day. These conditions were met by about three quarters of the sample. The sample of 336 students included in final data analyses consisted of 106 students, 74 boys and 31 girls. 337 Information about the gender of one student was missing. The average age of students was 338 15.86 (SD=.74), their average school grade was 9.88 (SD=.43). Due to technical difficulties 339 during the test day, test data was lost for a differing number of students. The resulting sample 340sizes for the different posttests can be found in Table 3. 341

Analysis of the collaboration process and the learning outcome

We analyzed the effects of scripted collaborative learning with the CTA in two steps: First, 343 we conducted analyses of the collaboration process of two dyads (one from the scripted and 344 one from the unscripted condition). The analyses were done using two rating schemes and a 345 narrative approach. Second, we statistically compared the learning outcomes of all 346

+3.1

Computer-Supported Collaborative Learning

	Scripted	Unscripted	Individual
Condition-specific reproduction	18 dyads	19 dyads	16 individua
Future learning	23 dyads	19 dyads	16 individua
Individual reproduction	38 individuals	39 individuals	17 individua

 Table 3 Number of participants included in data analysis of the three post tests

participants across the three conditions based on the posttest data. Table 4 gives an overview 347 of the dependent variables that are explained in more detail in the following two sections. 348

#### Analysis of the collaboration process

We recorded student interaction during the learning phase and during the collaborative 350reproduction posttest. A screen capture tool launched automatically when students started 351the CTA and stopped when students quit the software. The tool recorded students' verbal 352 interaction and their actions on the computer screen. For the analysis, we integrated the 353 screen recordings (audio-video data) with log data from the CTA using ActivityLens, a 354software program for the collaboration process analysis developed by Avouris and 355 colleagues (Avouris et al. 2007). The integration of the different data sources enabled us 356 to segment the interaction based on the task structure and to navigate to particularly 357 interesting collaboration sequences (e.g., interaction after hint requests or errors) based on 358the log data. We used ActivityLens both for the rating analyses and for the narrative analysis 359 approach. 360

We developed two *rating schemes* that assessed the quality of student interaction from 361 two perspectives. Table 5 provides an overview of all rating dimensions with examples for high and low ratings. Ratings were done on a five-point rating scale ranging from 0 (*very bad*) to 4 (*very good*). In addition, the second rating scheme included a variable evaluating the dyad's overall problem-solving strategy according to five distinct categories; this variable is shown in the last row of Table 5. 366

The first rating scheme focused on the quality of the collaborative behavior in more 367 general terms; here we assessed the interaction process throughout the solving of entire 368 problems (i.e. across all problem-solving steps, see Table 1). The dimensions for analyzing 369 the *quality of collaboration* were adapted from a rating scheme that we had developed and 370 evaluated in earlier research (Meier et al. 2007; Rummel et al. 2011). The dimension 371

Collaboration process	Rating schemes	Quality of the collaboration Quality of the problem-solving process
	Narrative approach	Actions and interactions
Learning outcomes (Posttest	s) Condition-specific reproduction	Error rate
		Assistance score
	Future learning	Error rate
		Assistance score
	Individual reproduction	Error rate
		Assistance score

t4.1 **Table 4** Overview of the dependent variables

### EDJhil 10 Rart S9126 Rooff 10 2004/2012

Dimension	Examples very bad (0 points)	Examples very good (4 points)
Quality of the collaboration	(rating scheme 1)	
Collaboration flow	there is little or no talk	partners communicate coherently and monitor each other's attention and understanding
Collaborative motivation	partners show a negative attitude towards the interaction/the task; there is an unequal contribution to the problem-solving process	partners show a highly positive attitude towards the joint problem-solving; both partners are actively involved in the interaction
Elaboration on content	there is little or no talk; partners talk about irrelevant topics (off-topic conversation)	partners give explanations of their actions proposals and make references to mathematical concepts
Elaboration on hint	partners do not read the hints, but immediately ask for the next hint	partners mutually discuss the hints in order to learn from them
Quality of the problem-solv	ing process (rating scheme 2)	
Mathematical understanding	partners need a lot of CTA assistance to solve the steps and show no understanding of the correction	partners solve step correctly on first attempt, revealing a deep understandin of the underlying principles
Capitalization on social resource	partners ignore each other's presence and joint potential to find a solution	partners make proposals how to derive the correct solution and discuss them together
Capitalization on system resource	partners engage in trial-and-error or hint abuse	partners mutually reflect on errors and hints
Dyad's strategy	(0) trial and error	
	(1) hint abuse	
	(2) immediate correction	
	(3) (proposal-) correct input	
	(4) elaborating with partner	

 Table 5 Examples for low and high ratings of interaction quality

collaboration flow assessed whether students were responsive to each other's actions and 372 utterances, and whether they maintained a joint focus. Students received low ratings if there 373 was only little talk and high ratings if they were responsive to each other's comments and 374monitored their partner's attention. Collaborative motivation assessed students' attitudes 375toward the joint problem-solving activity. Low ratings in this dimension were given if 376 students showed a negative attitude toward the interaction with their partner and toward 377 the joint problem-solving activity, while high ratings were only given if both learning 378 partners were actively involved in the problem-solving process. The dimensions elaboration 379on content and elaboration on hint evaluated the extent and quality of students' elaborations 380 of the learning content more generally and, specifically, in response to tutor hints. For 381 instance, students received low ratings in the dimension elaboration on hint if they did not 382 read the hints but immediately asked for the next hint until they reached the bottom-out hint 383 that gave them the correct answer; in contrast, they received high ratings if they jointly 384discussed the CTA hints. To analyze students' interactions concerning the quality of 385 collaboration, we segmented the recordings based on the problem-solving steps described 386 above (see Table 1). Each segment was rated separately; ratings then were averaged across 387 segments of each problem or posttest, respectively. 388 Computer-Supported Collaborative Learning

The second rating scheme evaluated the quality of the problem-solving process during 389 particularly challenging problem-solving steps. With this rating scheme we assessed whether 390students took advantage of the help resources in the learning environment. Based on the 391literature on learning in mathematics and based on the task structure, we chose two 392 particularly difficult steps of the system-of-equations problems for analysis: deriving the 393 expressions corresponding to the linear equations, and finding the intersection point (see 394Table 1). During these selected problem-solving sequences we evaluated students' interactions 395 concerning the following aspects: Mathematical understanding assessed the dyad's 396 comprehension of the problem steps, taking into account both the amount of CTA help they 397 needed for solving the steps and the level of understanding they expressed when reading hints 398 or correcting errors. We gave low ratings if the dyad needed a lot of CTA assistance to solve a 399 step and if they engaged in trial and error and hint abuse until they found the correct solution; we 400gave medium ratings if they needed CTA assistance, but revealed some understanding of the 401 correction in their following interaction, for instance, by referring to the underlying mathematical 402 principles; and finally, we gave the highest ratings if the dyad immediately solved a 403 problem step correctly and if their interaction revealed that their correct solution was not 404 due to chance but to a deeper understanding of the underlying mathematical principles. 405The dimensions capitalization on social resource and capitalization on system resource 406 assessed whether students took advantage of the support offered in the learning environ-407 ment by the CTA and by the learning partner to improve their collaborative learning 408 process. For instance, students received low ratings with regard to social resource if they 409ignored each other's potential for finding the solution and if they did not pay attention to 410 each other's suggestions. High ratings were given if students explained their problem-411 solving actions to their partner or discussed how to proceed in solving the problem. For 412system resource, students received low ratings if they engaged in trial-and-error behavior 413 or hint abuse. High ratings were given if they used the help offered by the CTA 414effectively to increase their learning; for instance, if they discussed and resolved errors 415flagged by the CTA. The categorical dimension dyad's strategy assessed the dominant 416 problem-solving strategy that students showed according to five distinct categories. The 417 first two strategies, trial and error and hint abuse, denote strategies ineffective for 418 learning. In contrast, the strategies immediate error correction, correct input, and elaboration 419with the learning partner prior to entering the correct solution are regarded as effective problem-420 solving strategies that potentially yield learning. In the presentation of the results, we 421summarize the dimension dyad's strategy by indicating the percentage of effective problem-422 solving strategies employed by the students. In a final step, the ratings of the two problem-423solving steps were averaged for each of the assessed dimensions. 424

The two rating schemes were applied to the interaction data from the 2 days of the learning 425phase and from the collaborative reproduction posttest on day 3. All problems solved during 426427 those days were rated. The results of the rating analyses thus provide a good overview of the development of the collaboration processes within the two dyads over the 3 days of the study. In 428 order to guide the raters' assessment, we developed a rating handbook that described the 429430dimensions in more detail and gave examples for high and low ratings similar to the way done in Table 5. Two raters independently assessed the quality of the interaction, and analysis of the 431inter-rater reliability showed good results (between r=.66 and r=1.00). 432

In addition to the ratings, we took a *narrative approach* in order to closely follow student 433 interaction during one particular problem-solving step: finding the intersection point. The 434 rating analysis revealed huge differences in interaction quality concerning this particular 435 problem-solving step, therefore it seemed interesting for further analysis. Also from a 436 theoretical point of view, this step seemed a good choice for analysis: While most other 437 parts of the problems required problem-solving steps that were already known to the 438 students participating in the study, this step was totally new to them. To investigate how 439students learned to tackle this problem-solving step, we prepared transcripts of the respective 440 interaction sequences of the two dyads. The analysis then involved multiple cycles of 441 reviewing the students' interaction in ActivityLens and carefully studying the transcripts. 442 When replaying and studying the interaction we took notes on the actions in the CTA 443environment, the interaction with the learning partner, and the reactions to script instructions. 444 Furthermore, we noted whether actions or interactions that should have occurred did not take 445 place; for instance, if students missed the opportunity to discuss a CTA hint. Although our 446 observations were also guided by those theoretical considerations that formed the basis for the 447 rating schemes, the detailed analysis allowed us to pay attention to additional aspects emerging 448 bottom-up from the data. 449

#### Analysis of the learning outcomes

In the test phase, we assessed the impact of the experimental conditions on learning 451 with two reproduction posttests and a future learning posttest (see Table 4). All three 452 tests took place on the computer with the CTA. During the test phase, script support 453 was no longer available in the scripted condition; neither were any of the other two 454 conditions scripted. 455

*Reproduction* was assessed by having students solve problems isomorphic to those during 456instruction. Depending on the condition, the first reproduction test was solved either 457 individually or collaboratively (condition-specific reproduction). The second reproduction 458test was solved individually in all conditions (*individual reproduction*). In both reproduction 459tests, a maximum of two problems could be solved. Second, students' future learning was 460 evaluated with a test that asked students to solve problems of a future CTA unit on 461 inequalities. The test comprised four inequality problems that instructed students to calculate 462two points and graph the inequality in a coordinate plane. The future learning test was solved 463 either individually or collaboratively according to the condition. However, no script support 464was available in the scripted condition. 465

For all tests, two variables were extracted from the CTA log data: The error rate measures 466 the relative number of steps that were not solved correctly on the first attempt, as indicated 467 by the student making an error or requesting a hint. An error rate of 0 means that the student 468solved each step correctly on the first attempt; an error rate of 1 indicates that the student 469needed CTA assistance (error feedback or hint) for each step of the problem. If a student's 470first attempt on a step was not correct, he often needed multiple attempts (i.e., made multiple 471errors or requested several hints) to solve this step correctly. Therefore, we additionally 472calculated an assistance score. The assistance score is the average number of incorrect 473attempts and hints requested across all steps, thus assessing the assistance a student needed 474 475to correctly solve the problems.

Prior knowledge as covariate

476

450

Students' prior knowledge in algebra can be expected to have a substantial impact on the477acquisition of new learning material. For instance, students need basic knowledge of478equation solving and plotting points. In order to statistically control for individual479differences, we collected data on students' prior knowledge to include it as covariate in480the statistical model. Prior knowledge was operationalized by students' current level of481performance in algebra (0–100 %) as reported by their teachers.482

#### Results

We analyzed the effects of scripted collaborative learning with the CTA in two steps: 484 First, we conducted analyses of the collaboration process of two dyads (one from the 485scripted and one from the unscripted condition). The analyses were done using two 486 rating schemes and a narrative approach. Results from the ratings are summarized in 487 Table 6 for the learning phase and in Table 7 for the condition-specific reproduction 488 posttest. The outcome data of the two dyads are provided in Table 8. Second, we 489statistically compared the learning outcomes of the three conditions based on the 490posttest data. The results of the two reproduction posttests and the future learning 491posttest are presented in Table 10. 492

#### Results of the rating analysis

As described above, we had aimed to record student interaction during the learning phase 494 and during the collaborative reproduction posttest. However, the screen capture tool failed to 495start recording several times leaving us with only a few complete process recordings. In 496addition, in a number of recordings, the audio quality was not sufficient to allow for an 497analysis of students' utterances. Thus the choice for our in-depth process analysis was 498severely limited. We chose two dyads for which we had complete or almost complete 499recordings of acceptable quality: The dyad Aristotle (scripted condition) and the dyad 500Telemann (unscripted condition). 501

As shown in Table 6, the scripted dyad Aristotle only solved two problems during the 502*learning phase*. After having completed the individual phase, students started the collabo-503rative phase of problem 1 on the first day (deriving expressions, and solving questions 1 and 5042, see Table 1) and finished it at the beginning of the second day (solving question 3: 505graphing, and finding intersection point; see Table 1). The collaborative phase of problem 2 506was solved on the second day of the learning phase. In contrast, the unscripted dyad 507Telemann solved four problems during the learning phase. Problem 1 was solved on the 508first day, and problems 2 to 4 were solved on the second day of the learning phase. 509Unfortunately the video of the first problem was incomplete. The recording stopped when 510students started to graph the lines in the Grapher; thus, for the following problem-solving 511process, only log data are available. Therefore, we were not able to rate the last two steps of 512this problem (i.e. graphing the equation and calculating the intersection point, see Table 1). 513The smaller number of problems that were solved in the scripted dyad as compared to the 514unscripted dyad is concordant with the ratio of solved problems in the whole study sample 515(unscripted condition M=3.50, SD=1.83; scripted condition M=1.79, SD=.80) and can be 516explained by the script instructions that directed students in their collaborative activities— 517and that asked for more than they would probably have engaged in when collaborating 518without script support. 519

When comparing the dyads Aristotle and Telemann with regard to the quality of the 520521collaboration process during the learning phase, we can see huge differences. The interaction 522of the dyad Aristotle is characterized by a constantly good *collaboration flow* and a high *collaborative motivation* during the learning phase. At the beginning of their interaction, the 523dyad Telemann also shows a good collaboration flow and a high collaborative motivation for 524the joint problem-solving (see Table 6). However, for both dimensions, ratings decreased 525526during the course of the second and third problem solved by Telemann. The slight improvement in the collaboration flow and the collaborative motivation for the fourth problem can be 527explained by an interaction sequence at the end of the third problem: During the second and 528

483

	1st problem	blem			2nd pt	2nd problem			3rd problem	blem			4th problem	blem		
	Quality	/ of the cc	Quality of the collaboration			D										
	CF	CM	EC	EH	CF	CM	EC	EH	CF	CM	EC	EH	CF	CM	EC	EH
Aristotle	3.7	3.7	3.0	3.0	3.8	3.3	1.8	2.0	_a	I	I	I	I	I	I	I
Telemann	$3.0^{b}$	3.0	2.0	1.5	2.0	1.8	1.3	0.0	1.3	1.0	0.8	0.0	2.5	2.0	1.5	0.0
	Quality	/ of the pr	oblem-solv	Quality of the problem-solving process	5											
	MU	SOR	SYR	$\mathrm{DS}^c$	MU	SOR	SYR	DS	MU	SOR	SYR	DS	MU	SOR	SYR	DS
Aristotle	3.0	4.0	3.0	100 %	4.0	2.0	<i>p</i> <sup>-</sup>	100 %	-a	Ι	I	I	I	I	I	I
Telemann	$2.0^{b}$	2.0	1.0	0 %	1.5	0.5	0.5	0 %	1.5	0.0	0.5	0%	3.0	1.0	1.0	50 %

t6.1

t6.2		1st problem	blem			2nd problem	oblem			3rd problem	blem			4th problem	blem		
t6.3		Quality	Quality of the collaboration	llaboration													
t6.4		CF	CM	EC	EH	CF	CM	EC	EH	CF	CM	EC	EH	CF	CM	EC	EH
t6.5	Aristotle	3.7	3.7 3.7	3.0	3.0	3.8	3.3	1.8	2.0	<i>a</i>	I	I	I	I	I	I	I
t6.6	Telemann	$3.0^b$	3.0	2.0	1.5	2.0	1.8	1.3	0.0	1.3	1.0	0.8	0.0	2.5	2.0	1.5	0.0
t6.7		Quality	Quality of the prob	oblem-solv	lem-solving process												
t6.8		MU	MU SOR	SYR	$\mathrm{DS}^c$	MU	SOR	SYR	DS	MU	SOR	SYR	DS	MU	SOR	SYR	DS
t6.9	Aristotle	3.0	4.0	3.0	100 %	4.0	2.0	<i>p</i>	100 %	a 	I	I	I	I	I	I	I
t6.10	Telemann	$2.0^{b}$	$2.0^{b}$ 2.0	1.0	% 0	1.5	0.5	0.5	0 %	1.5	0.0	0.5	0 %	3.0	1.0	1.0	50 %
	Quality of th	te collabo	ration: CF	collaborat	ion flow; Cl	d collabo	rative moti	vation; E0	Quality of the collaboration: CF collaboration flow; CM collaborative motivation; EC elaboration on content; EH elaboration on hint;	i on contei	ıt; <i>EH</i> elal	boration o	n hint;				

<sup>o</sup> The dyad's strategy is summarized as the percentage of effective strategies (i.e. immediate correction, correct input, elaborating with partner vs. trial and error and hint abuse)

<sup>d</sup> The dyad neither asked for hints nor made errors when solving the most challenging problem-solving steps of this problem

employed during interaction

ED

Computer-Supported Collaborative Learning

	Quality of the	collaboration		
	CF	СМ	EC	EH
Aristotle	4.0	4.0	2.8	2.0
Telemann	1.5	1.8	0.8	0.0
	Quality of the	problem-solving proces	SS	
	MU	SOR	SYR	$\mathrm{DS}^{a}$
Aristotle	2.5	3.5	3.0	100 %
Telemann	1.0	1.0	1.0	0 %

Ouality of the collaboration: CF collaboration flow; CM collaborative motivation; EC elaboration on content; EH elaboration on hint:

Quality of the problem-solving process: MU mathematical understanding; SOR capitalization on social resources; SYR capitalization on system resources; DS dyad's strategy

<sup>a</sup> The dyad's strategy is summarized as the percentage of effective strategies (i.e. immediate correction, correct input, elaborating with partner vs. trial and error and hint abuse) employed during interaction

third problem, Telemann B shows little interest in interacting, ignoring his partner's 566 utterances and solving the problem on his own; this causes Telemann A to complain about his 563partner's attitude, and he asks him to engage in the interaction as well, which leads to improve-564ment in their collaboration on the fourth problem. More detail on this instance will be provided in 565the results of the narrative analysis. As discussed in the theoretical background and indicated by 566the results in Table 6, the two dimensions collaboration flow and the collaborative motivation are 567important prerequisites for the overall collaboration quality. It is likely that if these dimensions are 568rated as low, a dyad also shows low ratings on the other dimensions (e.g., Telemann, third 569problem). But a high collaboration quality concerning collaboration flow and collaborative 570motivation is not sufficient, as a high amount of interaction does not guarantee deeper elabora-571tion. For instance, despite the high collaboration flow during the first problem, Telemann shows 572only a medium *elaboration on the content* and a low *elaboration on the hints* they receive. In fact, 573their elaboration on both dimensions is low throughout their interaction during the learning phase, 574whereas Aristotle shows high elaboration particularly during the first problem they solve, that is, 575when they encounter the system-of-equations task type for the first time. 576

We see even higher differences between the dyads' interactions during the learning phase 577 when comparing their ratings concerning the quality of their problem-solving process during 578the particularly challenging problem-solving steps: deriving the expressions and finding the 579

Gender	Aristotle		Telemann	
	Male	Male	Male	Male
Prior knowledge: unit in CTA	. 8	7	10	10
Condition-specific reproduction	on			
Error rate	0.38		0.31	
Assistance score	1.03		1.31	
Future learning				
Error rate	0.54		0.53	
Assistance score	3.17		3.11	

 Table 8 Descriptive variables and posttest results of Aristotle (scripted) and Telemann (unscripted)

t8.1

intersection point. The dyad Aristotle makes effective use of the opportunities provided by 580the collaborative learning environment: They discuss their solution approach and work 581together on solving the difficult problem-solving steps (capitalization on social resource). 582They reflect on the hints they have requested and capitalize on the errors they have made 583during the first problem (*capitalization on system resource*). Thus, they manage to solve the 584difficult problem-solving steps of the second problem without the need for CTA assistance. 585Furthermore, they exclusively engage in effective problem-solving strategies. As a 586consequence, the dyad Aristotle shows a high mathematical understanding during the first 587 problem; during the second problem they even receive the highest possible ratings on this 588dimension. The narrative analysis further illustrates how the collaboration script supported 589the interaction of the students in this dyad. 590

In contrast, the Telemann partners barely take advantage of the collaborative learning 591environment, that is, of the *social* and *system resources*. While the dyad still receives 592medium ratings on these dimensions during the first problem, the ratings are close to zero 593for the second and third problem they solve. Furthermore, with the exception of the final 594problem, they solely engage in ineffective problem-solving strategies (dvad's strategy), 595frequently showing trial and error and hint abuse behaviors. As a consequence, Telemann 596barely shows any progress in their *mathematical understanding* during the learning phase: 597 They need a large amount of CTA assistance to solve the problems, but show only a low 598understanding of the corrections and the hints they receive. The improved rating for the 599fourth problem does not indicate an improved understanding of the system-of-equations 600 concept (i.e., the target concept in our study): decomposing the ratings of the two analyzed 601 problem-solving steps reveals that only the step "deriving expressions" was rated higher 602 (with 4), whereas the step "finding the intersection point" still only received a rating of 2. 603 This also explains why the dyad Telemann did not succeed in finding the intersection point 604 in the condition-specific reproduction test. 605

Interestingly, the scripted dyad Aristotle shows a higher *quality of collaboration* not only 606 during the learning phase, but also during the condition-specific reproduction posttest (see 607 Table 7). The interaction of the dyad Aristotle shows a better *collaboration flow* and a higher 608 *collaborative motivation* than the interaction of the dyad Telemann. In the dyad Aristotle, 609 both learning partners are engaged in the interaction, while the learning partners of the dyad 610 Telemann do not establish a joint focus on the problem and do not contribute equally to the 611 problem-solving process. Moreover, Aristotle receives good ratings for the two dimensions 612 elaboration on the content and elaboration on the hints. Telemann on the other hand shows a 613 low level of elaboration on both dimensions. 614

Also the quality of the dyads' problem-solving process differs during the condition-615specific reproduction test. The dyad Aristotle shows a medium level of mathematical 616 understanding. Compared to the final problem during the learning phase (see Table 6) 617 the dyad thus receives a slightly lower rating on this dimension. Decomposing the 618 two averaged ratings reveals that this is mainly due to difficulties with deriving the 619 expressions from the story problem and not due to difficulties with the new and 620 621 central question type finding the intersection point: for the interaction sequence "deriving the expressions" Aristotle receives the rating 2; the sequence "finding the intersection 622 point" is rated with 3. As was the case during the learning phase, the dyad capitalizes 623 effectively on the social and system resources and engages in effective problem-624 solving strategies to solve the most difficult problem-solving steps. In contrast, Telemann 625 626 again barely capitalizes on the social and the system resources and engages in trial and error and hint abuse (ineffective dyad's strategy). Furthermore, the two students show a low level of 627 628 mathematical understanding.

#### Computer-Supported Collaborative Learning

#### Results of the narrative approach

In the previous section, we compared the ratings of the quality of the interaction process of 630 the dyads Aristotle and Telemann. The analysis showed how the students' interaction 631 evolved over the course of the learning phase and how it was rated in the condition-632 specific (i.e., collaborative) reproduction posttest. In the following sections, we analyze in 633 detail the interaction during the new and most challenging step of the system-of-equations 634 problems: finding the intersection point. The narrative analysis was based on transcripts and 635 video data. We reviewed the interaction multiple times and took notes on the actions and 636 interactions to describe the problem-solving process in detail. The results from the rating 637 analysis already indicated substantial differences in the interaction quality during this 638 particular problem step and we attempt to further illuminate these differences here. More-639 over, the in-depth analysis enables us to investigate the effects of the collaboration script on 640 student interaction and learning, answering questions like: Does the script promote equal 641 contribution to the problem-solving process? And is the adaptive support successful in 642 fostering student elaboration? 643

Analyzing the dyads' collaboration during the learning phase

When solving the intersection point question of the first problem, the dyad Aristotle starts by 645 reading the question out loud together: Aristotle A reads the first part "How much in weekly 646 sales would give him the same salary for both choices?", and Aristotle B the second part 647 "Find the answer algebraically". Thus, they start out with a joint focus of attention on the 648 task. Next, Aristotle A articulates his confusion about the question several times and 649proposes to guess the answer; meanwhile, Aristotle B attempts to understand the problem 650 posed by elaborating on the problem statement. He reads the question once again, accentu-651ating the significant information: "How much in weekly sales would give him the SAME 652salary for both choices? Find the answer algebraically". Furthermore, he gives an example to 653 describe the situation they are looking for: "... he's gonna make 600\$ in (.) you know first 654choice and then 600\$ in the second choice" (note: "first choice" and "second choice" refer to 655two job offers to be compared in this system-of-equations problem). This elaboration leads 656 his partner Aristotle A to conclude that "(t)here has to be a pattern" that should allow them to 657 find the answer. When he realizes that the salaries for the first and the second job offer 658 resulting from the previous question they have solved were quite similar (total weekly sales 659\$400; salary for first choice \$400, salary for second choice \$475), he simply enters a value 660 for the weekly sales (\$500) that is close to the one given in the previous question. The 661 answer is wrong, and an adaptive script message comes up, reminding the students to consult 662 with their partner or ask for a hint if they do not know how to find the solution. Following 663 this advice, Aristotle B suggests asking for a CTA hint. Even though the hint already tells 664 them quite clearly how to proceed ("Given that the expression for the salary from the first 665 choice and the salary from the second choice are equal, write an equation and solve it to find 666 the total weekly sales"), they click through the hints until—before the bottom-out hint—a 667 second adaptive script message (penultimate hint message) pops up, prompting them to 668 collaboratively make use of the hints received so far. The following episode is characterized 669 by productive co-construction. The two students work hand in hand proposing 670 problem-solving steps; they complete each other's sentences and build on each other's 671 comments. For example, when Aristotle B says "Now, just-", Aristotle A states at 672 the same time "And (do that) in there?"; then Aristotle B takes up and answers: 673 "Yeah, 75 plus point—or 0 or whatever point". This collaborative contributing to the 674

problem-solving process indicates that both students are learning together how to find 675 the intersection point. Aristotle A takes over the responsibility for typing in the CTA 676 as they solve the equation for x. Yet, both students are actively involved and pay 677 attention to the problem-solving steps: They always discuss the necessary steps before 678 entering them in the CTA. Despite their good collaboration, however, they are not 679 able to completely solve the equation on their own. They have difficulties with the 680 transformation step that requires combining both variable terms on one side. After two 681 unsuccessful attempts, the CTA automatically launches a hint message; however, the 682 hint message unfortunately is erroneous and does not propose a suitable next step, 683 thus the dyad asks the teacher how to proceed. The teacher helps them to solve the 684problem step, and the dyad finishes solving the equation for x. 685

During the second problem, the dyad Aristotle successfully applies the knowledge gained 686 from the first problem in order to find the intersection point. Again, Aristotle B reads out the 687 question. Immediately, both students agree on how to approach the question: to go to the 688 Solver and equate the two expressions of the problem. Aristotle A says: "We have to do that 689 thing again", and Aristotle B agrees: "Yeah, Solver, that's easy, new equation, all right, you 690 start typing in". The almost simultaneous start of their talking indicates that both students are 691 actively involved in problem-solving and that they have both gained an understanding of 692 what to do. The motivation to be equally engaged in problem-solving is also expressed in the 693 following sequence, in which they explicitly distribute the workload: When Aristotle B 694 suggests that his partner enters the equation: "All right, you start typing in", Aristotle A 695 agrees and suggests that Aristotle B tells him the equation to write down:"Ok, tell me what 696 to type in". Aristotle A's request does not imply that he would not be able to derive the 697 equation on his own. In fact, at one point he writes down an arithmetic operator before 698 Aristotle B tells him to. He pays attention to the problem solving and does not have to rely 699 on his partner to find the solution. As during the first problem, Aristotle A takes responsi-700 bility for mouse and keyboard as they solve the equation for x; however, in contrast to 701 Telemann B in the unscripted dyad (see below), he begins each problem-solving step by 702 proposing what to do next and then makes a short pause, allowing his partner to agree or 703 disagree. The dyad successfully solves the equation and enters their answer in the 704Worksheet. 705

In the following paragraphs, we elaborate on the difficulties of the unscripted dyad 706 Telemann in learning how to find the intersection point. When solving the intersection point 707 question of the first problem,<sup>1</sup> the two students enter the correct answer in the Worksheet 708 immediately after finishing the graphing (after about 57 s) and without using the Solver tool. 709 This indicates that the dyad does not find the intersection point algebraically, but they 710employ a graphical strategy: they identify the point's coordinates in the Grapher window. 711If the coordinates of the intersection point are integers, as was the case in the first problem, 712 this is a successful strategy that demonstrates students' understanding of the relationship 713 between the graphical and the tabular representation. However, the strategy fails if the 714 point's coordinates are decimal numbers, as was the case in the subsequent problems. 715

During the second problem, the dyad again tries the graphical strategy to find the 716 intersection point: At the end of the graphing step, Telemann A states that the intersection 717 point must be approximately at 7.2 min. He proposes entering 7 in the Worksheet, stating 718 that "it [the CTA] should correct it". This statement is a typical example of relying on the 719 CTA support functionalities and gaming the system. Even though the CTA marks their 720

<sup>&</sup>lt;sup>1</sup> For the first problem of the learning phase, video data of Telemann's interaction during this sequence were not available; therefore, the analysis is based on log data.

Computer-Supported Collaborative Learning

answer wrong, the dyad sticks to their strategy: They enter further numbers close to 7 until 721 the CTA automatically launches a hint message after the third incorrect attempt (trial and 722error). They click on the "next" button in the hint dialogue until the bottom-out hint is 723 displayed. It instructs them to equate the two expressions in order to find the answer, but the 724 725 dyad simply copies the equation given in the hint into the Solver window; a typical case of hint abuse as described in the introduction. During the subsequent equation solving, 726 Telemann B takes over the responsibility, entering actions and transforming the equation 727 in the CTA. However, he barely ever comments on what he is doing. Meanwhile, Telemann 728 A reads out loud some of his partners' actions and the error messages presented by the CTA. 729 The actions and verbal utterances of the two students often do not refer to each other, 730indicating that they are not really paying attention to what their partner is doing. For 731 732 instance, at one point Telemann A proposes a transformation step without realizing that his partner has already tried out exactly the same step without success a couple of seconds 733 ago. Telemann B, on the other hand, shows little interest in interaction in general: He neither 734explains his own actions nor does he react to the solution proposals of his partner. Telemann 735 A reacts to this behavior with off-topic talk and plays around with his microphone. The dyad 736 struggles most with transforming the equation -8 M=-6 M -100 to -2 M=-100. To 737 perform this step, students have to put all terms referring to the variable to one side (here, by 738 adding 6 M). After several unsuccessful attempts to transform this equation, Telemann B follows 739 his partner's proposal to ask for a hint. He clicks on the "next" button in the hint window as 740quickly as possible until he reaches the bottom-out hint that tells them the next problem-solving 741 742 step. In fact, the time interval between receiving one hint and clicking ahead to the next hint is too short to even read the hints. In other words, the dyad does not try to elaborate on the help they 743 receive, but deliberately abuses the hints. When performing the step suggested in the bottom-out 744 hint, Telemann B makes a typo, entering 6 instead of 6 M. Although the reaction of Telemann A 745 clearly expresses his confusion: "What the beef. It's like, er, what is it like, er", Telemann B does 746 not attempt to explain his actions when correcting the error. In the end, Telemann A no longer 747 insists on receiving an explanation, but merely comments: "Ok, you figured it out". 748

When solving the third problem, the dyad again initially tries to find the intersection point 749 by employing a graphical solution approach. After the first attempt is marked as wrong by 750the CTA, Telemann A remarks that they might have to use the Solver again: "...(oh) we'll 751have to do this on the solv-thingee". Telemann B does not follow his advice, but tries out two 752 more values until the CTA automatically launches a hint message telling them to approach 753the problem by writing an equation. Even though the dyad has just solved a similar problem, 754they do not capitalize on their previous experience and the information given in the hint; 755instead, Telemann B again immediately clicks to the bottom-out hint and copies the equation 756 given there. As in the previous problems, he takes control of the CTA. His obvious lack of 757 interest in collaboration also reduces the efforts by his partner: Although Telemann A still 758makes a few proposals on problem-solving steps, he mainly engages in off-topic talk. As in 759the previous problem, Telemann B does not follow his partner's proposals, but solves the 760 question on his own. When Telemann A suggests an erroneous problem-solving step (adding 7617629 instead of 9D), Telemann B does not correct him, but merely enters the correct step. The lack of interest in collaborating finally leads Telemann A to complain: When Telemann B 763 again enters a problem step while Telemann A is still trying to figure out what to do next, he 764verbally expresses his frustration: "Hey, why aren't you speaking at all? This is supposed to 765be a group effort here!". At first, Telemann B does not take the complaint seriously, but 766 rather plays it down, responding that "(s)omebody has to push buttons". Telemann A insists: 767 "but you are (also) supposed to explain how this is DONE!". In consequence, the collaboration 768 769 slightly improves during the solving of the fourth problem.

782

Even though using a graphical solution approach to find the intersection point had proven 770 unsuccessful in the previous three problems, the dyad Telemann again tries this strategy on 771 the fourth problem. In contrast to the previous problems, they do not even wait for the CTA 772 hint message to automatically launch after several errors, but ask for a hint immediately after 773 their second unsuccessful attempt. As before, they click through the hint dialogue and copy 774 the equation provided in the bottom-out hint (hint abuse). While the dyad's problem-solving 775 is still of low quality, their motivation to collaborate with each other has slightly increased 776 compared to the previous problems, and they pay attention to each other's utterances and 777 actions. For instance, when Telemann A proposes problem-solving steps, Telemann B 778 follows his proposals until they find the correct answer. The improved collaboration is also 779 reflected in the ratings of the dyad's interaction during the fourth problem (see Table 6 and 780 related result presentation above). 781

Short overview of dyads' collaboration during the reproduction test

Although none of the dyads was scripted during the condition-specific reproduction test, the 783 two dyads still differ in their interaction. The dyad Aristotle solved only two problems 784during the learning phase and thus had rather little opportunity to practice the new question 785type intersection point. Nevertheless they successfully solve the posttest problem with little 786 assistance by the CTA. The problem-solving process of the dyad Aristotle is again 787 characterized by mutual contributions and knowledge co-construction. For example, when 788 Aristotle B wonders: "Equals what, what has to be equal?", Aristotle A explains what they 789 need to do and tries to help his partner by referring to their earlier experiences: "Yeap, cause 790that's what we did yesterday". Finally Aristotle B gets it: "Ok, remember. So. Solver", and 791 enters the equation in the solver window. Furthermore, the dyad takes advantage of the CTA 792 learning environment and employs the strategy they were instructed to use by the script 793 during the learning phase: When they are stuck in their problem-solving or when the CTA 794marks one of their actions as error, they do not engage in trial and error, but ask for a hint, 795 which they then discuss and try to use to proceed. For instance, when a CTA hint tells them 796 to "subtract 0.35 M from both sides", the two students initially agree that this is what they 797 have just done and wonder. All of a sudden Aristotle A notices: "Oh, I forgot for M", and 798 Aristotle B concurs: "Oh yeah". Now they are able to proceed without clicking any further 799 through the hint hierarchy. 800

In contrast, although they solved four analogous problems during the learning phase and 801 although they receive ample support by the CTA (error flagging and hint messages), the 802 dyad *Telemann* does not succeed in finding the intersection point when collaboratively 803 solving the system-of-equations problem in the posttest. The inferior performance of the 804 dyad Telemann in finding the intersection point in the reproduction test can be attributed 805 both to their suboptimal problem-solving behavior during the learning phase and to their 806 unfruitful interaction during the test phase: As they did during the learning phase, they do 807 not effectively capitalize on the collaborative learning environment at hand. When Telemann 808 A tries to gain an understanding of the task and attempts to discuss it with his partner at the 809 beginning, Telemann B simply ignores him. Furthermore, when Telemann A tries to 810 understand what his partner is doing later in the process, he does not receive appropriate 811 answers. For instance, at some point during the problem-solving process Telemann A 812 requests an explanation: "Now what are you doing for this?", but Telemann B merely 813 responds: "Praying". At another point when Telemann A asks Telemann B how he found 814 a certain value: "How did you find the bottom one?", Telemann B answers: "Very carefully". 815 Telemann A insists: "And you did that how, other than carefully?", but receives no further 816 Computer-Supported Collaborative Learning

answer. Even after several unsuccessful attempts, Telemann B is not willing to start817interacting with his partner, but further engages in trial and error and hint abuse until time818is up. He does not leverage the competencies of his partner and in the end they fail to solve819the test problem.820

#### Learning outcome of the two dyads

If the hypothesized connection between collaboration quality and learning outcome holds 822 true, the interaction patterns of the two analyzed dyads should link to their posttest results. 823 Thus, in this section we descriptively relate the interaction quality with prior knowledge and 824 the learning outcome as assessed by the two posttest variables error rate and assistance score. 825 The two dyads entered the study with very different levels of prior knowledge: Of the dyad 826 Aristotle one student had gotten as far as unit 8 of the CTA, while the second student was 827 still working on unit 7, the unit that introduced linear equations, which was a prerequisite for 828 solving the system-of-equations problems during the study. In contrast, both students of the 829 dyad Telemann had already reached unit 10 of the CTA prior to the study. Yet, in the 830 collaborative posttests "condition-specific reproduction" and "future learning" the two 831 contrasting dyads show equally good performance (see Table 8): In the collaborative 832 reproduction test, Telemann has a slightly lower error rate, but needs more CTA assistance 833 to correct their errors and to find the right solution. In the future learning test, the dyads' 834 performance is approximately the same. Thus, the students of the dyad Aristotle learned 835 more: they both had entered with lower levels of prior knowledge, but reached comparable 836 learning outcomes as the two Telemann partners. This result is in line with the findings from 837 the process analyses and provides some initial support for the assumption that better 838 collaboration is likely to lead to better learning. 839

Learning outcome of the whole sample: Between-condition comparison

Can the differences in the learning gains we observed for the two case dyads also be found in the between-condition comparison of the whole sample? 842

As we had expected *prior knowledge* to have a substantial impact on the acquisition of new learning material and because we have seen differences in the prior knowledge of the two analyzed dyads, we first compared the three study conditions concerning their prior knowledge, assessed as students' current level of performance in algebra (0–100 %). Descriptively, prior knowledge was highest in the unscripted condition and lowest in the scripted condition (see Table 9), indicating a similar pattern as the one seen in the analyzed dyads. The differences were, however, not statistically significant, F(2,103)=1.77, p=.18.

Next, we tested the influence of prior knowledge on the learning outcomes. The theoretically assumed correlation between prior knowledge and outcome measures was confirmed by the empirical data: Prior knowledge had a significant impact on all outcome measures (r=.32-.54, p<.05). Therefore, it was included as covariate in the data analyses. For the collaborative posttests that were analyzed on the dyadic level, we used the dyad's average 854

t9.1 <b>Table 9</b>	Prior knowledge
---------------------	-----------------

	Scripted	Unscripted	Individual
Prior knowledge M (SD)	81.90 (10.37)	85.25 (6.03)	84.47 (8.35)

prior knowledge as a covariate. To balance the descriptive differences between conditions 855 we report the adjusted means for the following analyses (cf., Huitema 1980). These are the values that would be predicted if the covariate means of conditions were the same as the 857 grand covariate mean. 858

To analyze the effect of the study conditions, we computed a MANCOVA analysis for 859 each of the three posttests. Two independent a priori contrasts tested our hypotheses: First, 860 we compared the individual condition with the collaborative conditions to assess the impact 861 of collaboration; second, we contrasted the two collaborative conditions with each other to 862 evaluate the script's effect. As described above, the outcome variables of interest were the 863 error rate and the assistance score. The error rate measures students' ability to solve a step 864 correctly on the first attempt, while the assistance score evaluates the average amount of 865 assistance (errors and hint requests) needed to solve the problems. In those cases where we 866 found indications of an interaction between prior knowledge and condition (aptitude treat-867 ment interaction), the interaction term was included in the GLM model as the exclusion of 868 the interaction term would violate the assumption of homogenous regression slopes (Field 869 2005). 870

Adjusted means and standard errors for the three posttests are presented in Table 10. For 871 the condition-specific reproduction test, the MANCOVA analysis revealed a significant 872 aptitude treatment interaction of prior knowledge and condition, F(4,94)=3.30, p=.01, 873  $\eta^2$ =.12, thus the model including the interaction term was used in the following analyses. 874 As expected, prior knowledge had a strong influence on both outcome measures, F(2,46) =875 13.66, p=.00,  $\eta^2=.37$ . Furthermore, conditions differed significantly with regard to the 876 measures of condition-specific reproduction, F(4,94)=3.34, p=.01,  $\eta^2=.12$ . The subsequent 877 ANCOVA analysis of the error rate revealed a significant influence of the covariate prior 878 knowledge, F(1,47)=24.96, p=.00,  $\eta^2=.35$ . However, we did not find a significant interac-879 tion of prior knowledge and condition, F(2,47)=.14, p=.87, nor did we find a significant 880 effect of condition on the error rate, F(2,47)=.09, p=.92. In the ANCOVA analysis of the 881 assistance score, we found a marginally significant interaction of prior knowledge and 882 condition, F(2,47)=2.55, p=.09,  $\eta^2=.10$ . Again, prior knowledge had a significant effect, 883 F(1,47)=6.15, p=.02,  $\eta^2=.12$ . Furthermore, data analysis revealed a marginally significant 884 difference between conditions, F(2,47)=2.81, p=.07,  $\eta^2=.11$ , with most assistance needed 885

	Scripted	Unscripted	Individual
	M (SE)	M (SE)	M (SE)
Condition-specific rep	roduction		
Error rate	.41 (.03)	.38 (.03)	.36 (.03)
Assistance score	1.10 (.12)	.86 (.12)	.93 (.13)
Individual reproduction	n		
Error rate	.35 (.02)	.36 (.02)	.36 (.04)
Assistance score	1.01 (.11)	.98 (.11)	.97 (.17)
Future learning			
Error rate	.36 (.03)	.44 (.03)	.30 (.03)
Assistance score	2.01 (.34)	2.73 (.37)	1.85 (.40)

t10.1 Table 10 Posttest results

For error rate and assistance score, smaller numbers indicate better performance

\*\*p < .01; \ast p < .05; + p < .10; - = not assessed

Computer-Supported Collaborative Learning

by dyads of the scripted condition (see Table 10). The predefined contrasts did not reveal 886 significant results. To analyze the significant aptitude treatment interaction effect in more 887 detail, we calculated regression analyses with prior knowledge as the predictor and assis-888 tance score as the criterion separately for each of the three conditions. 889

As indicated by the regression slopes in Fig. 4, the influence of prior knowledge on the assistance score was highest in the scripted condition (regression coefficients: individual condition b=-.01, unscripted condition b=-.02, scripted condition b=-.04), thus the slight disadvantage of the scripted condition regarding the assistance score could at least partly be ascribed to the high amount of assistance needed by students with low prior knowledge. 894

Prior to analyzing the data of the *individual reproduction* test, we had to attend to a 895 methodological issue: The analysis of individual posttest data in a study on collaborative 896 learning and problem solving raises the question if the observations of two dyad partners can 897 be considered independently (e.g., Cress 2008). Following the methodological approach 898 suggested by Kenny and colleagues (1998), we therefore analyzed the intraclass correlations 899 between individual posttest scores of dyad partners in the individual reproduction test. 900 Neither the analysis of the variable error rate nor the analysis of the variable assistance 901score revealed a consequential nonindependence (i.e. an intraclass correlation between dyad 902partners that is higher than r=.45 and significant at an alpha level of .20, cf. Kenny et al. 903 1998). Thus, we were able to include both dyad partners in the analysis individually. 904

For the individual reproduction test, results of the MANCOVA revealed a significant 905 effect of prior knowledge on student performance, F(2,89)=17.63, p=.00,  $\eta^2=.28$ . 906 Condition did not show an effect, F(4,180)=.15, p=.96. Result of the subsequent 907 ANCOVAs were concordant with the MANCOVA analysis: Prior knowledge significantly 908 influenced the *error rate*, F(1,90)=35.37, p=.00,  $\eta^2=.28$ ; however, condition did not impact 909 the amount of errors on the first attempt, F(2,90)=.02, p=.98. Also the ANCOVA analysis 910

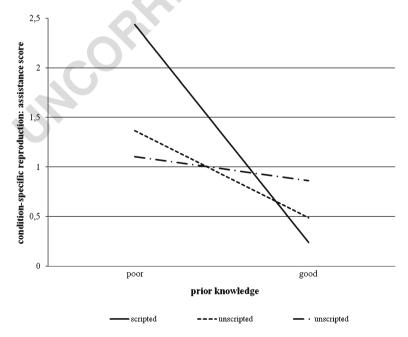


Fig. 4 Influence of prior knowledge on the assistance score in the condition-specific reproduction test (regression slopes)

of the *assistance score* showed a significant influence of prior knowledge, F(1,90)=26.83, 911 p=.00,  $\eta^2=.23$ , while study conditions did not differ in the amount of assistance needed to 912 solve problems, F(2,90)=.03, p=.97. 913

Results of the MANCOVA analysis of the *future learning* test showed, once more, that 914 prior knowledge influenced students' performance, F(2,53)=11.03, p=.00,  $\eta^2=.29$ . Further-915more, we found a significant effect of condition F(4,108)=2.74, p=.03,  $\eta^2=.09$ . The 916 separate ANCOVAs for the two outcome measures revealed that the significant result of 917 the multivariate analysis could be ascribed to the variable error rate: Conditions differed 918 with regard to the average number of errors on their first attempt, F(2,54)=5.46, p=.01, 919  $\eta^2$ =.17. Furthermore, both planned contrasts yielded significant results: The individual 920condition showed a lower error rate than the two collaborative conditions, t(54)=2.67, 921 p=.01, and dyads from the scripted condition had a lower error rate than dyads from the 922 unscripted condition, t(54)=2.11, p=.04. Prior knowledge had a significant influence on 923error rate, F(1,54)=21.86, p=.00,  $\eta^2=.29$ . Although the pattern was similar with regard to 924 the assistance score, neither the overall difference between conditions, F(2,54)=1.54, 925 p=.22, nor the planned contrasts reached statistical significance (for the first contrast t 926 (54)=.1.09, p=.28, for the second contrast t(54)=1.43, p=.16). Again, prior knowledge 927 had a significant influence on students' achievement, F(1,54)=14.53, p=.00,  $\eta^2=.21$ . 928

#### **Discussion and conclusions**

#### Summary of results

In the present study we tested collaboration extensions to the Cognitive Tutor Algebra (CTA, 931 © Carnegie Learning Inc.), a tutoring system for high-school mathematics, with the goal to 932promote student learning. As we argued in the introduction, research has demonstrated that 933 fruitful collaboration does not automatically result from having two students work together. 934 Therefore, we developed a collaboration script to support the interaction. In an experimental 935 classroom study we compared scripted collaboration to unscripted collaboration and 936 individual learning. In our analyses we tested two assumptions: First we compared the 937 collaboration process of one dyad from the scripted condition and one dyad from the 938 unscripted condition, in order to test the assumption that the collaboration script would 939 increase fruitful interaction and thus promote the collaborative learning process. We 940 analyzed the interaction of the two dyads with two rating schemes: one rating scheme 941 evaluated collaboration quality from a rather general point of view, and the other rating 942scheme looked at the quality of the problem-solving process in the specific setting 943 (i.e. collaborative learning with the CTA). In addition, we conducted an in-depth narrative 944 analysis of one particularly difficult step in the system-of-equations tasks that students 945encountered in our study: calculating the intersection point. Both types of process analyses 946 were carried out for the collaboration during the learning phase and during the condition-947 specific reproduction posttest, where dyads collaborated without script. We also related the 948process analyses to the learning outcomes of the two dyads. Second, we tested the assumption 949 that collaboration—and especially scripted collaboration—would lead to improved learning by 950 statistically comparing the learning outcomes across conditions for the whole sample. 951

In summary, in the *process analyses* we found clear differences between the interaction 952 patterns of the two analyzed dyads. The results of the *rating analysis* showed that the 953 interaction of the scripted dyad Aristotle during the learning phase was of higher quality than 954 the interaction of the unscripted dyad Telemann. The scripted dyad Aristotle collaborated in 955

Computer-Supported Collaborative Learning

a productive way, particularly after some adaptive support had been provided by our 956 collaboration script. On the other hand the unscripted dyad Telemann did not take advantage 957 of learning opportunities provided by the collaborative setting, but mainly abused the CTA 958 hints to solve problems faster. Moreover, the scripted dyad Aristotle continued to show a 959 higher quality in their collaboration and in their problem-solving during the condition-960 specific (i.e. collaborative) reproduction posttest than the unscripted dyad Telemann. In 961 other words, the two Aristotle students were rather successful in transferring their good 962 collaborative behavior from the scripted interaction during the learning phase to the test 963 phase, where script support was no longer available. 964

The in-depth *narrative analysis* of the intersection point problem-solving step supported 965 the results revealed by the ratings: The analysis of the relevant sequences in the problem 966 solving of the dyad Aristotle during the learning phase clearly showed that both students 967 learned how to find the intersection point algebraically. During the first problem, the two 968 students were initially unsure how to approach the question and had difficulties when 969 solving the equation. At this point we could see how the adaptive script element influenced 970 the interaction. An adaptive script message encouraged students to ask for a hint, in other 971 words, the script instructed them on a strategy fruitful for learning: asking for help. Next, a 972penultimate hint message prevented students from abusing the hint hierarchy to get the right 973 answer. Surprisingly, merely mentioning that they might be able to solve the problem step on 974their own was sufficient to keep these two students from requesting the final hint that would 975 have given them the answer, and stimulated them to collaboratively solve the step on their 976 own. In the second problem, Aristotle did not need CTA assistance (error flagging or hint 977 messages) anymore either to derive the equation or to solve it and compute the intersection 978 point. During the condition-specific reproduction test, the problem solving of the dyad 979 Aristotle was again characterized by mutual contributions and knowledge co-construction. 980 They succeeded in solving the intersection point question with only little assistance by the 981CTA. 982

In contrast, the analysis of the collaborative problem solving of the dyad Telemann during 983 the learning phase revealed that they did not achieve an understanding of how to find the 984intersection point algebraically. In none of the four problems did they derive the equations 985for calculating the intersection point on their own. During the whole learning phase, they 986 abused the hints given by the CTA to copy the solution from the bottom-out hint. In fact, 987 they even moved the hint window closer to the Solver tool in order to facilitate the copying. 988 They only collaboratively engaged in the problem-solving process after Telemann A 989expressed his frustration. Cleary, a more elaborative way of using the learning resources 990 available (system resources and social resources) would have been desirable. Unfortunately, 991 also during the collaborative reproduction posttest, the dyad Telemann failed to collaborate 992fruitfully and did not find the intersection point even though they received ample support by 993 the CTA (error flagging and hint messages). 994

The differences that we saw in the interaction patterns of the *two dyads* were also 995 confirmed to some extent when descriptively comparing their learning gains: the dyad 996 Aristotle started at a much lower level of prior knowledge than the dyad Telemann, but 997 performed as well as Telemann in the collaborative reproduction test and in the future 998 learning test. 999

We could not clearly establish benefits of the scripted collaboration condition in the 1000 between-condition comparison of the learning outcomes of the whole sample (for an overview of the results, see Table 10). While the analysis of the condition-specific 1002 reproduction test revealed no difference in the error rate, we found differences in the assistance students needed to solve problems. As the aptitude treatment interaction effect 1004

1017

and the subsequent regression analyses revealed, a high need of assistance was particularly 1005 found in those dyads of the scripted condition who had entered the collaboration with poor 1006 prior knowledge. On average, these dyads made more errors and asked for a higher amount 1007of hints per problem-solving step compared to students with a comparable prior knowledge 1008 level that learned in the individual or in the unscripted condition. In the *individual* 1009 reproduction test, however, the disadvantage of students of the scripted condition who had 1010 entered with low prior knowledge no longer persisted: There was no statistical difference 1011 between conditions concerning the number of errors made and the amount of assistance 1012 needed to solve the problems. In the *future learning* test, we found significant differences for 1013the variable error rate, favoring individual learning over collaborative learning, and scripted 1014 collaboration over unscripted collaboration. The assistance score showed the same pattern, 1015but the differences did not reach significance. 1016

#### Discussion of results

Why did the collaborative learning conditions not yield improved learning outcomes in the 1018 reproduction tests? First, it is possible that during the learning phase collaborative students, 1019and particularly those in the unscripted condition, did not engage in the types of elaborative 1020 collaborative behaviors considered beneficial for learning. This interpretation is in line with 1021 the results of process analyses of the dyads Aristotle and Telemann: The analyses revealed 1022 elaborative discussions, particularly after hints, in the scripted dyad Aristotle, while the 1023 unscripted dyad Telemann frequently engaged in ineffective learning behaviors. This 1024 problem became obvious in the rating analysis (see dimensions elaboration on the content 1025and *elaboration on hints*) and was further corroborated by the narrative analysis. Further-1026more, Aristotle showed a better collaboration flow and higher collaborative motivation, 1027 which are important prerequisites for an overall high collaboration quality as was discussed. 1028 Also, these dimensions can be regarded as indicators of increased accountability, a goal we 1029had intended to achieve by the jigsaw design of our collaboration script. This interpretation 1030 is further supported by the ratings of the mathematical problem-solving process: Aristotle 1031made good use of the social resources and the system resources and overall showed a good 1032problem-solving strategy. On a critical note we have to concede, however, that the results 1033revealed by the case analyses are promising, but we do not know if they would hold for the 1034 entire sample. This is a general problem of case methodology: case analyses permit much 1035more fine-grained evaluation of learning processes than could be gained by quantitative 1036cross-conditions comparisons. On the other hand, the generalizability of the results is 1037 limited. For instance, the question must be asked how cases were selected. As described 1038 above, our selection was dictated by practicality: Due to technical problems, only a few 1039 process recordings were complete and of a quality that enabled analysis of students' 1040utterances. 1041

Furthermore, it is possible that students' efforts were not enough to make up for the 1042 "collaboration forfeit", that is, the loss of practice opportunities during the learning phase 1043due to the time expenditure of the collaboration. Collaboration often takes more time than 1044 individual problem solving and thus can reduce the amount of practice (e.g., Lou et al. 2001; 1045Walker et al. 2008). This problem might have affected particularly the scripted condition as 1046 1047the script directed students in their collaborative activities and asked for more than they would naturally have engaged in when collaborating without script support. Statistical 1048 analyses confirm that the number of problems solved during the learning phase differed 1049 between conditions, F(2,40)=8.32,  $p<.01^2$ . More specifically, dyads in the scripted condition 1050solved significantly fewer problems than dyads in the unscripted condition, t(40)=2.42, p=.02, 1051

Computer-Supported Collaborative Learning

and taken together dyads in the two collaborative conditions on average solved significantly 1052fewer problems than students in the individual condition, t(40)=3.31, p=.00 (means and 1053standard deviations of solved problems: scripted condition M=1.79, SD=.80; unscripted 1054 condition M=3.50, SD=1.83; individual condition M=4.60, SD=2.50). This finding is also 1055mirrored in the number of problems solved by the two dyads whose learning processes we 1056analyzed: The scripted dyad Aristotle solved only two problems during the learning phase; the 1057unscripted dyad Telemann solved four problems. In other words, students in the collaborative 1058 conditions had fewer opportunities to practice the mathematical skills necessary to solve the 1059problems of the reproduction tests than students learning individually, and students in the 1060 scripted condition had the fewest opportunities. Furthermore, in related work (Mullins et al. 1061 2011) we found that collaborative settings can encourage students to divide the work, 1062 particularly when learning with task types that target procedural skill fluency, and that this type 1063of task distribution negatively affects procedural learning in mathematics. To conclude, 1064although we were not able to show that collaboration and in particular scripted collaboration 1065yielded improved reproduction at posttest, the results show that collaboration is at least as 1066 effective as individual learning even when the learning time is held constant. This is true even 1067 though the amount of practice in the collaborative conditions was significantly less than the 1068amount of practice in the individual condition; it appears, thus, that the interaction with the 1069learning partner was able to compensate for the loss in practice. 1070

Third, the higher need for assistance in the scripted condition particularly in the 1071 collaborative reproduction test could be explained by the increased demands on these 1072 students in the test phase: For students in the individual and in the unscripted condition, 1073 the problem-solving situation was exactly the same as during the learning phase, but 1074students in the scripted condition were now required, for the first time, to solve system-of-1075equations problems without script support. As illustrated by the results, the loss of support 1076 was particularly severe for students with low prior knowledge, while students with high prior 1077 knowledge were able to tackle the problems even though script support was no longer 1078 available. Along similar lines, the process analyses of the scripted dyad Aristotle indicate 1079 that requesting (and consequently receiving) CTA help just-in-time, when impasses occur, 1080 can be a useful learning strategy for students with low prior knowledge. Generally speaking, 1081 it could be promising to support students in an adaptive fashion, tailored to their individual 1082and changing needs for help. This hypothesis is supported by related studies in which we 1083 were able to demonstrate that intelligent tutoring technologies can be leveraged to provide 1084adaptive tutoring of collaboration, that is, to prompt fruitful collaborative behaviors in 1085relevant moments of the interaction and thus increase student learning (Walker et al. 1086 2009a, b, 2010, 2011; Diziol et al. 2010). The assumption that the higher amount of 1087 assistance needed by weaker students in the scripted condition was temporary, due to the 1088 new, unscripted problem-solving situation, and not due to inferior learning gains, is 1089 supported by the results of the individual reproduction test (which was administered last). 1090

Which conclusions can be drawn regarding the conditions' impact on *future learning*? 1091 Students of the individual condition made fewer errors when solving the new problem type 1092 (inequality problems) than students of the collaborative conditions; so apparently they were 1093better able to handle the new learning tasks in the CTA learning environment. In fact, this 1094result is not too surprising and is consistent with a phenomenon often reported in the 1095learning sciences: When confronted with a new learning strategy or a new learning 1096environment, students' learning outcome is often reduced initially as they have to abandon 1097 previous habits and accustom to the new situation; however, over time and with sufficient 1098 training, the advantages can become evident (e.g., Artelt 2000). In the present study, students 1099in the collaborative conditions had to learn how to take advantage of the collaborative 1100 learning setting while at the same time being confronted with a new problem type. However, 1101 all students had already gained a lot of experience in tackling new problem types with the 1102 help of the CTA during regular classroom sessions, which worked in favor of the individual 1103 condition. Interestingly, analysis of the future learning test showed that, compared to 1104 unscripted collaboration, scripted collaboration helped students to get accustomed to the 1105new collaborative learning situation: The amount of errors made in the future learning test 1106 was lower for dyads of the scripted condition than for dyads of the unscripted condition even 1107 though script support was no longer available. This gives at least some indication that the 1108 guidance of the collaboration script prepared students for the future collaborative learning 1109 situation (cf., script as objective, Dillenbourg and Jermann 2007) and that dyads had learned 1110 to take advantage of the resources available. 1111

Along these lines, it could be hypothesized that benefits of collaborative learning would 1112 increase in future learning situations if collaboration was practiced over longer periods of 1113 time, and that this increase would be accelerated if script support was provided to students 1114 initially. In other words, in the present study the learning time might have been insufficient 1115to establish differences between conditions large enough to be detected by the statistical 1116 analysis. Indications supporting this hypothesis can be found in the study conducted by Berg 1117 (1993). She compared scripted collaboration with individual learning in a traditional teacher-1118 dominated classroom structure. The treatment lasted for 30 days in total. Scripted collaboration 1119did not only improve students' learning of the material that was taught during the learning 1120phase, but also their achievement in future chapters that were taught in traditional fashion in 1121 both conditions. Moreover, results from another, recent study support this hypothesis: In a 1122 collaborative learning study using a similar script approach as the present study, Westermann 1123and Rummel (2012) found significant differences between a collaborative learning condition 1124and a non-collaborative control condition from the second week onwards. The advantage of the 1125collaborative condition continuously increased after the second week until the end of the study 1126 in the fourth week. 1127

#### Outlook

Finally, we would like to note that the present study cannot give final answers regarding the 1129impact of collaboration and in particular of scripted collaboration on student learning. In 1130 future research it would be desirable to study the effects of collaborative learning with 1131research designs that span a longer term and more instructional sessions. However, implement-1132ing the script over a longer period of time might still result in problems due to overscripting. 1133Thus, adaptive support not only concerning the problem-solving process, but also concerning 1134the collaborative support would still be a desirable goal of future research. Just recently, Walker 1135and colleagues (2011) were able to establish learning benefits of adaptive collaboration support 1136in a peer tutoring setting with the CTA. 1137

The current study was conducted as an in vivo experiment at one of the LearnLab 1138 research facilities of the Pittsburgh Science of Learning Center (PSLC, http://learnlab.org): 11391140 That is, the study was conducted in classrooms, by teachers, during school time. We tried to address criticism brought forward against classic classroom research by trying to execute our 1141 study with the same methodological rigorousness we would have used in the lab, and a 1142cautious awareness towards aspects of the situation we could not control in the same way. As 1143reported, during data collection we struggled with "in vivo problems", such as student 1144 attrition and a server breakdown during the test day. We addressed these issues in our data 1145analysis and controlled them as much as possible a posteriori. Yet, they may still limit the 1146generalizability of our study results. Furthermore, we might have been unable to establish 1147

Computer-Supported Collaborative Learning

existing differences between conditions due to the data loss. Our study thus clearly has some 1148 limitations. Nevertheless we would like to advocate this type of research in order to achieve 1149the goals Levin (2004, p. 182) formulated for educational research: scientific credibility, 1150contextual "accretability", and educational credibility. 1151

Acknowledgements This research was supported by the Pittsburgh Science of Learning Center, NSF Grant # 11520354420, by the Landesstiftung Baden-Württemberg, Germany, and by the Virtual PhD Programm, VGK 1153(DFG). We thank Bruce McLaren for his valuable contributions during initial stages of the project. We are 11541155grateful to Jonathan Steinhart, Erin Walker, Dale Walters and Sung-Joo Lim for their support concerning the technical implementations of the Tutor environment; and to Kathy Dickensheets and Lars Holzäpfel 1156for their support in "getting the math right". Further we would like to express our gratitude to the 11571158teachers from CWCTC for their motivated involvement in the project. Also, we would like to thank 1159our student research assistants Martina Rau and Katharina Westermann, and Michael Wiedmann, for their help on data coding and data analysis. Special thanks go to Katharina Westermann for her help 11601161 in preparing this manuscript.

1162

1163

- References
  - Aleven, V., McLaren, B., Roll, I., & Koedinger, K. R. (2004). Toward tutoring help seeking: Applying 1164cognitive modelling to meta-cognitive skills. In J. C. Lester, R. M. Vicari, & F. Paraguaçu (Eds.), 11651166 Proceedings of Seventh International Conference on Intelligent Tutoring Systems, ITS 2004 (pp. 227–239). Berlin: Springer.
  - Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. Journal of the Learning Sciences, 4(2), 167–207.
  - Aronson, E., Blaney, N., Sikes, J., Stephan, C., & Snapp, M. (1978). The jigsaw classroom. Beverly Hills: Sage.
  - Artelt, C. (2000). Strategisches Lernen [Strategic learning]. Münster: Waxmann.
  - Avouris, N., Fiotakis, G., Kahrimanis, G., Margaritis, M., & Komis, V. (2007). Beyond logging of fingertip actions: Analysis of collaborative learning using multiple sources of data. Journal of Interactive Learning Research, 18(2), 231-250.
  - Baker, R. S., Corbett, A. T., & Koedinger, K. R. (2004). Detecting student misuse of intelligent tutoring systems. Paper presented at the Proceedings of the 7th International Conference on Intelligent Tutoring Systems.
  - Berg, K. F. (1993). Structured cooperative learning and achievement in a high school mathematics class. Paper presented at the Annual Meeting of the American Educational Research Association, Atlanta.
  - Berg, K. F. (1994). Scripted cooperation in high school mathematics: Peer interaction and achievement. Paper presented at the Annual meeting of the American Educational Research Association, New Orleans, Louisana.
  - Bransford, J. D., & Schwartz, D. L. (1999). Rethinking transfer: A simple proposal with multiple implications. Review of Educational Research, 24, 61–100.
  - Cress, U. (2008). The need for considering multi-level analysis in CSCL research. An appeal for the use of more advanced statistical methods. International Journal of Computer-Supported Collaborative Learning, 3(1), 69-84.
  - Dillenbourg, P. (2002). Over-scripting CSCL: The risks of blending collaborative learning with instructional design. In P. A. Kirschner (Ed.), Three worlds of CSCL. Can we support CSCL (pp. 61-91). Heerlen: Open Univeriteit Nederland.
  - Dillenbourg, P., & Jermann, P. (2007). Designing integrative scripts. In F. Fischer, I. Kollar, H. Mandl, & J. Haake (Eds.), Scripting computer-supported collaborative learning. Cognitive, computational, and educational perspectives (pp. 275-301). New York: Springer.
  - Dillenbourg, P., Baker, M., Blaye, A., & O'Malley, C. (1996). The evolution of research on collaborative learning. In P. Reimann & H. Spada (Eds.), Learning in humans and machines: Towards an interdisciplinary learning science (pp. 189-211). Oxford: Elsevier/Pergamon.
  - Diziol, D., Rummel, N., Spada, H., & McLaren, B. (2007). Promoting learning in mathematics: Script support 1196 1197 for collaborative problem solving with the Cognitive Tutor Algebra. In C. A. Chinn, G. Erkens & S. Puntambekar (Eds.), Mice, minds and society. Proceedings of the Computer Supported Collaborative 1198 1199Learning (CSCL) Conference 2007, Vol 8, I (pp. 39–41). International Society of the Learning Sciences, Inc. ISSN 1819-0146 1200

- 11671168
- 11691170
- 117111721173
- 1174 1175

1176 1177

11781179

1180 1181

1182

1183 1184

11851186

1187 1188

1189

1190

1191

1192

1193

1194

### EDJhill 10 Rait S9 126 Rooff Of 04/2012

Diziol, D., Walker, E., Rummel, N., & Koedinger, K. (2010). Using intelligent tutor technology to imp	plement 1201
adaptive support for student collaboration. Educational Psychology Review, 22(1), 89-102.	1202
Dubinsky, E., Mathews, D., & Reynolds, B. E. (Eds.). (1997). Readings in cooperative learni	ing for 1203
undergraduate mathematics. Washington: Mathematical Association of America.	1204
Field, A. P. (2005). Discovering statistics using SPSS (2nd ed.). London: Sage.	1205
Hausmann, R. G. M., Chi, M. T. H., & Roy, M. (2004). Learning from collaborative problem solvin	-
analysis of three hypothesized mechanisms. In K. D. Forbus, D. Gentner, & T. Regier (Eds.), 26nd A	
Conference of the Cognitive Science Society (pp. 547-552). Mahwah: Erlbaum.	1208
Huitema, B. E. (1980). The analysis of covariance and alternatives. New York: Wiley.	1209
Kenny, D. A., Kashy, D. A., & Bolger, N. (1998). Data analysis in social psychology. In D. Gilbert, S. Fisk	
Lindzey (Eds.), Handbook of social psychology (Vol. 1) (4th ed., pp. 233-265). Boston: McGraw-Hi	
King, A. (2007). Scripting collaborative learning processes: A cognitive perspective. In F. Fischer, I.	
H. Mandl, & J. Haake (Eds.), Scripting computer-supported collaborative learning. Cognitive, of	
tational, and educational perspectives (pp. 18–19). New York: Springer.	1214
Koedinger, K. R. (1998, June 5-6, 1998). Intelligent cognitive tutors as modeling tool and instru-	
model. Paper presented at the NCTM Standards 2000 Technology Conference.	1216
Koedinger, K. R., Anderson, J. R., Hadley, W. H., & Mark, M. A. (1997). Intelligent tutoring goes to sci	
the big city. International Journal of Artificial Intelligence in Education, 8, 30-43.	1218
Koedinger, K. R., Corbett, A. T., Ritter, S., & Shapiro, L. J. (2000). Carnegie Learning's Cognitive Tu	
Summary Research Results. Retrieved January 16, 2006, from http://www.carnegielearning	
approach_research_reports.cfm	1221
Kollar, I., Fischer, F., & Hesse, F. W. (2006). Computer-supported collaboration scripts-a cond	
analysis. Educational Review, 18(2), 159–185.	1223
Kollar, I., Fischer, F., & Slotta, J. D. (2007). Internal and external scripts in computer-supported collab	
inquiry learning. Learning & Instruction, 17(6), 708-721.	1225
Levin, J. R. (2004). Random thoughts on the (in)credibility of educational-psychological interv	
research. Educational Psychologist, 39(3), 173–184.	1227
Lou, Y., Abrami, P. C., & d'Apollonia, S. (2001). Small group and individual learning with technological states and the state of the st	
meta-analysis. Review of Educational Research, 71(3), 449–521.	1229
Meier, A., Spada, H., & Rummel, N. (2007). A rating scheme for assessing the quality of computer-sup	
collaboration processes. International Journal of Computer-Supported Collaborative Learning, 2,	
Mullins, D., Rummel, N., & Spada, H. (2011). Are two heads always better than one? Differential eff	
collaboration on students' computer-supported learning in mathematics. International Journal of	
<i>puter Supported Collaborative Learning, 6</i> (3), 421–443. doi:10.1007/s11412-011-9122-z.	1234
National Council of Teachers of Mathematics. (2006). Overview of principles and standards for	
mathematics. Retrieved June 5, 2006, from http://www.nctm.org/standards/overview.htm	1236
O'Donnell, A. M. (1999). Structuring dyadic interaction through scripted cooperation. In A. M. O'Dor	
A. King (Eds.), <i>Cognitive perspectives on peer learning</i> (pp. 179–196). Erlbaum.	1238
Organisation for Economic Co-operation and Development [OECD] (n.d.). Programme for Interna	
Student Assessment. Retrieved May 25, 2005, from http://www.pisa.oecd.org/pages/0	
en 32252351 32235968 1 1 1 1 1,00.html	1241
PSLC. (2006). Learnlab. Pittsburgh Science of Learning Center. Retrieved January 16, 2006, from learnlab.org	124 <b>Q2</b> 1243
Reimann, P. (2007). Time is precious: Why process analysis is essential for CSCL (and can also help to	
between experimental and descriptive methods. In C. A. Chinn, G. Erkens & S. Puntambekar	· · · · · · · · · · · · · · · · · · ·
Mice, minds and society. Proceedings of the Computer Supported Collaborative Learning ( Conference 2007, Vol 8, II (pp. 590–607). International Society of the Learning Sciences.	1240
Rummel, N., & Spada, H. (2005). Learning to collaborate: An instructional approach to pro	
collaborative problem solving in computer-mediated settings. <i>Journal of the Learning Science</i>	
(2), 201–241.	1249
(2), 201–241. Rummel, N., & Spada, H. (2007). Can people learn computer-mediated collaboration by following a sci	
F. Fischer, H. Mandl, J. M. Haake, & I. Kollar (Eds.), Scripting computer-supported communica	1
knowledge Cognitive, computational, and educational perspectives (pp. 39–55). New York: Sprin	5
Rummel, N., Deiglmayr, A., Spada, H., Karimanis, G., & Avouris, N. (2011). Analyzing collab	
interactions across domains and settings: An adaptable rating scheme. In S. Puntambekar, C. F	
Silver, & G. Erkens (Eds.), Analyzing interactions in CSCL: Methods, approaches and issues (pp	
390). Berlin: Springer.	1250 = 1250
Slavin, R. E. (1992). When and why does cooperative learning increase achievement? Theoretic	
empirical perspectives. In R. Hertz-Lazarowitz & N. Miller (Eds.), <i>Interaction in cooperative g</i>	
The theoretical anatomy of group learning (pp. 145–173). New York: Cambridge University Pres	
The medical anatomy of group learning (pp. 145-175). New Tork, Cambridge University 116	55. IZOU

Computer-Supported Collaborative Learning

COK

Slavin, R. E. (1996). Research on cooperative learning and achievement: What we know, what we need to know. *Contemporary Educational Psychology*, 21(1), 43–69. 1262

Teasley, S. D. (1995). The role of talk in children's peer collaborations. *Developmental Psychology*, *31*(2), 207–220. 1263 Walker, E., Rummel, N., & Koedinger, K. R. (2008). To tutor the tutor: Adaptive domain support for peer 1264

- Walker, E., Rummel, N., & Koedinger, K. R. (2008). To tutor the tutor: Adaptive domain support for peer tutoring. In B. P. Woolf, E. Aïmeur, R. Nkambou, & S. P. Lajoie (Eds.), *Proceedings of the Ninth International Conference on Intelligent Tutoring Systems (ITS 2008), Lecture Notes in Computer Science, Vol. 5091* (pp. 626–635). Springer, ISBN 978-3-540-69130-3
- Walker, E., Rummel, N., & Koedinger, K. (2009a). CTRL: A research framework for providing adaptive collaborative learning support. User Modeling and User-Adapted Interaction: The Journal of Personalization Research (UMUAI), 19(5), 387–431.
- Walker, E., Rummel, N., & Koedinger, K. (2009b). Integrating collaboration and intelligent tutoring data in evaluation of a reciprocal peer tutoring environment. *Research and Practice in Technology Enhanced Learning*, 4(3), 221–251.
- Walker, E., Rummel, N., & Koedinger, K. (2010). Automated adaptive support for peer tutoring in high-school mathematics. In K. Gomez, L. Lyons, & J. Radinsky (Eds.), *Learning in the Disciplines*. *Proceedings of the 9th International Conference of the Learning Sciences (ICLS 2010)*, Vol 2 (pp. 151–153). International Society of the Learning Sciences, Inc.
- Walker, E., Rummel, N., & Koedinger, K. (2011). Designing automated adaptive support to improve student helping behaviors in a peer tutoring activity. *International Journal of Computer Supported Collaborative Learning*, 6(2), 279–306.
- Webb, N. M., Troper, J. D., & Fall, R. (1995). Constructive activity and learning in collaborative small groups. Journal of Educational Psychology, 87(3), 406–423.
- Wecker, C., Kollar, I., Fischer, F., & Prechtl, H. (2010). Fostering online search competence and domain-specific knowledge in inquiry classrooms: Effects of continuous and fading collaboration scripts. In K. Gomez, L. Lyons, & J. Radinsky (Eds.), *Learning in the disciplines. Proceedings of the 9th International Conference of the Learning Sciences (ICLS 2010)*, Vol. 1 (pp. 810–817). International Society of the Learning Sciences (ICLS 2010), Vol. 1 (pp. 810–817).
- Westermann, K., & Rummel, N. (2012). Delaying instruction—Evidence from a study in a university relearning setting. *Instructional Science*. doi:0.1007/s11251-012-9207-8.

1288 1289 1290

 $1265 \\ 1266$ 

1267

1268

 $1269 \\ 1270$ 

1271

1272

 $1273 \\ 1274$ 

 $1275 \\ 1276$ 

1277

1278

 $1279 \\ 1280$ 

1281