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The Computer-Based Assessment of Complex Problem Solving and How It Is Influenced by Students' Information and Communication Technology Literacy

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The 21st-century work environment places strong emphasis on nonroutine transversal skills. In an educational context, complex problem solving (CPS) is generally considered an important transversal skill that includes knowledge acquisition and its application in new and interactive situations. The dynamic and interactive nature of CPS requires a computer-based administration of CPS tests such that the assessment of CPS might be partially confounded with information and communication technology (ICT) literacy. To establish CPS as a distinct construct that involves complex cognitive processes not covered by other general cognitive abilities and not related to ICT literacy, it is necessary to investigate the influence of ICT literacy on CPS and on the power of CPS to predict external educational criteria. We did so in 3 different samples of either high school or university students using a variety of instruments to measure ICT literacy and general cognitive ability. Convergent results based on structural equation modeling and confirmatory factor analyses across the studies showed that ICT literacy was weakly or moderately related to CPS, and these associations were similar to those between ICT and other general cognitive abilities. Furthermore, the power of CPS to predict external educational criteria over and above general cognitive ability remained even if the influence of ICT literacy on CPS was controlled for. We conclude that CPS is a distinct construct that captures complex cognitive processes not generally found in other assessments of general cognitive ability or of ICT literacy.

Keywords: ICT literacy, complex problem solving, reasoning, working memory, MicroDYN

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Occupational demands are changing rapidly in the 21st century (Autor & Dorn, 2009; Organisation for Economic Co-Operation and Development [OECD], 2010; Spitz-Oener, 2006), and nonroutine skills are becoming more and more important, whereas the importance of routine skills that are characterized by the repetitive occurrence of similar situations is decreasing (Autor, Levy, & Murnane, 2003). As nonroutine skills can be used in many situations and for different problems, these skills are by definition transversal rather than domain specific. Furthermore, facilitating transversal competencies is a central objective in a number of educational programs (Mayer & Wittrock, 2006), and transversal skills such as complex problem solving (CPS) play an important role in everyday life (Funke, 2010). Although transversal skills are found in a number of areas and encompass skills such as metacognition, creativity, as well as collaborative and CPS, this last skill is a particularly important and promising transversal skill that has recently received a lot of attention, especially in educational contexts. For instance, Mayer and Wittrock (2006) stated that one of education's greatest challenges is making students good problem solvers. Therefore, it is not surprising that CPS is now an integral part of international educational large-scale assessments such as the Programme for International Student Assessment (PISA), arguably the most influential educational large-scale survey worldwide (OECD, 2009a). According to Buchner (Frensch & Funke, 1995), CPS can be defined as:

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> The successful interaction with task environments that are dynamic (i.e., change as a function of user's intervention and/or as a function of time) and in which some, if not all, of the environment's regularities can only be revealed by successful exploration and integration of the information gained in that process. (p. 14)

CPS has some unique characteristics that distinguish it from other abilities such as reasoning or working memory (cf. Dörner, Kreuzig, Reither, & Stäudel, 1983; Fischer, Greiff, & Funke, 2012; Funke, 2001). It refers to complex and nontransparent situations because not all of the necessary information to solve the problem is available until the problem solver interacts with the problem dynamically. That is, some information is hidden at the outset (Frensch & Funke, 1995). Furthermore, dynamic changes and highly interrelated elements in CPS require problem solvers to actively generate information by applying adequate strategies. Finally, multiple goals have to be taken into account when trying to solve a problem. Thus, a dynamic interaction between the problem solver and the task situation is an inherent feature of CPS (Wirth & Klieme, 2003), and this kind of interaction is not conceptually inherent to other cognitive abilities. These characteristics of CPS are typical of transversal skills, and this is why CPS has a prominent relevance among them.

In general, CPS is composed of two overarching processes: the active acquisition of knowledge about a problem situation (knowledge acquistion; Mayer & Wittrock, 2006) and the active use of this knowledge, that is, finding a solution to a problem (knowledge application; Novick & Bassok, 2005). According to the definition of CPS and the aforementioned characteristics, especially those of interactivity and dynamics, the assessment of CPS should be particularly fruitful in the context of computer-based assessment (CBA). CBA provides a unique assessment environment for the required dynamic and interactive situations that cannot be provided by the use of paper-and-pencil instruments (Kyllonen, 2009; Williamson, Mislevy, & Bejar, 2006).

In the area of assessment, there has always been high interest in CPS as a higher order thinking skill (Kuhn, 2009) that may both conceptually and empirically complement assessments of other general cognitive abilities such as reasoning, working memory, perceptual speed, and so forth. In fact, recent findings have suggested that CPS has an added value beyond other general cognitive abilities. For example, an added value of CPS above and beyond reasoning abilities has been found in predictions of academic achievement (e.g., Greiff et al., 2013; Greiff, Wüstenberg, & Funke, 2012; Wüstenberg, Greiff, & Funke, 2012) and supervisor ratings of professional success (Danner, Hagemann, Schankin, Hager, & Funke, 2011). In general, it is assumed that the underlying cognitive processes of CPS are correlated with and yet distinct from other general cognitive abilities (cf. Schweizer, Wüstenberg, & Greiff, 2013; Wüstenberg et al., 2012) and that in addition, more complex cognitive processes related to knowledge acquisition and knowledge application are responsible for the added value of CPS in predicting relevant external criteria (cf. Gonzalez, Thomas, & Vanyukov, 2005; Greiff, Wüstenberg, et al., 2013; Wenke, Frensch, & Funke, 2005). However, a final embedding of CPS in the nomological network of theories on cognitive ability (e.g., in the Cattell-Horn-Carroll [CHC] theory; McGrew, 2009) has not yet been fully accomplished (cf. Greiff, Wüstenberg, et al., 2013).

ICT Literacy and How It Might Be Related to CPS

In recent studies that have demonstrated the incremental validity of CPS beyond other cognitive abilities, it has been argued that there are unique characteristics and complex cognitive processes inherent in CPS and that these are not found in the conceptualizations of other general cognitive abilities (Raven, 2000). However, due to the fact that CPS assessment instruments require computer-based test administration, researchers cannot rule out the possibility that the added value of CPS may stem from an influence of computer literacy on CPS test results. In this line of thinking, CPS tests would then provide an indirect measure of information and communication technology (ICT) literacy.

Due to the enhanced complexity and attractiveness of CBAs, it has been assumed that ICT literacy might have a strong impact on performance in CBAs, especially if these assessments require more complex interactions with the computer, a requirement that holds in particular for CPS. In a comprehensive definition, Tsai (2002) described ICT literacy as "the basic knowledge, skills, and attitudes needed by all citizens to be able to deal with computer technology in their daily life" (p. 69). Thus, declarative, procedural, and attitudinal aspects are covered by this conceptualization, which indicates that it is not only computer knowledge and skills that are important for handling CBAs. Affective components can influence performance as well. For instance, high computer anxiety may lead to discomfort when using the computer, resulting in lower performance on exploratory behavior. Thus, the added value of CPS above and beyond general cognitive ability could be due to tests of CPS inadvertently providing an indirect assessment of ICT literacy rather than to CPS representing additional complex cognitive processes required by the problem-solving situation. As a consequence, the overall validity of the CPS construct as a complex cognitive skill that is distinct from other general cognitive abilities might be threatened because empirical access to this construct is inevitably bound to the computer-based administration mode (cf. Parshall, Spray, Kalohn, & Davey, 2002; Russell, Goldberg, & O'Connor, 2003).

This concern is an important one especially against the background of the general shift from paper-pencil tests toward CBA (Goldhammer, Naumann, & Keßel, 2013). For example, early large-scale assessments (e.g., the PISA survey in 2003) used only paper-and-pencil assessments. Computer-based testing was partly introduced in PISA 2006 (OECD, 2007), substantially extended in PISA 2012 (OECD, 2010), included in the Programme for the International Assessment of Adult Competencies (OECD, 2009b), and, finally, will constitute the major mode of delivery in PISA 2015 (OECD, 2012). This progression can be accounted for by several general advantages of CBA (cf. Scheuermann & Björnsson, 2009; Van der Linden & Glas, 2000) such as high standardization and test efficiency, the logging of behavioral and process data, the possibility of automatic scoring, and the application of adaptive testing.

As any computer-administered test requires the test taker to interact with the computer, the influence of ICT literacy can be considered a general threat to the validity of any construct assessed via this mode of administration; thus, the issue is not limited to CPS. Studies concerning mode-of-delivery effects in general have addressed this topic but have provided inconsistent results. In an older meta-analysis, Mead and Drasgow (1993) found no overall difference between paper-pencil and CBAs. Nevertheless, the authors warned against drawing the conclusion that there is no test mode effect and thus no influence of ICT literacy at all. Therefore, it is not surprising that several studies have reported relevant test-mode effects (for an overview, see Clariana & Wallace, 2002; Russell et al., 2003). These inconsistent results might also be due to the fact that different types of tests imply more or less complex interactions with the computer and thus require different levels of ICT literacy.

In this sense, constructs such as CPS, which are based on more innovative item types that reflect the dynamic interaction and display features that are offered by the computer, are also more prone to the undesirable influence of ICT literacy. At the same time, for tests that rely on these new item types such as CPS, it is not possible to conduct studies on test-mode administration effects because the classical paper-and-pencil mode of administration is simply not available for these item types and thus cannot be compared with the computer-administrated mode. For other general cognitive abilities such as reasoning and working memory, empirical studies can be conducted to examine how assessment may be affected by changing the mode of delivery from paper-and-pencil to computer based. The question then arises: How can researchers understand and quantify the influence of ICT literacy on an assessment of complex cognitive skills such as CPS when the assessment can be administered only on the computer (Kyllonen, 2009)? That is, for CPS, it is yet unclear whether its added value in predicting external criteria (e.g., Schweizer et al., 2013; Wüstenberg et al., 2012) originates from the indirect assessment of ICT literacy or from the assessment of additional and relevant cognitive processes as mentioned above and as conceptually assumed.

The Added Value of CPS: Cognitive Processes or Merely ICT Literacy?

The central question of the current study is about the influence of ICT literacy on the CBA of CPS. Specifically, we asked how we could explain the added value in terms of the incremental validity of CPS in predicting relevant external criteria above and beyond general cognitive ability. We proposed two conspicuous explanations: additional cognitive processes, on the one hand, and additional demands on students' ICT literacy, on the other hand. Establishing the construct of CPS as a transversal skill would be warranted and an assessment of CPS in international large-scale studies would be justified only if the first explanation were to hold.

To tackle this question, we had to examine the simultaneous influence of general cognitive ability and ICT literacy on CPS. In general, cognitive abilities and CPS share cognitive processes to a certain extent (cf. Greiff, Wüstenberg, et al., 2013; Wüstenberg et al., 2012). However, according to the definition and characteristics of CPS, unique processes are supposed to be inherent to CPS. Different from general cognitive ability, which mainly requires a mere sequence of simple cognitive processes, CPS requires a series of different cognitive processes such as action planning and implementing, strategic development, knowledge acquisition, and self-regulation (Funke, 2010; Raven, 2000).

As outlined above, ICT literacy might also have an influence on CPS as a consequence of the mode of delivery. Each CBA requires at least basic computer knowledge as well as the related perceptual and motor skills that are needed to use the computer interface. Furthermore, by definition, higher ICT literacy leads to a more familiar and intuitive handling of the computer interface, or to look at it the other way around, if a student's ICT literacy in an assessment context is very low, cognitive resources have to be used to understand the computer interface, for example. This would tie up a large amount of cognitive capacity that would then not be available for CPS even if the core interest of the assessment lies in CPS (Goldhammer et al., 2013; see also cognitive load theory; Sweller, 2005). In conclusion, to determine whether CPS is more than general cognitive ability and ICT literacy combined, the relations of both of them to CPS must be examined simultaneously.

Surprisingly, there are hardly any empirical findings with regard to the impact of ICT literacy on CPS and none at all with regard to the relations between ICT literacy, general cognitive ability, and CPS. Hartig and Klieme (2005) reported small relations between CPS and self-reported ICT literacy. Further, Süß (1996) reported moderate to high correlations between objective indicators of ICT literacy and CPS. However, these early studies did not account for the development of innovative, more user-friendly computer interfaces or the substantial changes in the use and importance of computers in everyday life; these changes have thus resulted in study participants who can be considered "digital natives" (Prensky, 2001). In a recent study, Sonnleitner, Keller, Martin, and Brunner (2013) highlighted that an added value of CPS beyond reasoning is found only in academic achievement criteria that are assessed via computer but not in paper-pencil-assessed criteria. They concluded that the added value of CPS is merely an effect of test mode and thus of ICT literacy.

Overall, there are two possible explanations for the added value of CPS recently reported in the literature: complex cognitive processes that are not included in concepts of general cognitive ability or an indirect but substantial influence of ICT literacy on the CBA of CPS. However, there are very few studies that have targeted this issue, and these studies have produced inconsistent findings. The purpose of the current study was to take a deeper look into the impact of ICT literacy on CPS and on CBAs of transversal skills in general.

Purpose of the Study

Generally speaking, we want to advance knowledge on the question of how CPS and ICT literacy are related to each other and whether CPS indeed yields a valuable marker of additional complex cognitive processes or whether it is a confounded indicator of general cognitive ability and ICT literacy. Thus, we addressed the question of whether the added value of CPS reported in some studies could be explained by ICT literacy or, in other words, whether CPS is something other than general cognitive abilities such as reasoning or working memory and ICT literacy combined. To this end, we derived three research questions.

Research Question 1: How are ICT literacy and CPS related to each other?

For the first question, we examined latent correlations between ICT literacy and the CPS dimensions of knowledge acquisition and knowledge application.

Research Question 2: Does ICT literacy more strongly predict a CBA of CPS than ICT literacy predicts the assessment of general cognitive ability?

In the next step, we analyzed the latent regression of CPS and general cognitive ability on ICT literacy and tested whether ICT literacy would predict CPS more strongly than it predicted general cognitive ability.

Research Question 3: Can the added value of CPS be explained by ICT literacy or are distinct cognitive processes in CPS responsible for the added value?

For the last question, we examined whether CPS could explain academic achievement above and beyond general cognitive ability and ICT literacy combined or whether controlling for general cognitive ability and ICT literacy would result in the nonsignificant prediction of external criteria such as academic achievement by CPS.

To answer these questions, we used three different and diverse samples containing both high school and university students. In all these samples, the added value of CPS beyond general cognitive ability has been shown to exist in previously published articles (Study A: Wüstenberg et al., 2012; Study B: Greiff, Fischer, et al., 2013; Study C: Schweizer et al., 2013). However, the added value of CPS beyond ICT literacy and general cognitive ability was not tested in any of these studies. Thus, we extended the original analyses by adding ICT literacy, which was operationalized in diverse ways. According to its definition (see above; Tsai, 2002), ICT literacy is a broad concept composed of cognitive and affective aspects. Thus, a valid assessment of ICT literacy needs to endorse different operationalizations and methods (Ballantine, McCourt Larres, & Oyelere, 2007; Goldhammer et al., 2013; Van Braak, 2004). Therefore, we used subjective self-reports and different objective performance tests. Consequently, we used different operationalizations of general cognitive ability as well: figural reasoning and working memory capacity. Finally, an acknowledged and well-validated measure of CPS, namely MicroDYN (Greiff et al., 2012), was used in all three samples. To sum up, this approach allowed us to examine our research questions in different samples with heterogeneous assessments of ICT literacy and general cognitive ability. Our findings can thus be cross-checked to ensure that they are replicable and generalizable (Brennan, 1983).

Method

Assessment Instrument for CPS: MicroDYN

In all three studies (Study A, Study B, and Study C), a set of tasks used in the MicroDYN approach (Greiff et al., 2012) was used to assess CPS. In MicroDYN, students are first asked to detect causal relations in a dynamic system composed of several input and output variables. Subsequently, they are asked to control the system. These two tasks directly relate to the two characteristic CPS dimensions introduced above, knowledge acquisition and knowledge application, thus ensuring the theoretical embedding of the MicroDYN approach.

Recent results have indicated that MicroDYN is a reliable (consistent Cronbach's αs $>$ .70; cf. Greiff et al., 2012; Wüstenberg et al., 2012) and valid assessment instrument (Greiff, Wüstenberg, et al., 2013; Molnár, Greiff, & Csapó, 2013; Schweizer et al., 2013; Wüstenberg et al., 2012) that sufficiently reflects the theoretical concept of CPS. For instance, MicroDYN as an operationalization of CPS shows incremental validity in predicting academic achievement beyond general cognitive abilities such as reasoning and working memory (Greiff, Wüstenberg, et al., 2013; Schweizer et al., 2013; Wüstenberg et al., 2012). Further, a substantial number of the items used to assess CPS in 15-year-old students across a number of countries in the PISA 2012 study were developed within the MicroDYN approach.

A set of MicroDYN tasks typically encompasses five to 10 independent complex problems (also referred to as *microworlds* in the literature; cf. Funke, 2001), with time on task being approximately 5 min for each CPS task. Each task has an underlying causal structure unknown to the student and is divided into two subsequent phases: Phase 1, in which knowledge acquisition is assessed, and Phase 2, in which knowledge application is assessed. As an illustration, consider the MicroDYN task *handball training* displayed in Figure 1. There, input variables (i.e., different training strategies labeled Strategy A, Strategy B, Strategy C) influence several output variables (i.e., characteristics of the team labeled Motivation, Power of the throw, Exhaustion). In Phase 1, students can freely explore the task (duration: 3 min) by manipulating the sliders on the left and by observing subsequent changes in the output variables on the right (cf. Figure 1). During this free exploration, students are asked to specify the relations between variables on a concept map displayed at the bottom of Figure 1 by drawing arrows between input and output variables (e.g., between Strategy A and Motivation), thereby capturing their mental representation of the underlying system structure. In Phase 2, students are instructed to reach given goal values on the output variables (e.g., increasing the Power of the throw to five) by manipulating the input variables in the correct way (e.g., increasing Strategy B; duration: 1.5 min). Each MicroDYN task is embedded in a different cover story, and inputs as well as outputs are labeled without deep semantic meaning to increase motivation and minimize the influence of prior knowledge.

Depending on the specific number of tasks, a CPS assessment with MicroDYN takes between 40 and 60 min including instructions. Detailed information on the rationale underlying these types of tasks can be found in Funke (2001), and the MicroDYN approach is described in detail in Greiff et al. (2012) and Schweizer et al. (2013).

In all three samples, a set of MicroDYN tasks was used to capture knowledge acquisition and knowledge application as core dimensions of CPS (eight tasks in Study A, 10 tasks in Study B, and seven tasks in Study C). However, with regard to differences in cognitive potential across the three samples (e.g., high-ability university students with above-average cognitive performance in Study A and average-ability high school students in Grade 8 in Study C), MicroDYN task difficulty was adjusted accordingly. To increase difficulty for the more able samples, the underlying system structures of the MicroDYN tasks were designed to be more complex by increasing the number of inputs and outputs, by increasing the number of relations between them, and by introducing outputs that changed by themselves over time without active manipulation of the inputs (for details on altering difficulty in MicroDYN, cf. Greiff et al., 2012).

With regard to the scoring of MicroDYN, full credit for knowledge acquisition was given if students' models contained no mistakes. If additional relations were reported or actual relations were

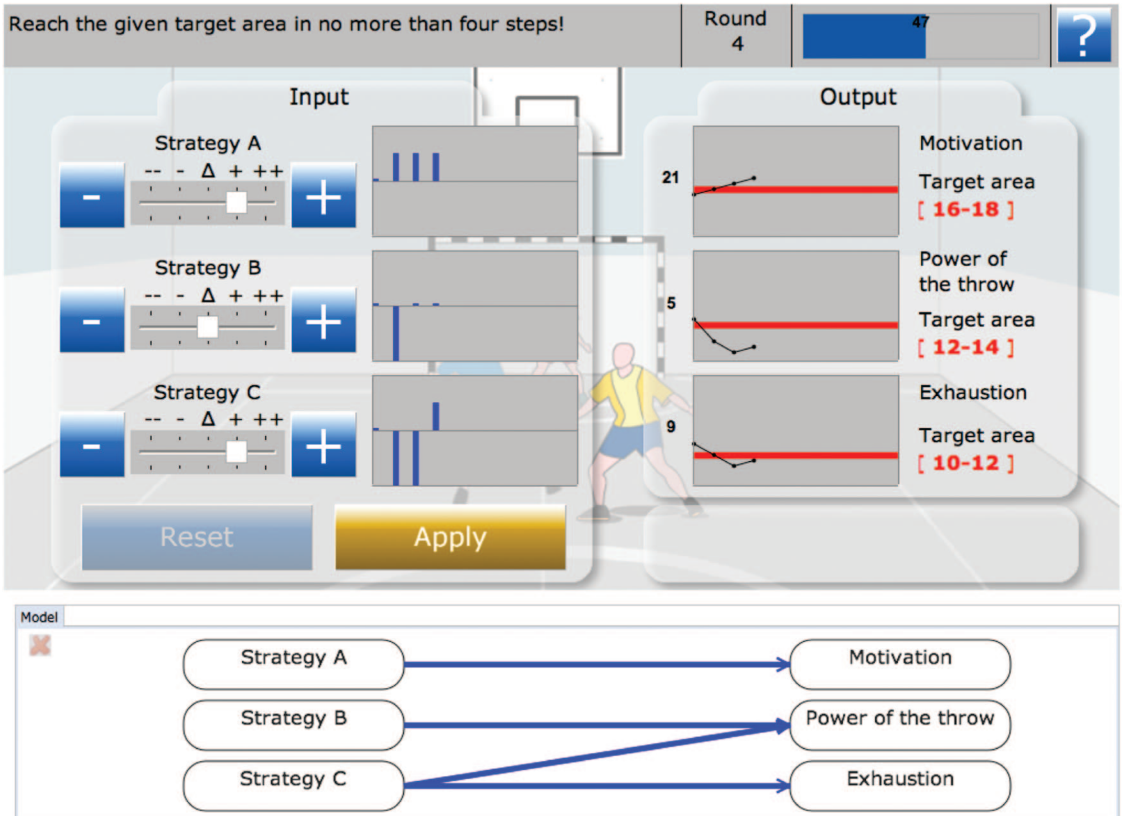

Figure 1. Screenshot of the MicroDYN task *handball training*. The controllers of the input variables range from "- -" (value = −2) to "++" (value = +2). The current values and the target values of the output variables are displayed numerically (e.g., current value for Motivation: 21; target values: 16–18) and graphically (current value: dots; target value: red line). The correct model is shown at the bottom of the figure (cf. Wüstenberg et al., 2012).

omitted, zero credit was assigned. A full score in knowledge application was given if goal values were reached, whereas no credit was given if target values were not reached (for details on scoring, cf. Greiff et al., 2012; Kröner, Plass, & Leutner, 2005). Thus, each MicroDYN task yielded indicators on knowledge acquisition and knowledge application totaling eight, 10, and seven indicators in Studies A, B, and C, respectively, for each of the two CPS dimensions.

Study A: Relations Among CPS Components, Computer Knowledge, Computer Anxiety, Figural Reasoning, and Final Grade-Point Average

Participants. The final sample consisted of N = 222 high-ability university students (69% female; age: M = 22.8; SD = 4.0) majoring mainly in psychology. In psychology, admission depends on final school grade-point average (GPA), and the selection process is highly competitive. As a consequence, psychology students at German universities usually have above-average cognitive performance. Students received partial course credit for participation and an additional obol (€5 [about $6 U.S.]) for working conscientiously. Missing data that occurred due to software problems or a failure of participants to work conscientiously led to n = 16 exclusions from the initial sample. The study took place in the Department of Psychology at the University of Heidelberg, Germany.

Materials.

CPS. MicroDYN with eight different tasks was used for the CPS assessment.

ICT literacy. ICT literacy was assessed using two subtests from the German inventory for the assessment of computer literacy, computer-related attitudes, and computer anxiety (Revised Computer Literacy Inventory, INCOBI-R; Richter, Naumann, & Horz, 2010). Both tests were administered on computers. The first subscale, Practical Computer Knowledge (PRACOWI), contains 20 written scenarios of commonly occurring computer problems. For each scenario, one of four presented solutions is correct. The subscale is substantially correlated with measures of computer use and predicts the ability to master everyday computer tasks (Appel, 2012; Naumann, Richter, & Groeben, 2001; Richter, Naumann, & Groeben, 2001; Richter et al., 2010). It distinguishes between computer experts and novices (Naumann et al., 2001) and is best described by a one-dimensional model (Richter et al., 2010). The scale shows good internal consistency (Cronbach's α = .83), and the items are one-dimensional according to the Rasch model. Thus, PRACOWI is a reliable and valid (e.g., $r = .60$ with basic computer skills) measure of the ability to deal successfully with everyday computer tasks and problems. It represents the declarative knowledge scope of ICT literacy described by Tsai (2002). The second subscale, Computer Anxiety (COMA), captures worries about the personal use of computers and computer-related anxiety. Computer anxiety is seen as a trait that includes cognitive and affective components (Morris, Davis, & Hutchings, 1981; Richter et al., 2010). The items refer to feelings of anxiety (e.g., "Working with the computer makes me uneasy") as well as to cognitions of concern (e.g., "When working with the computer, I am often afraid of breaking something"). The subscale covers the scope of attitudes toward ICT literacy (cf. Van Braak, 2004). Discriminant and criterion validity ($r = -.33$ with duration of computer experience) and good reliability (Cronbach's $\alpha = .82$) of the COMA have been shown in several samples (e.g., Appel, 2012; Richter et al., 2010). The subscale consists of eight self-report items that are rated on a 5-point Likert scale (from -2 = *do not agree* to 2 = *agree*), with higher values indicating higher anxiety.

General cognitive ability. Figural reasoning as a general cognitive ability was assessed using a computer-adapted version of the Advanced Progressive Matrices (APM; Raven, 1958). This test is viewed as a valid indicator of fluid intelligence (Raven, Raven, & Court, 1998) and shows good internal consistency (Cronbach's $\alpha = .85$). Each item was scored dichotomously.

Academic achievement. Academic achievement was measured as students' self-reported final school GPA at the end of schooling. As usual in German schools, school marks ranged from 1 (*excellent*) to 6 (*poor*). For further analyses, we reversed the school marks so that higher numerical values reflected better performance.

Procedure. Testing was split into two sessions, each lasting approximately 50 min. In the first session, students worked on MicroDYN. In the second session, the APM, PRACOWI, and COMA were administered. Afterwards, students provided demographic data as well as school marks.

Study B: Relations Among CPS Components, Basic Computer Skills, Computer Anxiety, Figural Reasoning, and Final School Marks

Participants. The sample consisted of 341 university students (67% female; age: $M = 22.3$; $SD = 4.0$) with a broad study background who were majoring mainly in social sciences. Students received either partial course credit or a financial reimbursement of €20 (about $25 U.S.) for their participation. The study took place in the Department of Psychology at the University of Heidelberg, Germany.

Materials.

CPS. MicroDYN with 10 different tasks was used for CPS assessment.

ICT literacy. ICT literacy was assessed with two different instruments. First, a further developed version of the Basic Computer Skills Test (BCS; Goldhammer et al., 2013) was used; it is considered a computer-based, objective, and performance-based measure of basic ICT skills in line with Tsai (2002). The 20 tasks require students to access, collect, and provide information in simulated graphical user interfaces of several computer environments (e.g., web browser, text editor). The environments, although only an abstract representation of real software, share general characteristics of real computer environments (for more details and task descriptions, see Goldhammer et al., 2013). Further, Goldhammer et al. (2013) reported substantial correlations with other measures of computer skills (e.g., $r = .60$ with PRACOWI), discriminant validity (e.g., $r = .32$ with word recognition), unidimensionality, and good reliability (Cronbach's $\alpha = .70$). Therefore, the BCS can be considered to be a valid measure of ICT literacy. For each task, the correct user response (BCS ability according to Goldhammer et al., 2013) was given full credit; otherwise, no credit was given. As a second measure, the COMA of the INCOBI-R (Richter et al., 2010) as in Study A (see above) was used.

General cognitive ability. Figural reasoning as a general cognitive ability was assessed using a computer-adapted version of the matrices subtest of the Intelligence Structure Test-Revised (Beauducel, Liepmann, Horn, & Brocke, 2010). This test is viewed as a good indicator of reasoning (cf. Carroll, 1993) but consists of more diverse task contents than the APM test used in Study A. According to the test manual, the matrices subtest showed an acceptable reliability (Cronbach's $\alpha = .71$) and validity (Beauducel et al., 2010). Each item of the subtest was scored dichotomously.

Academic achievement. Academic achievement was reported as final school marks when leaving high school in four natural science subjects (math, physics, chemistry, and biology) and five subjects that consisted of either social sciences or languages (German, English, history, geography, and social studies). School marks were reversed for all analyses so that higher numerical values reflected better performance.

Procedure. Testing was divided into two sessions of 2.5 and 2 hr. In the first session, students worked on MicroDYN and provided demographic data as well as school marks. In the second session, the IST, BCS, and COMA were administered. Additional measures that were not relevant for this article were administered in both the first and second sessions.

Study C: Relations Among CPS Components, Computer Anxiety, Working Memory Capacity, and Annual School Marks

Participants. The sample consisted of 389 high school students (60% female; age: $M = 17.1$; $SD = 1.1$). Students were offered individual feedback on their results in return for their participation. From the initial sample, $n = 16$ students were excluded from the analyses because of software errors. The study took place at two German high schools, both located in southwestern Germany.

Materials.

CPS. MicroDYN with seven different tasks was used for the CPS assessment.

ICT literacy. ICT literacy was assessed using the COMA from the INCOBI-R (Richter et al., 2010) as in Study A.

General cognitive ability. Numerical and spatial working memory capacity were assessed as measures of general cognitive ability using a computer version of the memory updating numerical task (MUN; Oberauer, Süß, Schulze, Wilhelm, & Wittmann, 2000; Sander, 2005). The aim of the MUN task is to remember the values and the locations of several numbers displayed on the screen, to mentally modify the values according to the task ("updating"), and to return the modified numbers in the proper places (for a detailed description, see Schweizer et al., 2013). Thus, the MUN requires the storage and transformation of information as well as its coordination. The MUN task is used as a marker task for working memory (cf. Oberauer, Süß, Wilhelm, & Wittmann, 2003) because of its good reliability (Cronbach's $\alpha = .81$) and validity (e.g., substantial factor loadings on the working memory factor simultaneous storage and transformation and the factor coordination). For each item, the percentage of correctly reproduced numbers was used as the performance indicator.

Academic achievement. Academic achievement was reflected in school marks from the latest annual school certificate in four natural science subjects (math, physics, chemistry, and biology) and three social science subjects (history, geography, and social studies). School marks were reversed for all analyses so that higher numerical values reflected better performance.

Procedure. Testing consisted of one session of 1.5 hr. Students worked on MicroDYN, the MUN, and COMA and provided demographic data as well as school marks. Additional measures that were not relevant for this article were administered subsequently.

Summary of Measures

Overall, two dimensions of CPS, knowledge acquisition and knowledge application, were assessed on the computer by MicroDYN (in all three studies); ICT literacy was assessed on the computer by measuring practical computer knowledge (PRACOWI; Study A), basic computer skills (BCS; Study B), and computer anxiety (COMA; Studies A, B, and C); general cognitive ability was assessed on the computer by measuring figural reasoning (the APM in Study A, a subtest of the IST in Study B) and working memory capacity (Study C); and academic achievement was measured by overall GPA (Study A), final school marks when leaving high school (Study B), and school marks from the students' latest annual school certificate (Study C).

Statistical Methods

Data were analyzed using confirmatory factor analysis (CFA) and structural equation modeling (SEM; cf. Bollen, 1989); that is, all reported results and coefficients were measured on a latent level without measurement error. All models were estimated with the software MPlus 7.0 (Muthén & Muthén, 2012). To evaluate model fit for SEM, we applied standard fit indices such as the comparative fit index (CFI), Tucker-Lewis Index (TLI), root-mean-square error of approximation (RMSEA), standardized root-mean-square residual (SRMR), and weighted root-mean-square residual (WRMR) by endorsing the cutoff values recommended by Hu and Bentler (1999). Unless noted otherwise, we applied standard maximum likelihood estimation and used the full information maximum likelihood estimation method to adjust for missing data in order to ensure high statistical power for the detection of small effects.

In all three studies, we used the following statistical analyses for each research question:

To tackle the first research question, we analyzed the relation between CPS and ICT literacy by computing latent correlations (i.e., correlations adjusted for measurement error).

To tackle the second research question, we analyzed latent relations between CPS and general cognitive ability as criteria and ICT literacy as a predictor in a first model. In this model, the path coefficients from ICT literacy to CPS and general cognitive ability indicated the corresponding impact of ICT literacy. However, even if the path coefficient from ICT literacy to CPS were stronger than the path coefficient from ICT literacy to general cognitive ability, it would not be clear whether ICT literacy had a greater influence on CPS or whether the variation in path coefficients occurred merely by chance. To test this question statistically, we modified the first model to derive a second model. In this second model, the path coefficients from ICT literacy to CPS and general cognitive ability were constrained to equality to simulate an equal impact of ICT literacy on CPS and general cognitive ability. The subsequent change in model fit between the first and the second models provided the answer about whether the difference in impact of ICT literacy was statistically meaningful. If the chi-square difference between the unconstrained (i.e., first) and constrained (i.e., second) model turned out to be significant, this would indicate that constraining the parameters to equality significantly worsened the model fit, and, therefore, we would have to assume an unequal impact of ICT literacy on CPS and general cognitive ability. If several measures of ICT literacy were used in one study (i.e., in Studies A and B), constraints were imposed separately for each measure in order to be able to quantify the impact of the specific ICT literacy measure on CPS and general cognitive ability. We used chi-square difference tests with the mean- and variance-adjusted maximum likelihood estimator (cf. Muthén & Muthén, 2012) for these analyses.

To tackle the third research question, we analyzed the incremental validity of CPS with regard to academic achievement as the criterion in all three studies. In other words, after controlling for general cognitive ability and ICT literacy, we entered CPS as a third predictor in the equation. In detail, we checked the predictive validity of ICT literacy and general cognitive ability in a single model. In a second step, we further added CPS and thus entered all constructs into one model. In this latter model, CPS was regressed on general cognitive ability and ICT literacy first. The CPS residuals of this regression as well as general cognitive ability and ICT literacy were then used to predict academic achievement. If the path coefficients of the CPS residuals ended up being significant, this would indicate that CPS explained additional variance above and beyond general cognitive ability and ICT literacy. That is, the added value of CPS would then not be attributable to an indirect assessment of ICT literacy within CPS measures (for more details on this specific regression procedure, see Wüstenberg et al., 2012). When several indicators of academic achievement were available (Studies B and C), we used CFA to calculate latent grade factors (one factor for natural sciences and one factor for social sciences and languages) instead of using a manifest grade marker of academic achievement (Study A). Furthermore, if the indicators for academic achievement were ordered categorical variables, we used the weighted least squares mean- and variance-adjusted estimator (Muthén & Muthén, 2012) for the statistical analysis of the last research question.

Results

The purpose of this article was to examine the influence of ICT literacy on CPS. Therefore, instead of turning our attention to verifications of different measurement models, we referred to already existing research to derive the measurement models. That is, the structure and dimensionality as well as the model fit of the measurement models were described in the corresponding articles: for CPS and general cognitive ability, Wüstenberg et al. (2012; Study A), Greiff, Wüstenberg, et al. (2013; Study B), and Schweizer et al., (2013; Study C); for basic computer skills, Goldhammer et al. (2013; Study B); and for practical computer knowledge and computer anxiety, Richter et al. (2010; Study A and all three studies, respectively). On this basis, we created parcels (according to the item-to-construct balance recommended by Little, Cunningham, Shahar, & Widaman, 2002) for each measurement (i.e., measures of CPS, ICT literacy, and general cognitive ability) in order to better capture the latent constructs and to increase the accuracy of parameter estimations. The model fit for all parceled measurement models in our study was at least acceptable (i.e., CFI and TLI $> .95$; RMSEA $< .06$; SRMR $< .05$ or WRMR $< .90$). Comprehensive correlation tables are available in the supplementary material.

Results for Research Question 1: How Are ICT Literacy and CPS Related to Each Other?

For each analysis used to address this research question, all structural models showed good model fit (i.e., CFI and TLI $> .95$; RMSEA $< .06$; SRMR $< .05$ or WRMR $< .90$).

Study A. The latent correlation between the two measures of ICT literacy used in Study A (i.e., practical computer knowledge and computer anxiety) of $r = -.73$ ($p < .01$) was about the same size as the original $r = -.59$ reported by Richter et al. (2010). However, the latter correlation was on a manifest level and was thus uncorrected for measurement error, whereas the former was corrected for measurement error. Correlations between practical computer knowledge and both knowledge acquisition ($r = .44$, $p < .01$) and knowledge application ($r = .36$, $p < .01$) were moderate in size. Furthermore, correlations between computer anxiety and both knowledge acquisition ($r = -.25$, $p < .01$) and knowledge application ($r = -.20$, $p < .05$) were small in size but statistically significant.

Study B. The two measures of ICT literacy used in Study B (i.e., basic computer skills and computer anxiety) were moderately correlated ($r = -.30$, $p < .01$). Correlations between basic computer skills and both knowledge acquisition ($r = .58$, $p < .01$) and knowledge application ($r = .63$, $p < .01$) were large and significant. Smaller, but still significant, were the correlations between computer anxiety and both knowledge acquisition ($r = -.22$, $p < .01$) and knowledge application ($r = -.31$, $p < .01$). Although the latter were slightly higher than in Study A, the relations between computer anxiety and CPS were similar between the two studies.

Study C. There were small but significant correlations between computer anxiety and both knowledge acquisition ($r = -.17$, $p < .01$) and knowledge application ($r = -.21$, $p < .01$). Again, the sizes of the coefficients were similar to the other studies.

In conclusion, in all three studies, there were significant relations between different operationalizations of ICT literacy and CPS. In detail, the relations between both knowledge-based and behavioral measures of ICT literacy (i.e., practical computer knowledge and basic computer skills) and CPS were higher than the relation between attitudinal measures of ICT literacy (i.e., computer anxiety) and CPS. The expected modest correlations between the CPS components and operationalizations of ICT literacy indicate that the two constructs are separable.

Results for Research Question 2: Does ICT Literacy More Strongly Predict a CBA of CPS Than ICT Literacy Predicts the Assessment of General Cognitive Ability?

Study A. The model with practical computer knowledge and computer anxiety as simultaneous predictors of CPS and reasoning showed a good overall model fit (Model A.1 in Table 1; see Figure 2 for an illustration of the type of model evaluated in Research Question 2). As expected, practical computer knowledge predicted knowledge acquisition ($\beta = .59$, $p < .01$), knowledge application ($\beta = .47$, $p < .01$), and reasoning ($\beta = .55$, $p < .01$). However, computer anxiety was not a significant predictor at all in this model (knowledge acquisition: $\beta = -.23$; knowledge application: $\beta = -.20$; reasoning: $\beta = -.19$; all *p*s $> .05$; see Figure 2) even though in the bivariate analysis used to address Research Question 1, computer anxiety was correlated with CPS. The high correlation

Table 1
Fit Indices for Different Models for Research Question 2

Model	χ^2	*df*	*p*	CFI	TLI	RMSEA	WRMR
Model A.1	116.43	94	.06	.976	.969	.037	.798
Model A.2: constrained for PRACOWI	117.43	96	.07	.977	.971	.035	.800
Model A.3: constrained for COMA	117.12	96	.07	.977	.972	.035	.797
Model B.1	90.08	80	.21	.987	.983	.024	.908
Model B.2: constrained for BCS	91.39	82	.22	.988	.984	.023	.907
Model B.3: constrained for COMA	93.49	82	.18	.985	.981	.026	.962
Model C.1	69.55	59	.16	.992	.989	.023	.754
Model C.2: constrained for COMA	77.91	61	.07	.987	.984	.029	1.157

Note. χ^2 and *df* estimates are based on mean- and variance-adjusted maximum likelihood. CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root-mean-square error of approximation; WRMR = weighted root-mean-square residual; PRACOWI = Practical Computer Knowledge; COMA = Computer Anxiety; BCS = Basic Computer Skills.

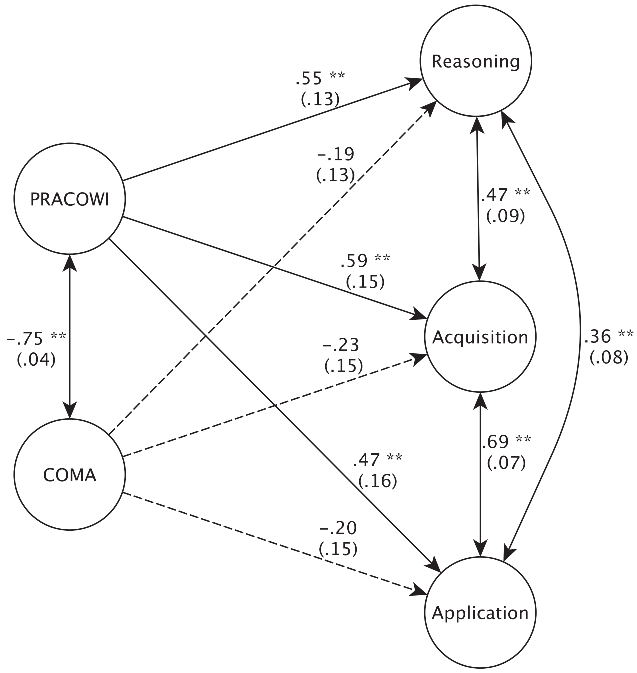

Figure 2. Model A.1 for Research Question 2. Reasoning, knowledge acquisition, and knowledge application were regressed on practical computer knowledge (PRACOWI) and computer anxiety (COMA). Parcels are not depicted. Standard errors are in parentheses. ** $p < .001$.

between practical computer knowledge and computer anxiety (see Study A with regard to Research Question 1) as well as the lower power of this analysis due to the increased number of variables in the model in Figure 2 were possible explanations for the nonsignificant prediction of computer anxiety.

If the paths from practical computer knowledge to CPS and reasoning were constrained to equality (Model A.2), model fit did not decrease significantly, $\chi^2(2) = 1.338$, $p > .05$. Constraining the paths from computer anxiety to CPS and reasoning to equality did not significantly decrease model fit either (Model A.3), $\chi^2(2) = 0.670$, $p > .05$. Thus, CPS was not more strongly predicted by ICT literacy than was general cognitive ability.

Study B. The model in which basic computer skills and computer anxiety simultaneously predicted CPS and reasoning showed a good overall model fit (Model B.1 in Table 1). Basic computer skills predicted knowledge acquisition ($\beta = .44$, $p < .01$), knowledge application ($\beta = .52$, $p < .01$), and reasoning ($\beta = .47$, $p < .01$). Computer anxiety was a significant predictor of knowledge acquisition ($\beta = -.14$, $p < .05$) and knowledge application ($\beta = -.23$, $p < .05$), but not of reasoning ($\beta = -.04$, $p > .05$). If the paths from basic computer skills to CPS and reasoning were constrained to equality, the model did not fit significantly worse (Model B.2), $\chi^2(2) = 1.616$, $p > .05$. Constraining the paths from computer anxiety also did not significantly decrease the model fit (Model B.3), $\chi^2(2) = 4.177$, $p > .05$.[1] In sum, CPS was not more strongly predicted by ICT literacy than was general cognitive ability.

Study C. The model with computer anxiety as a predictor of CPS and working memory capacity showed a good overall model fit (Model C.1 in Table 1). Computer anxiety predicted knowledge acquisition ($\beta = -.18$, $p < .01$) and knowledge application ($\beta = -.24$, $p < .01$) but not working memory capacity ($\beta = -.01$, $p > .05$). If the paths from computer anxiety to CPS and working memory capacity were constrained to equality, the model fit decreased significantly (Model C.2), $\chi^2(2) = 9.027$, $p < .05$. Results indicated that CPS was more strongly predicted by ICT literacy than was general cognitive ability.

In summary, the findings of two out of the three studies demonstrated that CPS was not more strongly predicted by ICT literacy than was general cognitive ability. In detail, both behavioral and attitudinal operationalizations of ICT literacy impacted CPS in a manner that was similar to their impact on different assessments of figural reasoning. However, CPS was more strongly predicted by attitudinal measures of ICT literacy (i.e., computer anxiety) than was working memory capacity.

Results for Research Question 3: Can the Added Value of CPS Be Explained by ICT Literacy or Are Distinct Cognitive Processes in CPS Responsible for the Added Value?

Study A. In these analyses, we used GPA as a manifest variable. The first model with reasoning, practical computer knowledge, and computer anxiety as predictors of GPA (manifest) showed a good model fit (Model A.1 in Table 2). However, only reasoning ($\beta = .39$, $p < .01$) and computer anxiety ($\beta = -.25$, $p < .05$) significantly predicted GPA but practical computer knowledge did not ($\beta = .05$, $p > .05$). Altogether, about 16% of the variance in GPA was explained in this model. In a second model (A.2), the residuals of CPS after controlling for reasoning and ICT literacy were added simultaneously to the predictors that were already included in the first model (see Figure 3 for an illustration of the type of model evaluated in Research Question 3). Again, GPA was significantly predicted by reasoning ($\beta = .40$, $p < .01$) and computer anxiety ($\beta = -.25$, $p < .05$) but not by practical computer knowledge ($\beta = .06$, $p > .05$). Furthermore, the residuals of CPS after controlling for reasoning, computer anxiety, and practical computer knowledge predicted GPA beyond general cognitive ability and ICT literacy (residuals of knowledge acquisition: $\beta = .24$, $p < .05$; residuals of knowledge application: $\beta = -.09$, $p > .05$; see Figure 3). In the second model, 21% of the variance was explained by CPS, indicating that 5% of the variance was additionally explained in comparison to the first model.

Study B. The measurement model for school marks as the criterion in these analyses with the two dimensions natural sciences and social sciences along with languages showed a good model fit, $\chi^2(26) = 24.03$, $p > .05$; CFI = 1.000; TLI = 1.000; RMSEA = .000; WRMR = .528.

Beginning with a model in which final school marks in the natural sciences were significantly predicted by reasoning ($\beta = .48$, $p < .01$) but not by basic computer skills ($\beta = -.04$, $p > .05$)

[1] The maximum difference in path size was between knowledge application in CPS and reasoning. Therefore, we tested another more conservative model. However, the results for this more conservative model did not change if just the paths from computer anxiety to knowledge application and reasoning were constrained to equality, whereas the path to knowledge acquisition was freely estimated, $\chi^2(1) = 3.252$, $p > .05$.

Table 2
Fit Indices for Different Models for Research Question 3

Model	χ^2	*df*	*p*	CFI	TLI	RMSEA	WRMR
Model A.1: g, PRACOWI, and COMA predict GPA	49.714	39	.12	.990	.987	.035	.035[a]
Model A.2: g, PRACOWI, COMA, and CPS predict GPA	134.39	105	.03	.983	.977	.036	.041[a]
Model B.1: g, BCS, and COMA predict school marks	142.33	125	.14	.984	.980	.020	.741
Model B.2: g, BCS, COMA, and CPS predict school marks	260.09	233	.11	.980	.977	.018	.733
Model C.1: MUN and COMA predict school marks	94.33	71	.03	.987	.984	.029	.697
Model C.2: MUN, COMA, and CPS predict school marks	193.98	155	.02	.984	.980	.025	.695

Note. χ^2 and *df* estimates are based on maximum likelihood (ML; Models A.1 and A.2) and weighted least squares mean- and variance-adjusted estimator (Models B.1 to C.2 because of ordered categorical school marks), respectively. CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root-mean-square error of approximation; WRMR = weighted root-mean-square residual; g = Reasoning; PRACOWI = Practical Computer Knowledge; COMA = Computer Anxiety; GPA = grade-point average; CPS = complex problem solving; BCS = Basic Computer Skills; MUN = memory updating numerical.
[a] Standardized root-mean-square residual because of ML estimator for Models A.1 and A.2.

or by computer anxiety ($\beta = -.01$, $p > .05$), and school marks in the social sciences and languages were predicted only by computer anxiety ($\beta = -.20$, $p < .05$) but not by reasoning ($\beta = .17$, $p > .05$) or by basic computer skills ($\beta = .14$, $p > .05$), we found 21% explained variance in school marks in the natural sciences and 8% explained variance in school marks in the social sciences and languages. The overall model fit was good (see Model B.1 in Table 2). In a second model with good overall model fit (Model B.2 in Table 2) and with the CPS residuals as an additional predictor, there was no substantial change in the pattern of results for reasoning (natural sciences: $\beta = .48$, $p < .01$; social sciences and languages: $\beta = .15$, $p > .05$), basic computer skills (natural sciences: $\beta = -.04$, $p > .05$; social sciences and languages: $\beta = .15$, $p > .05$), and computer anxiety (natural sciences: $\beta = .00$, $p > .05$; social sciences and languages: $\beta = .20$, $p < .05$). Additionally, the residuals of knowledge application significantly predicted school marks in the natural sciences ($\beta = .18$, $p < .05$), but no variance in school marks in the social sciences and languages was incrementally predicted by CPS. Overall, 24% of the variance in the natural sciences and 8% of the variance in the social sciences and languages were explained by the second model, indicating that 3% of the variance in the natural sciences and 0% in the social sciences and languages were additionally explained when CPS was included as a third predictor.

Study C. The measurement model for school marks as the criterion in these analyses with the two dimensions natural sciences and social sciences showed a good model fit, $\chi^2(13) = 19.56$, $p > .05$; CFI = .986; TLI = .978; RMSEA = .036; WRMR = .637.

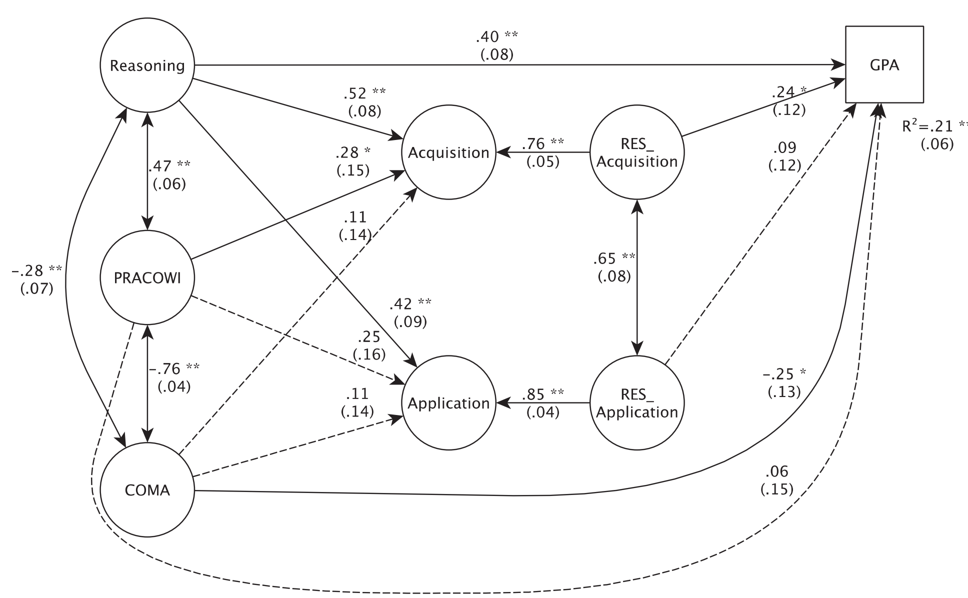

Figure 3. Model A.2 for Research Question 3. Knowledge acquisition and knowledge application were regressed on reasoning, practical computer knowledge (PRACOWI), and computer anxiety (COMA). The computer problem-sovling residuals (RES) of this regression as well as reasoning, practical computer knowledge, and computer anxiety were used to predict grade-point average (GPA). Parcels are not depicted. Standard errors are in parentheses. * $p < .05$. ** $p < .001$.

The first model with working memory capacity and computer anxiety as predictors of annual school marks showed a good model fit (Model C.1 in Table 2). Working memory capacity significantly predicted natural science school marks ($\beta = .26$, $p < .01$), but computer anxiety did not ($\beta = -.02$, $p > .05$). Similar results held for the social sciences. There, working memory capacity was a significant predictor ($\beta = .11$, $p < .05$), but computer anxiety was not ($\beta = .00$, $p > .05$). For school marks in the natural sciences, 7% of the variance was explained, and for social science school marks, 1% was explained. If CPS residuals were included in the second model (Model C.2) as additional predictors, only the residuals of knowledge acquisition significantly predicted marks in the natural sciences ($\beta = .25$, $p < .01$) and social sciences ($\beta = .26$, $p < .01$). There was no change in the pattern of results for working memory capacity (natural sciences: $\beta = .26$, $p < .01$; social sciences and languages: $\beta = .11$, $p < .05$) and computer anxiety (natural sciences: $\beta = -.02$, $p > .05$; social sciences and languages: $\beta = .00$, $p > .05$). In the second model, 18% of the variance in natural science school marks and 7% of the variance in social science school marks were explained, indicating that 11% and 6%, respectively, were additionally explained by including the CPS residuals in comparison to the first model.

Overall, all three studies demonstrated an added value of CPS beyond different operationalizations of general cognitive ability and ICT literacy. In detail, CPS additionally explained up to 11% of the variance in academic achievement. As indicated by the findings of Studies B and C, CPS was a stronger predictor of academic achievement in the natural sciences than in the social sciences and languages.

Discussion

The aim of the current study was to deepen the understanding of how individual CPS skills, which are currently receiving considerable interest in educational contexts as a highly relevant transversal skill (Mayer & Wittrock, 2006), are influenced by ICT literacy. To cover the construct comprehensively, this question was pursued in three different samples with a number of different measures of ICT literacy. Furthermore, we controlled for different general cognitive abilities such as reasoning and working memory when relating CPS and ICT literacy. In general, the results of our study supported the assumption that an assessment of CPS allows complex cognitive processes to be captured. These processes are related to ICT literacy and general cognitive ability to a certain extent but not exclusively so. More specifically, CPS skills were weakly to moderately related to ICT literacy (Research Question 1). However, the relations between CPS and different assessments of ICT literacy were (with one exception) just as strong as between general cognitive ability and ICT literacy (Research Question 2). Most importantly, we were able to determine that the added value of CPS recently reported in the literature is not attributable to an indirect assessment of ICT literacy in CPS measures. That is, ICT literacy assessment and CPS assessment were not confounded in such a way that the validity of the latter was threatened. In fact, when controlling for general cognitive ability and ICT literacy, the incremental validity of CPS in predicting relevant external criteria remained substantial (Research Question 3).

In accordance with previous research (Hartig & Klieme, 2005; Süß, 1996), we found a noteworthy relation between CPS and ICT literacy. We can therefore repeat Mead and Drasgow's (1993) word of caution that the influence of ICT literacy in CBA should not be underestimated and that any computer-delivered measurement instrument should be carefully designed and examined. This may be even more important for assessment instruments that reflect rather complex skills such as CPS or serious games (cf. Michael & Chen, 2006; Russell et al., 2003) that require a somewhat more complex graphical user interface. However, in contrast to recently reported results by Sonnleitner et al. (2013), the added value of CPS independent of ICT literacy was demonstrated consistently in three studies. Sonnleitner et al. (2013) reported an added value of CPS only if the assessment of academic achievement as a criterion was computer based, an idea that indirectly suggests a strong effect of ICT literacy. A reason for the discrepancy between studies could lie in the different operationalizations of CPS. GeneticsLab, the CPS assessment used by Sonnleitner et al. (2013), requires more advanced human–computer interactions than MicroDYN concerning the documentation of acquired knowledge and thus, arguably, an even higher level of ICT literacy. In MicroDYN, students are asked simply to draw arrows between variables on a concept map displayed at the bottom of the screen (see Figure 1), whereas in the GeneticsLab, the concept map is presented in a separate display, and students are asked to draw the relations and to label the strengths of the relations between the variables on a more comprehensive and also more complicated concept map. As a consequence, the GeneticsLab has a longer instruction phase, several user-interface environments for different CPS dimensions, more differentiated knowledge inquiry, and so forth. These features that are characteristic of CPS may increase the validity of the CPS assessment but at the same time may also increase the potential impact of ICT literacy and, thus, the prediction of computer-based external criteria as reported by Sonnleitner et al. (2013). Taking into account the different results concerning the influence of ICT literacy on CPS, we conclude that the impact of ICT literacy depends on the operationalization of CPS and the specific implementation of the assessment. For MicroDYN as a CPS assessment tool, ICT literacy was no threat to its validity. However, this article's purpose, which was to examine the impact of ICT literacy, should be considered for every new operationalization of CPS.

This study was driven by two mutually exclusive explanations for the added value of CPS. It was argued that either (a) CPS assessment captures unique characteristics and complex cognitive processes that are not inherent to general cognitive ability or (b) the assessment of CPS is a confounded assessment of general cognitive ability and ICT literacy. Our findings did not support the second explanation. With regard to the incremental validity of CPS in particular, we came to the conclusion that the assessment of CPS allows researchers to consider complex cognitive processes beyond general cognitive ability (cf. Raven, 2000), indicated by the finding that up to 11% of the variance in academic achievement was additionally explained by CPS beyond the variance explained by general cognitive ability and ICT literacy even though the prediction of social science and language grades was considerably lower. However, the overall result pattern provides important evidence for the validity of CPS in line with recent research (Greiff et al., 2012; Greiff, Wüstenberg, et al., 2013; Wüstenberg et al., 2012).

Furthermore, we discuss two details of our findings more specifically. First, with regard to the different operationalizations of general cognitive ability, we found a stronger influence of the attitudinal component of ICT literacy on CPS than on working memory. In fact, the MUN tasks that were used to assess working memory in Study C were not related to computer anxiety at all. Working memory is supposed to be a general, albeit basic, cognitive ability (cf. Oberauer, Süß, Wilhelm, & Wittmann, 2008), and, thus, its assessment requires just simple human–computer interactions. In contrast to MicroDYN, for which students are asked to use several input and display elements (e.g., sliders, concept maps, diagrams) in different user interfaces, the only computer interaction in the MUN task is indeed just to successively press a number key on the keyboard to interact within a simple and uniform graphical user interface. Thus, we argue that a less complex human–computer interaction will be less influenced by ICT literacy (i.e., at least by the attitudinal component of ICT literacy). Therefore, our findings are rendered even more powerful because, despite increased interactions within the user interface of our CPS assessment (cf. Figure 1), the predictive validity of CPS was not reduced in any of the three studies.

The second detailed result that is worth mentioning is the differential predictive power of the two CPS dimensions: knowledge acquisition and knowledge application. In previous research (e.g., Schweizer et al., 2013; Wüstenberg et al., 2012), knowledge acquisition was the stronger predictor of academic achievement. However, our findings from Study B with regard to Research Question 3 showed a different pattern: Knowledge application was the strongest predictor rather than knowledge acquisition. There may be two different explanations for this result. First, the two dimensions are empirically separable but are highly correlated as found in previous studies (latent correlation around .70–.80). As a consequence, the differences in the relations of the two dimensions to external criteria could be due to a random capitalization on chance with knowledge acquisition being more strongly related to external criteria in some samples and knowledge application in others. Thus, a replication of the finding in Study B should be the next step taken to gain further insights into this issue. The second explanation addresses the demands that the CPS assessment places on students. As mentioned above, the difficulty of the CPS assessment was adjusted with regard to differences in the cognitive potential of the samples. In Study B, the study with the cognitively most able sample, the participants' goal values when their knowledge application was assessed were more complex and interactive compared with in the two other studies. For example, to reach the given target values in knowledge application, more simultaneous inputs were necessary, and multiple targets had to be considered at the same time. Thus, in Study B, we might have captured complex cognitive processes by placing additional demands on the assessment of knowledge application. These additional demands may require processes beyond the complex processes that were already assessed by the knowledge acquisition dimension. Thus, the predictive power of knowledge application surpassed that of the knowledge acquisition dimension. In general, we interpret this finding as an additional potential of the knowledge application dimension, and this has not yet been examined systematically. In conclusion, to increase knowledge about CPS, further research concerning the differential importance of knowledge acquisition and knowledge application is needed to better understand the differential predictive power of the two CPS dimensions (cf. Sonnleitner, Brunner, Keller, & Martin, 2014).

Finally, some limitations of this article and outlooks for future research should be discussed. As noted above, we used broad operationalizations of ICT literacy and general cognitive ability; thus, the generalizability of our findings was not limited to single-assessment instruments of ICT literacy and general cognitive ability. Specifically, reasoning and working memory are good indicators of general cognitive ability. However, they do not cover the entire range of general cognitive ability, which additionally encompasses attention, long-term memory, processing speed, perception, verbal ability, crystallized intelligence, and so forth. Furthermore, ICT literacy is composed of a variety of aspects. Not all of them were covered in our study. However, our results provided indications of differential effects of ICT literacy on cognitive abilities. For example, computer anxiety as part of ICT literacy had an influence on CPS but not on working memory capacity. Therefore, future research should explore other cognitive abilities and more diverse operationalizations of ICT literacy when relating them to CPS (cf. Wittmann & Süß, 1999). Additionally, only MicroDYN was used as an assessment of CPS. To expand the nomological network, several operationalizations are necessary. Regarding this, the approaches of finite state automata (Buchner & Funke, 1993) or classical microworlds (Funke, 2001) would be worthwhile extensions to MicroDYN. To this end, not only on the level of operationalizations but also with regard to theoretical considerations, additional efforts are needed to more comprehensively understand CPS in the context of cognitive theories such as the theory of situated cognition (Brown, Collins, & Duguid, 1989) or CHC theory (McGrew, 2009). In conclusion, further operationalizations of general cognitive ability and CPS should be considered and theoretical considerations should be made in future research.

We put forward two explanations for the added value of CPS: the additional assessment of complex cognitive processes beyond general cognitive ability and a confounded assessment of general cognitive ability and ICT literacy. However, one could invoke other factors that may account for the added value of CPS, for example, motivation. The issue of motivation and acceptance has been discussed since the beginning of CPS assessment (cf. Kersting, 1998; Sonnleitner et al., 2012; Vollmeyer & Funke, 1999). Gamelike features and attractive graphical setups may enhance motivation, which in turn may explain the added value of CPS. In our studies, we used attitudinal measures of ICT literacy, but we did not include motivational aspects in our research. If we want to be sure that the added value of CPS is mainly based on complex cognitive processes, it will be necessary to extend our research strategy to comprehensively consider other possible explanations such as motivation as well.

We used three different samples for this research: high-ability university students, university students with a broad study background, and high school students. Although these samples covered three relevant groups from the population of students, they are not completely representative of the entire population. With regard to generalizability (Brennan, 1983), we note that our results may be biased by low variability and may be different in other subgroups (e.g., in adults). In this sense, today's students are described as "digital natives" (Prensky, 2001), indicating a generally high level of ICT literacy and, thus, restricted variance. However, the impact of ICT literacy may not be linear across the entire range of ability. On the one hand, poor ICT literacy (i.e., not being familiar with the operations necessary to handle the computer) may cause severe difficulties, but on the other hand, a high level of ICT literacy may not be helpful in solving CPS tasks. It is important to consider such a nonlinear relation (cf. Leutner, 2002) for a deeper understanding of the differentiated impact of ICT literacy on CPS. However, such analyses need more heterogeneous samples, which should be considered in future research.

In conclusion, our aim was to extend the understanding of the assessment of CPS and, thus, to make a contribution to the validation of the CBA of transversal skills. CPS as one of the most promising of these skills is an important part of international educational large-scale assessments such as PISA. The results of these large-scale assessments have extensive and substantial implications, for example, on further developments of educational systems. Thus, we believe that our research will lead to a better understanding of the results of educational large-scale assessments and, hopefully, to well-founded decisions that are aimed at benefitting students' transversal skills in a quickly changing world.

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