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**A Digital Safe Space for Learning: How Computer-Assisted Instruction Supports  
Students with Lower Academic Self-Concept**

*Running title:* CAI, ASC, and ACADEMIC PERFORMANCE

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### **Abstract**

Computer-assisted instruction (CAI) is a valuable approach for managing classroom heterogeneity by providing feedback tailored to students' individual needs. While previous research has primarily focused on the cognitive mechanisms underlying CAI's effectiveness, it has often overlooked the social-cognitive processes that may contribute to its success by offering students a private learning space away from the judgement of their peers. The present study compared CAI to conventional classroom instruction over a two-week period with 389 tenth-grade history-geography students. First, we expected that CAI would result in better academic learning compared to conventional classroom instruction. Second, we tested alternative hypotheses, that learning gains in CAI would vary depending on students' levels of academic self-concept (social-cognitive hypothesis) and prior knowledge (cognitive scaffolding hypothesis). Consistent with the social-cognitive hypothesis, multilevel modeling revealed that students with initially lower levels of ASC experienced higher learning gains in CAI compared to conventional classroom instruction, while no benefits were observed for students with lower prior knowledge. Additionally, our results indicate a disruption of the predictive relationship between ASC and subsequent academic performance in the CAI group, compared to the presence of this association in the conventional classroom instruction group. These findings suggest that CAI benefits low-confidence students regardless of their initial ability level and that this method offers a protective effect against the impact of perceived incompetence on subsequent performance.

**Keywords:** computer-assisted instruction; academic performance; academic self-concept; social comparison.

## Introduction

The classroom is, by its very nature, a public and heterogeneous space, leading to visible differences in school success and failure among students. This visibility is believed to drive social comparison, which can motivate some students but cause others to disengage cognitively, particularly when they feel inferior to their peers (Monteil & Huguet, 2013; Pulford et al., 2018). This perspective has often been overlooked in discussions about the implementation of learning methods in CAI (Wang et al., 2023a), classroom orchestration (Dillembourg, 2021), or computer-based collaborative platforms (Jeong et al., 2019, for a meta-analysis). However, recent research in digital education has begun to focus on the socio-cognitive processes underlying students' participation and achievement (Demir et al., 2023), or to explicitly explore how tools designed for individual learning might improve academic performance, partly by providing a degree of anonymity (Ge et al., 2024). Technologies like CAI inherently create anonymous learning environments for students, which can help manage or mitigate the socio-contextual factors affecting academic performance. This issue may have significant implications for addressing educational inequalities, where anonymity, if used strategically, could help prevent the development and consolidation of negative self-perceptions—particularly those arising from the public context of the classroom—that affect students' daily academic performance.

Our research question seeks to determine whether the use of CAI, understood as an 'anonymity provider' during learning, can improve students' academic performance. To answer this question, the primary focus of the study used a quasi-experimental design to compare the academic performance of 389 tenth-grade students in history-geography lessons after they received either a two-week intervention with CAI (a relatively anonymous learning context) or two weeks of conventional classroom instruction (a relatively public learning context). The secondary focus employed a correlational approach to investigate the mechanisms underlying

the benefits of CAI on academic performance by examining the moderating roles of students' levels of academic self-concept (ASC) and prior knowledge. If the benefits of CAI are greater for students with lower levels of prior knowledge and/or lower levels of ASC, this may provide insight into whether CAI is effective in addressing students' needs with respect to cognitive factors and, more importantly for this study, socio-cognitive factors.

In the following sections, we will first discuss the relationship between ASC and academic performance, and how public classroom situations impact these through sustained experiences of failure and success. Second, we will explore the role of CAI in reducing the impact of perceived incompetence on subsequent academic performance.

### **The Relationship Between Academic Self-Concept and Academic Performance**

Academic self-concept refers to a person's self-perceptions shaped by experiences and interpretations of their environment in relation to academic success (Marsh et al., 2019). Strong evidence supports the reciprocal causal relationship between ASC and academic performance (Marsh, 2023; Marsh et al., 2022). On the one hand, the causal influence of academic performance on subsequent ASC includes the possibility that students who frequently fail in a given subject may re-experience their past failures when confronted with that subject again, leading to the development of a low ASC (Monteil & Huguet, 2013). On the other hand, the causal influence of ASC on subsequent academic performance can be explained by feelings of incompetence that reduce motivation, or conversely, feelings of competence that increase the effort invested in tasks where success is anticipated (Eccles & Wigfield, 2020).

## **The Influence of Social-cognitive Factors on Academic Self-Concept and Academic Performance**

Beyond true competence, ASC is influenced by social-cognitive factors, including evaluations by significant others, such as teachers and peers, and their reinforcement through positive and negative feedback, all of which occur in the school environment. Notably, the public context of the classroom, where grades and feedback are given, makes students' performances visible to one another, fostering continuous social comparisons—an essential function for self-evaluation (see Crusius et al., 2022, for a conceptual review). Previous research in non-digital, conventional classroom settings found that lower perceived ranking within the class is associated with a lower ASC, and more interestingly, that this effect is mediated by social comparison with peers (Huguet et al., 2009). These findings have led researchers to explore the effects of invisibility versus visibility of performance gaps among learners in the classroom, which either allow or prevent students from comparing themselves to others (Goudeau & Croizet, 2017; Monteil & Huguet, 2013). Their results consistently show that the visibility of peer performances benefits high-achieving students but hinders low-achieving students when they can publicly compare themselves to others—an effect that tends to disappear in a private context.

High achievers are also impacted by social comparisons, particularly in selective schools, as documented by research on the Big-Fish-Little-Pond Effect (BFLPE) (Fang et al., 2018; Holm et al., 2020). Although successful overall, students in selective schools tend to have a lower ASC than their counterparts in mainstream schools who achieve similar results. This indicates that a student's ability level is not necessarily protective against the effects of social comparisons on ASC; rather, the target of the comparison and the class context play a more significant role (Chiu, 2012; Marsh et al., 2008).

Collectively, these studies strongly suggest the presence of social-cognitive phenomena that modulate students' performances, not based on their ability level but rather on their perceived ranking and perceptions of other students in the classroom, which serves as the main theoretical assumption for the present study.

Importantly, since a lower ASC is likely to decrease subsequent academic performance, the private learning space offered by digital technologies such as CAI may benefit students who are prone to social comparisons and inferiority-related thoughts, regardless of their ability level. A reasonable inference, therefore, is that CAI benefits may be greater for students with a lower ASC, independent of their academic abilities, which we investigated in the present study.

### **Computer-Assisted Instruction as a Protective Strategy Against the Detrimental Effects of Low Academic Self-Concept.**

The coined 'social-cognitive account,' derived from studies comparing private versus public learning contexts and the BFLPE, suggests that the anonymity provided by CAI is potentially beneficial for educational outcomes. For example, the work of Graesser and colleagues demonstrated an increase of up to 27 generated questions per hour using various CAI tools (Sullins et al., 2010; Wisher & Graesser, 2007), compared to approximately 0.1 generated questions in conventional classrooms (Graesser and Person, 1994). This significant discrepancy strongly indicates that the private dimension of CAI plays a role in promoting students' participation. Consistent with this, more recent research suggests that anonymity in digital technologies, such as CAI, can positively affect academic performance in different paradigms involving student participation. For instance, Miyazoe and Anderson (2011) found higher online participation in a writing production task performed in an anonymous digital context, particularly among students less inclined to participate in traditional classroom settings. Jong et al. (2012) investigated the effects of anonymity in peer discussions during the

preparation and realization of a final exam, comparing face-to-face and anonymous interactions, and found higher learning achievement among peers interacting anonymously. More recently, Ge et al. (2024) found that students who adopted an anonymized profile in a vocabulary competitive learning program were associated with higher posttest performance scores. Collectively, these studies suggest that anonymity may foster a '*safe, reprisal-free*' learning environment (Velamazán et al., 2023), helping students cope with a form of '*perceived social danger*' (Demir et al., 2023). In this context, students are less influenced by interpersonal relationships and peer pressure, which may enhance academic performance.

Translating these findings to the present study, we expect the beneficial effects of anonymity to manifest in higher academic performance among students who have used CAI. As predicted by the social-cognitive account, this benefit should be particularly evident in students with low ASC, regardless of their academic ability level. Furthermore, if anonymity indeed provides a safe and reprisal-free learning environment, students using CAI should experience fewer inferiority-related thoughts induced by social comparisons. Therefore, our prediction is that the use of CAI should reduce the influence of initial ASC levels (reported before the intervention) on subsequent (post-intervention) academic performance.

### **The Social-cognitive Account of CAI Benefits Relative to Classical Cognitive Accounts**

It is well established that CAI offers robust benefits compared to conventional classroom learning situations (Chevalère et al., 2021; 2022; Kulik & Kulik, 1991; Ma et al., 2014; Major et al., 2021; Murphy et al., 2020; Steenbergen-Hu & Cooper, 2014). These benefits are traditionally explained by 'cognitive' accounts, where the design of CAI environments plays a crucial role in adapting to students' cognitive characteristics (Vandewaetere et al., 2011; Wang et al., 2023a). Ideally, CAI allows students to progress through learning tasks at their own pace, often by providing adaptive support tailored to their needs. When CAI is sufficiently



flexible, it can adapt both upwardly and downwardly (Graesser et al., 2018). Upward adaptation occurs when students experience continuous success and are presented with more complex and challenging tasks, stimulating problem-solving skills, autonomy, engagement, and preventing boredom (Chevalère et al., 2023a; Kuldass et al., 2014; Nett et al., 2011). However, in practice, most CAI systems tend to adapt downwardly by offering gradual assistance following failures (Baker et al., 2016). In such cases, the pedagogical strategies in CAI need to decrease task difficulty by increasing instructional structure without changing the learning objectives (Hardy et al., 2006; van de Pol et al., 2015). Techniques to scaffold students on various cognitive dimensions in CAI include reducing mental workload (VanLehn, 2011), maximizing attention to the task at hand (D’Mello et al., 2012; Maniktala et al., 2020), delivering contingent feedback and hints (Biswas et al., 2016), and promoting effective learning strategies (Azevedo et al., 2022; Kinnebrew et al., 2013). When simple CAI systems can only provide downward assistance through hints and feedback after a student's failures, as in the present study, the benefits of scaffolding are ideally expected to be greater for students with lower prior knowledge, who typically need more instructional structure than students with higher prior knowledge (van Riesen et al., 2022). Two large-scale studies using ‘ASSISTments,’ a CAI for mathematics (Heffernan & Heffernan, 2014), confirmed these expectations: Roschelle et al. (2016) and Murphy et al. (2020) consistently showed that ‘ASSISTments’ was more effective for 7th-grade students with lower prior knowledge compared to their counterparts with higher prior knowledge over a one-year period. The idea that students with lower prior knowledge benefit more from CAI is referred to here as ‘the cognitive scaffolding account’ and represents an alternative explanation in contrast to the social-cognitive account discussed earlier.

Translating these findings to the present study, we expect the beneficial effects of instructional structure to manifest in higher academic performance among students who have used CAI. As predicted by the cognitive scaffolding account, we anticipate that this benefit will

be particularly evident in students with lower prior knowledge, regardless of their ASC level. Furthermore, if CAI provides more instructional structure than conventional classroom instruction, leading to higher learning gains, the influence of prior knowledge on subsequent academic performance should be weaker in the CAI group compared to the conventional classroom instruction group.

### **The Present Study**

The present study's main contribution to the existing literature is its examination of whether and why CAI is effective for learning by investigating its overall effects and testing alternative accounts that could potentially explain its benefits. The originality of our study lies in providing a new perspective on CAI effectiveness by suggesting that part of its benefits may stem from the private space it offers during learning, which could protect against the influence of low ASC on subsequent academic performance. To this end, we conducted this study in authentic school contexts with 389 10th-grade students in history-geography classes.

The first objective was to use a quasi-experimental design to compare the academic performance of a group of 10th-grade students taught for two weeks with a CAI tool—jointly developed by secondary school teachers, school inspectors, programmers, designers, and researchers—to a group of 10th-grade students taught through conventional classroom instruction for an equal duration on an identical history-geography lesson. The second objective was to investigate the underlying mechanisms of CAI effects on academic performance by examining whether students' initial levels of ASC and prior knowledge modulated CAI benefits according to the social-cognitive account and the cognitive scaffolding account, respectively.

Students' prior knowledge and ASC in history-geography were evaluated using a self-developed pretest consisting of short-answer and multiple-choice questions, along with a self-report Likert-type questionnaire on ASC administered before the intervention. These variables

served as moderators in multilevel models that analyzed the effects of the instructional methods (CAI versus conventional classroom instruction) on students' academic performance. Multilevel models are statistical techniques that account for the dependencies of students within their classes and schools. Academic performance was measured again after the intervention with a posttest—comprising different short-answer and multiple-choice questions from the pretest—to assess knowledge gains.

The present study posed the following research questions (RQs) to examine the effectiveness of CAI and its underlying mechanisms:

RQ1: Does CAI yield learning benefits compared to conventional classroom instruction?

RQ2: Are the expected benefits larger in students with lower ASC?

RQ3: Are the expected benefits larger in students with lower prior knowledge?

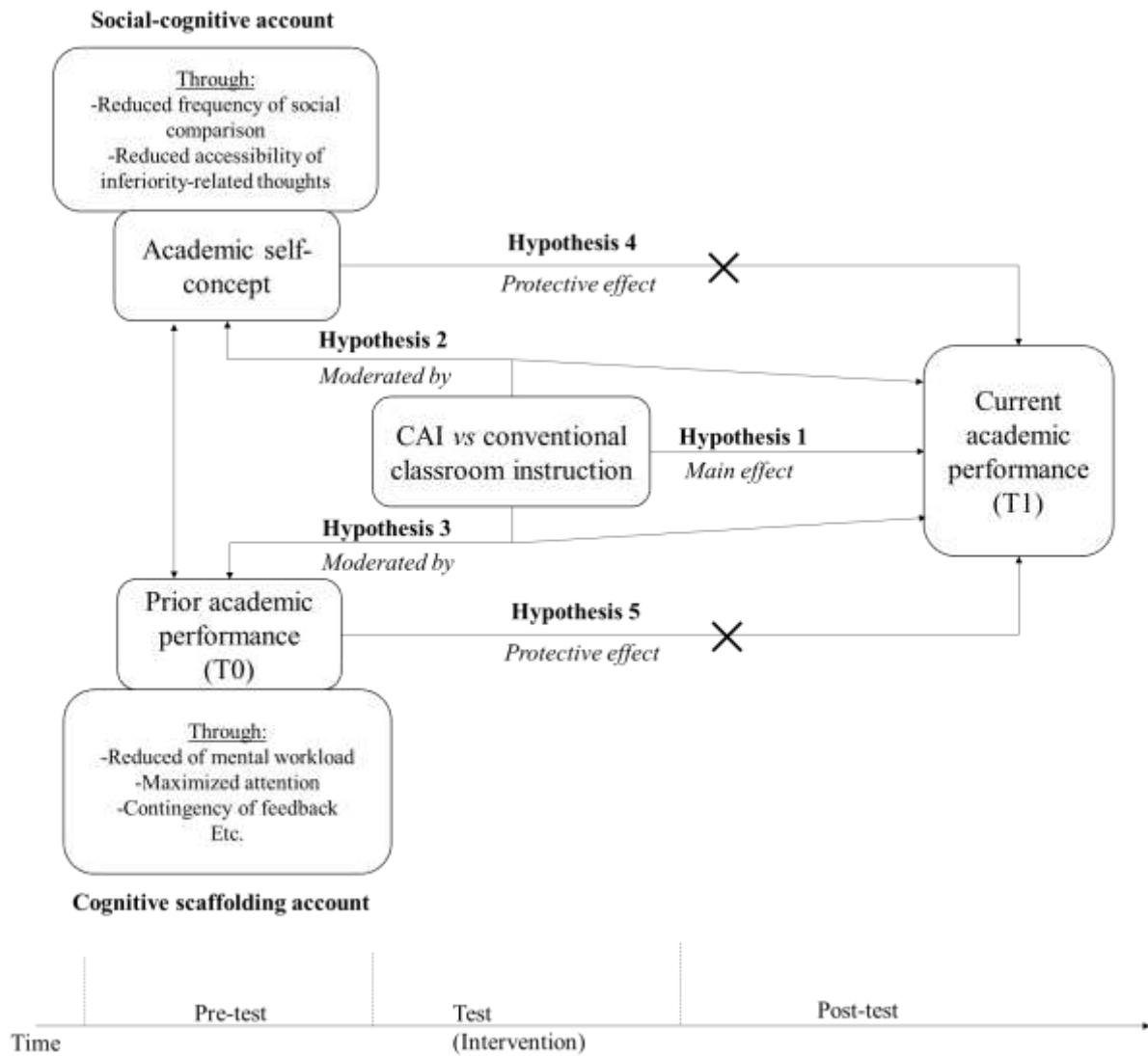
RQ4: Can CAI disrupt the influence of ASC on subsequent academic performance?

RQ5: Can CAI disrupt the influence of prior knowledge on subsequent academic performance?

The theoretical assumptions discussed in the Introduction are depicted and summarized in Fig. 1.

**Fig. 1**

*Theoretical Model of Computer-Assisted Instruction Benefits on Academic Performance After Intervention and Overview of Hypotheses*



To answer these questions, we formulated the following hypotheses based on the theoretical framework discussed above:

**Hypothesis 1 – Main effect of CAI:** Students in the CAI group will show higher learning gains post-intervention, as measured by T1 posttest scores controlled for T0 pretest scores, compared to students in the conventional classroom instruction group.

**Hypothesis 2 – Social-Cognitive Account:** The benefits of CAI, in terms of learning gains, will be larger for students with lower ASC, independent of their prior knowledge.

**Hypothesis 3 – Cognitive Scaffolding Account:** The benefits of CAI, in terms of learning gains, will be larger for students with lower prior knowledge, independent of their ASC.

Hypothesis 4 – Protective effect of CAI due to anonymity: The relationship between ASC and subsequent academic performance (T1) will be weaker in the CAI group compared to the conventional classroom instruction group.

Hypothesis 5 – Protective effect of CAI due to enhanced instructional structure: The relationship between prior academic performance (T0) and subsequent academic performance (T1) will be weaker in the CAI group compared to the conventional classroom instruction group.

## **Method**

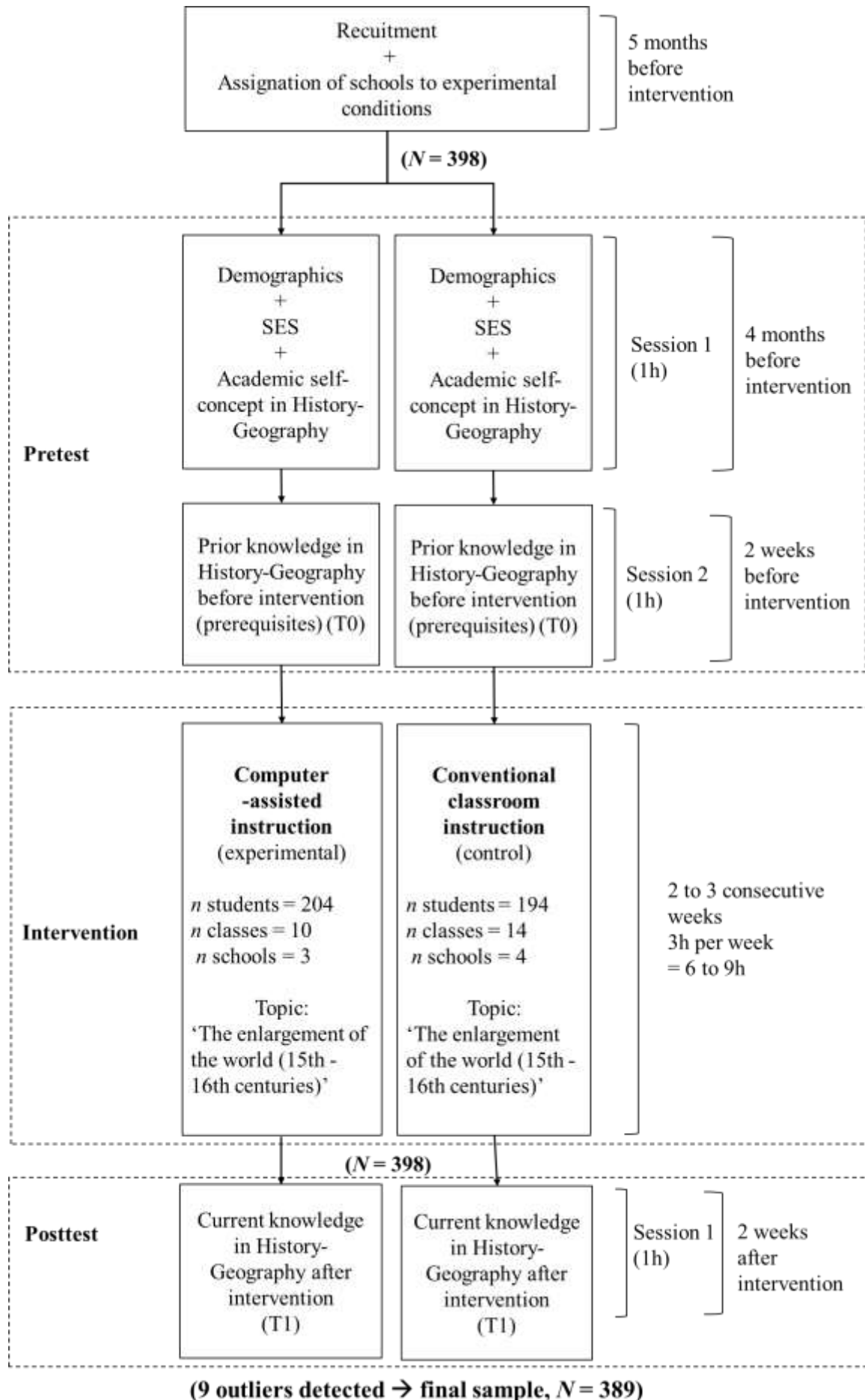
### **Setting**

The study was conducted in public schools located within the perimeter of the Auvergne region across four geographical areas belonging to the Clermont-Ferrand school district. The final sample included 389 students in 10th grade. The quasi-experimental design depicted in Fig. 2 was utilized to test our predictions, allowing students to engage in one topic of the French national curriculum in history and geography for grade 10 (high school) over a period of 2 to 3 consecutive weeks (3 hours per week) regardless of whether they received CAI or conventional classroom instruction. Students completed a test of prior knowledge (i.e., an assessment of the level of knowledge prior to the teaching intervention) and a current knowledge test (i.e., an assessment of the knowledge acquired as a result of the intervention). The content of the knowledge tests and the instructional intervention were identical in the two experimental conditions. Random assignment to experimental conditions within a school or a class (i.e., CAI vs conventional classroom instruction groups) was simply not possible here, as optimal use of CAI required essential hardware features such as an adequate Internet connection or a sufficient number of up-to-date computers per student, which were not necessarily available across

schools. These are field constraints typical of many large-scale studies (Bray et al., 2008), which are accentuated in studies of digital learning given the uneven distribution of technological resources at school level (for a few exceptions, see Fairlie & Loyalka, 2020). To remedy these constraints, we followed the recommendations of Xiao et al. (2019) and conducted multilevel models with additional precautions. In particular, we conducted preliminary analyses to examine possible pretest imbalances in students' sex and socioeconomic status (SES) (control variables) and, ASC and prior knowledge (predictor variables).

**Fig. 2**

*The Quasi-Experimental Design of the Present Study*



*Note.* All data were collected in real classroom environments via an online platform dedicated to the present research, including demographics and academic tests.

## **Participants**

The study is part of a larger research project ‘*eP3C*’ interested in the impact of CAI on various dimensions of academic achievement, which received approval from the Clermont Auvergne University Ethics Committee in conformity with French bioethical law (covering Psychology). The recruitment process was motivated by a research collaboration between the LAPSCO and several schools involved in the ‘*eP3C*’ project, willing to examine experimentally whether and how digital technologies may benefit learning. We focused specifically on the data of 10th-grade students of the ‘*eP3C*’ project as this sample contained a sufficiently large number of participants, allowing us to model the relationships between CAI, ASC, and academic performance while controlling for students’ sex and SES. The current study focused on an initial sample of 398 participating students enrolled in the secondary school curriculum of history and geography in grade 10,  $M_{\text{age}} = 15.90$ ,  $SD_{\text{age}} = 0.53$ , 53.01% females). All participants were recruited in their usual school by a referent teacher participating in the large ‘*eP3C*’ study. The recruitment process was overseen by an established collaboration between a school inspector and the LAPSCO. For underage participants, parents or legal guardians received a written informed consent form five months before the study, which they were required to read and sign to allow their child to participate. The procedure was identical for legal adults (tenth graders aged 18 years or above), except that they signed the informed consent form themselves. Students were assigned to either the CAI or control group—with 51.26% of the students (49.02% females) assigned to the experimental group and 48.74% of the students (56.70% females) assigned to the control group. Of the initial sample, 52.51% were categorized as either disadvantaged or middle-class students (grouped together as the low SES category) and 47.49% as either privileged or highly privileged students (grouped together as the high SES



category) according to the nomenclature of professions and socio-professional categories (PCS) of the French Ministry of Education. Nine participants (2.31%) were identified as outliers using a univariate detection procedure (interquartile range) conducted separately on prior knowledge, current academic performance, and ASC, and were therefore removed from analyses. The final sample comprised 389 participants, whose characteristics are detailed in Table 1. The study complies with APA ethical standards in the treatment of the human sample.

**Table 1***Participants' Characteristics in the Final Sample*

<i>N</i>			Sex		SES		Instruction Method	
Stu.	Cla.	Sch.	F	M	High	Low	CAI	Control
389	24	7	207 (53.21)	182 (46.79)	186 (47.81%)	203 (52.19%)	199 (51.16%)	190 (48.84%)

*Note.* Stu. = students; Cla. = classes; Sch. = schools; F = females; M = males; SES = socioeconomic status; CAI = computer-assisted instruction; control = conventional classroom instruction.

## Material and Procedure

### *Academic Self-Concept*

To examine whether CAI benefits are moderated by students' ASC as posed in RQs 2 and 4, and Hypotheses 2 and 4, we utilized a 6-item scale adapted from Huguet et al. (2009), originally designed for assessing ASC in mathematics and French literacy. It comprises five straightforward items and one reverse-coded item, all loading on a single-factor structure, and has demonstrated high reliability in previous studies—Maths ( $\alpha = .88$ ) and French literacy ( $\alpha = .89$ ). Each response was scored on a 6-point Likert scale, ranging from 1 (*'I strongly disagree'* [in French]) to 6 (*'I strongly agree'* [in French]). Although initially adapted for math and literacy, this study adapted the scale for history-geography by changing relevant wording. For example, one item specific to history-geography was phrased, *'You quickly understand history-geography,'* [in French]. Students completed this ASC scale online four months before the intervention, and the reliability of this adapted version was found to be excellent ( $\alpha = .91$ , Taber, 2017). All ASC scores were converted into Z-scores prior to analyses. Unstandardized scores for each item of the ASC scale are available in Table 2.

**Table 2**

*Descriptive Statistics for Tests of Prior knowledge, Current Knowledge and Academic Self-Concept*

	<i>N</i>	Mean	<i>SD</i>	Median	Min	Max	Range	Skew	Kurtosis	<i>SE</i>
Test of Prior Knowledge (T0)	389	13.63	4.49	14.00	1.00	20.00	19.00	-0.60	-0.35	0.23
Test of Current Knowledge (T1)	389	12.76	3.36	13.00	4.00	20.00	16.00	-0.23	-0.20	0.17
ASC Item 1	389	3.93	1.31	4.00	1.00	6.00	5.00	-0.31	-0.48	0.07
ASC Item 2	389	3.74	1.19	4.00	1.00	6.00	5.00	-0.05	-0.37	0.06
ASC Item 3	389	4.00	1.04	4.00	1.00	6.00	5.00	-0.29	-0.02	0.05
ASC Item 4	389	4.24	1.08	4.00	1.00	6.00	5.00	-0.38	0.10	0.05
ASC Item 5	389	3.81	1.11	4.00	1.00	6.00	5.00	-0.14	-0.14	0.06
ASC Item Reverse	389	4.50	1.15	5.00	1.00	6.00	5.00	-0.73	0.39	0.06

*Note.* ASC = academic self-concept; SD = standard deviation; Skew = skewness; SE = standard errors.

### ***Socioeconomic Status***

The present study aimed to control for students' SES to rule out any group-related differences that could be explained by SES disparities at the individual level across experimental conditions. In France, the nomenclature of professions and socio-professional categories (PCS) is a commonly used SES indicator, established by the National Institute of Statistics and Economic Studies (INSEE) (INSEE, 2018). The PCS index, which classifies the population based on professional status, hierarchical position, and economic status, was obtained for each participating student's family from the Rectorate of the Clermont-Ferrand academy four months before the intervention. This index can be subdivided into four categories according to an earlier nomenclature proposed in 1982, which corresponds to increasing levels of social status, ranging from disadvantaged to middle class, privileged, and highly privileged backgrounds. In this study, disadvantaged and middle class were combined into a low SES category, while the latter two categories were grouped into a high SES category.

### ***Test of Prior Knowledge (T0) Before Intervention***

To examine whether CAI benefits are moderated by students' prior academic performance (referred to as *prior knowledge*), as explored in RQs 3 and 5 (Hypotheses 3 and 5), a measure of prior knowledge was administered. This test assessed content from the French national education curriculum that students had acquired *during the previous year and the current year up to the time of the study*, corresponding to the knowledge prerequisites necessary for learning the content taught during the intervention. The test of prior knowledge served as a performance baseline, allowing us to control for initial individual differences in knowledge and to explore a potential interaction with the instructional methods (Hypothesis 3).

The prior knowledge test consisted of 27 short-answer and multiple-choice questions, which were developed by a group of participating teachers to reflect typical classroom assessments. The scoring scheme was established collaboratively by the group of teachers. During data collection, the test's scoring process was fully automated by an online platform specifically built for this research, which accepted several valid entries for short-answer questions to allow some tolerance for typos. The raw scores were converted into scores out of 20 points for ease of interpretation, as shown in Table 2. Students took the T0 test at least two weeks before the experimental intervention.

### ***Lesson Plan Implementation During Intervention in Experimental Groups***

An identical history-geography lesson was implemented in both the CAI environment and conventional classroom instruction to allow for a direct comparison (addressing RQ1, Hypothesis 1). The knowledge content taught in history-geography focused on ‘The Enlargement of the World (15th - 16th centuries).’ For the CAI, secondary school teachers, school inspectors, programmers, designers, and researchers collaborated to transcribe the knowledge content from the official French national education curriculum into the system. The selection of content was overseen by an academic inspector specializing in history-geography. In conventional classroom instruction, the teaching method was left to the discretion of the teacher, provided it remained teacher-led and did not involve digital technology.

The CAI version of the lesson was developed using the Tactileo© tool, created by Maskott©. This computer-based learning environment resulted from a synergistic effort where programmers integrated the material content provided by the teachers while configuring the CAI according to the recommendations of the teachers and researchers. For this study, we relied on the idea that technologies created or adapted by research teams with teacher involvement are more effective for learning than those from the commercial market or those that merely use technology as a delivery system (Moran et al., 2008). The involvement of teachers ensured

better alignment of the knowledge content and pedagogical resources with the school's curriculum and standards.

The implementation of the lesson in CAI followed typical training methods commonly represented in the CAI literature, including 'Learning Modules,' which are presentations of the content knowledge, and 'Training Modules,' which consist of problem-solving exercises and tutorials that include hints, corrective feedback, and explanations (Kulik, 2003; O'Neil et al., 1991). The detailed learning sequence for the first three-hour session is available in Appendix A (including Text A.1, Figs A.1, A.2, A.3, A.4, A.5, A.6, A.7, A.8, A.9, A.10 and Text A.2 in French). About half of the students ( $n = 199$ , 51.16%) received CAI, while the other half ( $n = 190$ , 48.84%) received conventional classroom instruction. All students assigned to the CAI condition were provided with one tablet computer per student and interacted with the CAI tool in their usual classrooms in the presence of their history-geography teachers. The teachers' role was to introduce the subject, then allow students to learn independently by interacting with the CAI tool, intervening only if there were problems or questions from the students. Students were instructed not to collaborate with each other to maximize the time spent on their tablet computers.

### ***Test of Current Knowledge (T1) After Intervention***

To assess academic performance, the dependent variable of the study (addressing RQs 1 to 5, Hypotheses 1 to 5), a test of current knowledge was administered after the intervention. Similar to the T0 test, the T1 assessment consisted of short-answer and multiple-choice questions focused on content from the French national education curriculum related to 10th-grade history-geography. The scoring procedure for T1 was consistent with that used for T0.

However, unlike T0, the T1 test assessed content taught during the current academic year (10th grade) *through the intervention* using one of the two instructional methods (CAI

versus conventional classroom instruction). The T1 test specifically covered the topic of ‘The Enlargement of the World (15th - 16th centuries).’ The T1 test was not identical to the pretest (T0) because it focused on newly taught material rather than the foundational knowledge acquired in the previous year.

The T1 test consisted of 25 short-answer and multiple-choice questions, which were developed by a group of participating teachers to reflect typical classroom assessments. The scoring scheme was established collaboratively by this group of teachers. During data collection, the scoring process for the T1 test was fully automated by the online platform, which accepted multiple valid entries for short-answer questions, allowing for some tolerance of typos. The raw scores were converted into scores out of 20 points for clarity in Table 2. Students took the T1 approximately two weeks after the intervention. Both T0 and T1 scores were converted into Z-scores prior to analysis. Unstandardized scores for each knowledge test are available in Table 2.

### **Statistical Analyses**

The statistical analyses modeled the effects of the instructional method comparison on students’ academic performance in the current knowledge test (the study's dependent variable) after two weeks of intervention, while also considering the influence of initial ASC levels and prior knowledge in history-geography. The analyses controlled for students’ sex and SES. This approach allowed for the simultaneous investigation of the study's two main objectives: the effectiveness of CAI and the underlying mechanisms, while accounting for the hierarchical structure of the data organized into student (Level 1), class (Level 2), and school (Level 3) levels. Technical details of the statistical procedure are available in Appendix Text B.1. All analyses were conducted using R software version 4.1.2 (R Core Team, 2022).



We employed a three-step procedure to investigate the research questions. Step 1 involved a series of preliminary analyses, detailed in Appendix Text B.1, including the examination of pretest imbalances in study variables across experimental conditions and an analysis of contextual effects. This step ensured that the predictors' averages were comparable across experimental conditions and that their influence on academic performance was not due to variations in averages at the class and school levels. The main analyses (Steps 2 and 3) directly addressed the five research questions and hypotheses.

As the second step, we addressed the first three hypotheses using a random intercept model (Model 1). This model allows current academic performance (T1) to vary across classes (Level 2) and schools (Level 3). We included the main effects of instructional methods (Hypothesis 1), prior knowledge (T0), ASC, the Instruction Method \* ASC interaction (Hypothesis 2), and the Instruction Method \* T0 interaction (Hypothesis 3). By including prior knowledge in Model 1, *learning* is reflected as the residual score of the posttest knowledge test, net of the influence of the pretest knowledge test (Xiao et al., 2019). Students' sex and SES were included as covariates. Given that all students were in the 10th grade and thus of similar ages ( $SD_{\text{Age}} = 0.47$ ), age was not included as a covariate.

As the third and final step, we conducted additional analyses to explore the role of CAI in disrupting the influence of ASC (Hypothesis 4) and prior knowledge (Hypothesis 5) on subsequent/current academic performance by comparing the strength of the associations between ASC and T1, and between T0 and T1, in the control and experimental groups. For this, we performed path analyses using the R package 'lavaan' (Rosseel et al., 2012) version 0.6.16, modeling these relationships separately for the CAI and control groups. The magnitude of the ASC → T1 and T0 → T1 links were compared across groups using a Wald test (Klopp, 2019) while controlling for students' sex and SES. The relationship between ASC and T0 was also examined and was expected to remain consistent across groups.

All model parameters for multilevel and path analyses (steps 2 and 3) were estimated using maximum likelihood estimation, with 95% confidence intervals generated using bootstrapping (5,000 resamples) and percentile methods (Efron & Tibshirani, 1993). We used the R packages “nlraa” version 1.1 (Miguez, 2022) and “lavaan” (Rosseel et al., 2012) version 0.6.16 for multilevel and path analyses, respectively.

## Results

Results of the preliminary analyses are available in Appendix Text C.1, Fig. C.1, Text C.2, and Table C.1. A correlational analysis among the study variables is provided in Appendix Text C.3 and Table C.2. The following sections present the main analyses addressing the five research questions and hypotheses.

### **RQs 1, 2, and 3 - Analyses of CAI Intervention and Moderation with Academic Self-Concept and Prior Knowledge.**

We addressed the first three research questions by examining the overall influence of instructional methods on students' current academic performance (Hypothesis 1) and whether this influence was moderated by students' ASC (Hypothesis 2) and prior knowledge (Hypothesis 3). As shown in Table 3, and contrary to Hypothesis 1, CAI did not benefit all students compared to conventional classroom instruction, as indicated by the non-significant main effect of Instruction Method on current academic performance,  $\beta = .07$ ,  $SE = .08$ ,  $t = .84$ ,  $p = .44$  [-.04; .15]. According to the social-cognitive account (Hypothesis 2), we expected that students with lower ASC would benefit more from CAI. Confirming Hypothesis 2, students with lower ASC did indeed benefit more from CAI compared to students with higher ASC, as indicated by the significant Instruction Method \* ASC interaction effect in Table 3,  $\beta = -.10$ ,  $SE = .05$ ,  $t = -2.13$ ,  $p = .034$  [-.20; -.02]. Fig. 3 clarifies this result by illustrating a progressive

shift from a positive slope in students with lower ASC ( $-3 SD$ ) to a negative slope in students with above-average ASC. Alternatively, according to the cognitive scaffolding account (Hypothesis 3), we expected that students with lower prior knowledge would benefit more from CAI compared to students with higher prior knowledge. However, this was not supported by the data, as shown in Table 3 by the non-significant Instruction Method \* T0 interaction effect,  $\beta = -.002$ ,  $SE = .05$ ,  $t = -.04$ ,  $p = .96$  [-.11; .07], displayed in Fig. 4.

**Table 3**

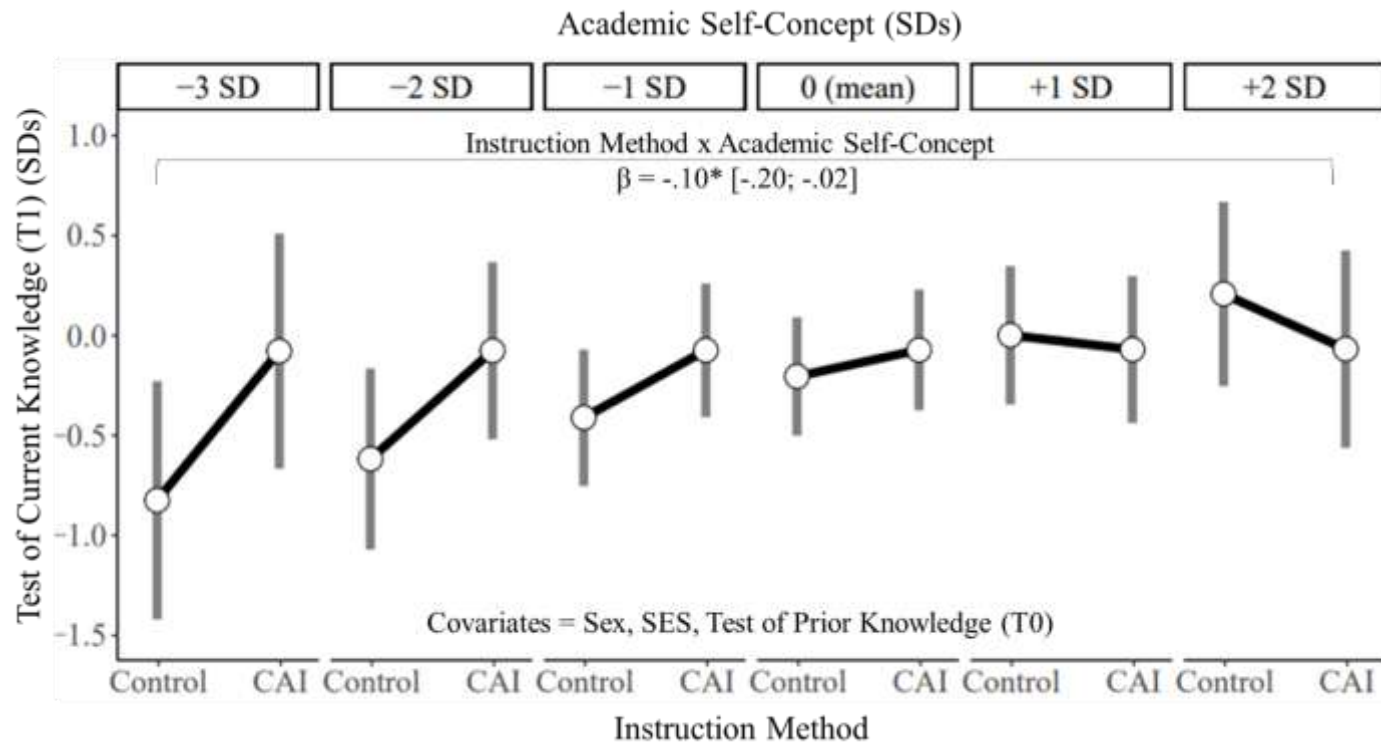
*The Influence of Instruction Method (CAI vs Control) on Students' Academic Performance (Test of Current Knowledge – T1) and Moderation by Academic Self-Concept and Prior Knowledge (T0)*

<i>n</i> students = 389, <i>n</i> classes = 24, <i>n</i> schools = 7	Model 1	
	<i>E</i>	95% CI
Fixed Effects		
<i>Student Level</i>		
Intercept	-.02	[-.11; .07]
Sex	-.05	[-.15;.02]
SES	-0.10*	[-.19; -.01]
T0	.23***	[.15;.32]
ASC	.10*	[.02; .21]
<i>School Level</i>		
<b>IM (H1)</b>	<b>.07</b>	<b>[-.03; .15]</b>
<i>Cross-level Interactions</i>		
<b>IM x T0 (H2)</b>	<b>-.002</b>	<b>[-.11; -.07]</b>
<b>IM x ASC (H3)</b>	<b>-.10*</b>	<b>[-.20; -.02]</b>
Random Effects		
<i>Residual variance (also ICC)</i>		
Student Level ( <i>SD</i> )	.84	-
Class Level ( <i>SD</i> )	.08	-
School Level ( <i>SD</i> )	.00	-
Log Likelihood	-515.57	-
AIC	1055.15	-
BIC	1120.71	-

*Note.* Rows in bold correspond to the first 3 hypotheses tested in the model; \*  $p < .05$ ; \*\*\*  $p < .001$ ; T0 = test of prior knowledge; SES = socioeconomic status; IM = instruction method = CAI (effect) vs control; E = estimate; CI = confidence interval; SD = standard deviation; df = degrees of freedom; ICC = intraclass correlation coefficient; AIC = Akaike information criterion; BIC = Bayesian information criterion.

Fig. 3

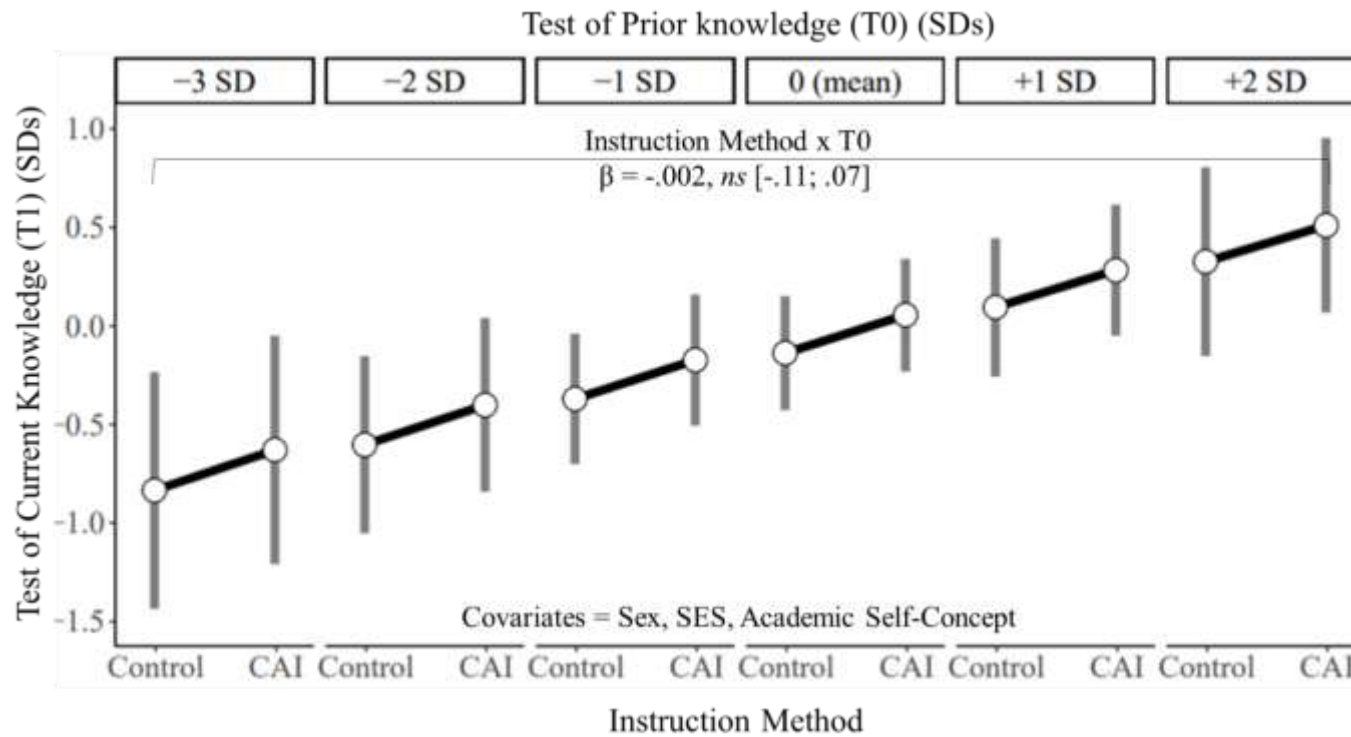
*The Moderation of Instruction Method by Academic Self-Concept*



Note. \*  $p < .05$ ; Control = teacher-led conventional instruction; CAI = computer-assisted instruction; SD = standard deviations; Grey vertical bars represent 95% confidence intervals; SES = socioeconomic status.

Fig. 4

*The Absence of Moderation of Instruction Method by Prior Knowledge – T0*



*Note.* *ns* = non-significant; Control = teacher-led conventional instruction; CAI = computer-assisted instruction; SD = standard deviations; Grey vertical bars represent 95% confidence intervals; SES = socioeconomic status.

### **RQs 4 and 5 – Comparison of the ASC- T1 and T0 – T1 Relationships in the Computer-Assisted and Conventional Classroom Instruction Groups**

Lastly, we addressed the fourth and fifth research questions (i.e., the potential disruption of the relationships between ASC and subsequent academic performance, and between prior knowledge and subsequent academic performance in CAI relative to conventional classroom instruction) by comparing these regression coefficients across experimental groups while controlling for sex and SES using path analyses<sup>1</sup>.

Confirming Hypothesis 4, the pattern of results shown in Fig. 5 indicates no significant association between ASC (before intervention) and current academic performance (T1, after intervention) among students receiving CAI,  $\beta = .02$ ,  $SE = .08$ ,  $t = .23$ ,  $p = .82$  [-.14; .17]. Conversely, a lower ASC was associated with lower current academic performance among students in the control group,  $\beta = .22$ ,  $SE = .07$ ,  $t = 3.18$ ,  $p = .001$  [.08; .35], with the two coefficients being significantly different from each other,  $W(1) = 3.87$ ,  $p = .049$ . Meanwhile, the association between ASC and prior knowledge (T0, before intervention) was significant in both the CAI group,  $\beta = .17$ ,  $SE = .06$ ,  $t = 2.67$ ,  $p = .008$  [.04; .29], and the control group,  $\beta = .25$ ,  $SE = .08$ ,  $t = 3.26$ ,  $p = .001$  [.10; .39], with no significant difference in their magnitudes,  $W < 1$ .

Finally, contrary to Hypothesis 5, the results shown in Fig. 5 indicate no significant difference in the magnitude,  $W < 1$ , of the relationship between prior knowledge (T0) and

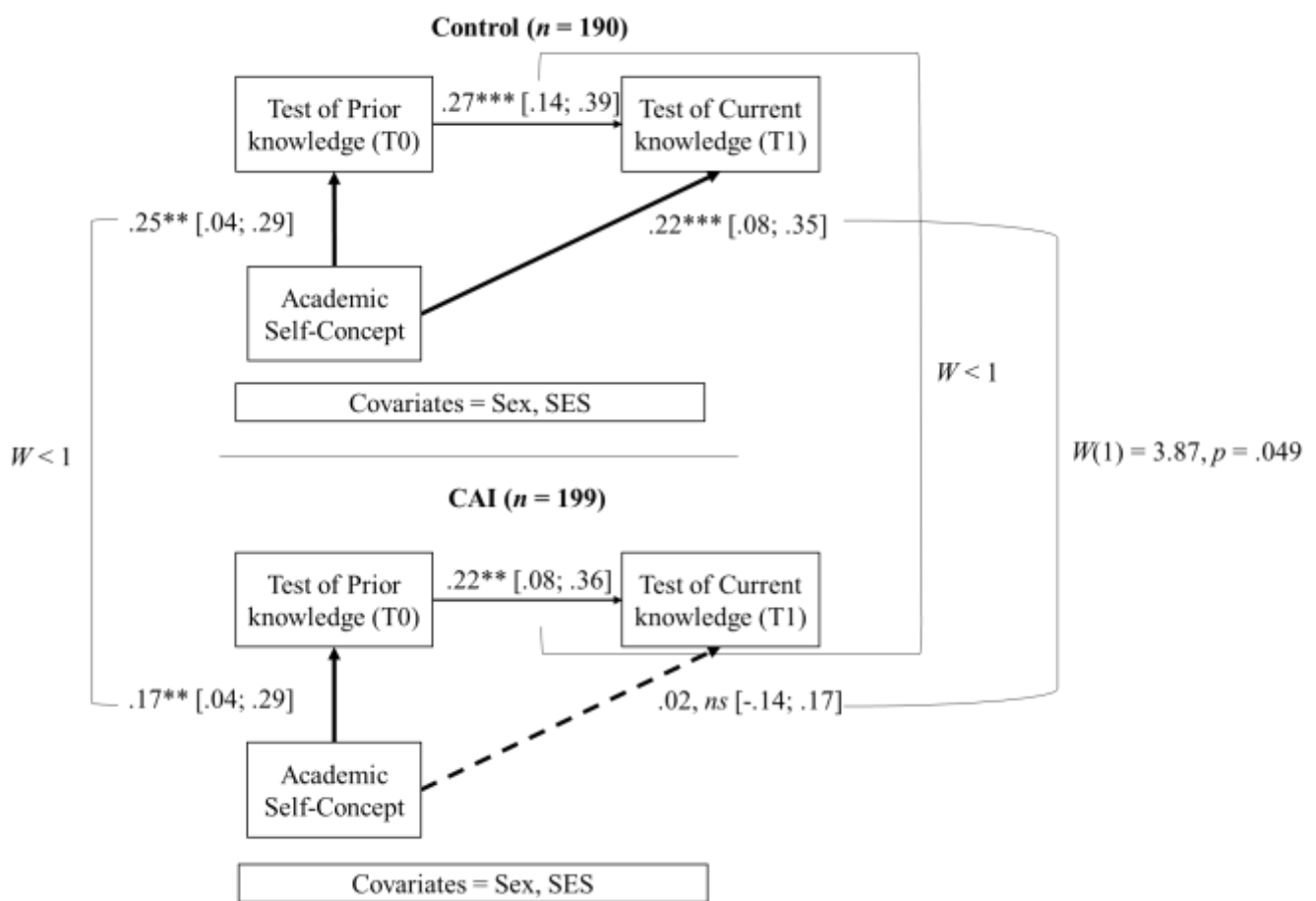
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<sup>1</sup> Given that previous analyses found small amounts of variance for current academic performance at the school ( $ICC_{\text{school}} = 0\%$ ) and class ( $ICC_{\text{class}} = 8\%$ ) levels relative to the student level ( $\varepsilon = 84\%$ ), and more importantly, also found no relevant contextual effects, we focused on the student level only. Besides, since we used a saturated model (i.e., with zero degrees of freedom), fit indices become less relevant and are therefore not reported (Kenny, 2024).

current academic performance (T1) in the CAI group,  $\beta = .27$ ,  $SE = .07$ ,  $t = 4.10$ ,  $p < .001$  [.14; .39], and the control group,  $\beta = .22$ ,  $SE = .07$ ,  $t = 3.06$ ,  $p < .001$  [.08; .36].

**Fig. 5**

*Comparison of the Associations Between Academic Self-Concept, Tests of Prior (T0) and Current Knowledge (T1) in the Computer-Assisted Instruction and Control Groups*



*Note.*  $W$  = Wald coefficient;  $ns = p \geq .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$ ; SES = socioeconomic status. CAI = computer-assisted instruction; Control = teacher-led conventional instruction.

## Discussion

The advantage of CAI for learning is undoubtedly its flexibility, particularly in offering a range of pedagogical strategies that engage students' cognitive processes to support and



optimize their learning. However, CAI designs vary significantly in the pedagogical strategies they employ (Vandewaetere et al., 2011), making these tools heterogeneous despite a few general principles common to all, including the provision of individual support (Baker et al., 2016). For individual support to be effective, it must deliver feedback to each student personally, which inherently provides private feedback. The privacy of feedback, independent of its effectiveness, is an interesting characteristic common to nearly all CAI tools, yet it has been surprisingly overlooked until now. In light of psychological studies documenting social comparison phenomena, a key prediction related to the existence of a private learning space in CAI is the reduced accessibility of performance-related information from other students—information known to negatively impact ASC for a significant proportion of students who engage in social comparisons with their classmates in public settings. Since high-achieving students can also engage in social comparisons and develop a low ASC (Fang et al., 2018), we reasoned that students' ASC, more than their prior academic ability, should moderate CAI benefits. If this is the case, then the private space provided by CAI should offer protective effects against the influence of students' self-perceptions on their learning processes. Alternatively, if CAI benefits are solely explained by the tools' cognitive affordances (e.g., instructional structure) enhancing learning processes, then CAI benefits should be more apparent when students' resources generally fail to meet the demands of conventional learning situations (typically in students with lower academic ability) compared to when students' resources can meet these demands (in high achievers) (Haruehansawasin & Kiattikomol, 2018). These two alternative accounts were coined here as 'social-cognitive' and 'cognitive scaffolding'. Our data suggest that the social-cognitive account might be a possible explanation underlying CAI effects. Indeed, we found that ASC levels conditioned the emergence of CAI

effects on academic performance more than students' prior knowledge levels did. In the following sections, we discuss these findings with respect to our five research questions.

### **RQs 1, 2 and 3 – Absence of Global CAI Benefits and Moderation by Prior Academic Performance along with a CAI Benefits Found in Students with Lower Academic Self-Concept**

Our first research question aligned with a long tradition in the CAI literature, which typically reports medium-sized benefits of CAI on academic performance (Kulik & Kulik, 1991; Ma et al., 2014). Surprisingly, the present study did not replicate these findings. We found similar learning gains in students from both the CAI and conventional classroom settings, despite having adequate statistical power. Furthermore, CAI benefits were not more pronounced in students with lower prior knowledge, which, when considered together, suggests that the CAI used in this study may have been insufficiently adaptive to meet students' cognitive needs. The scaffolding strategies embedded in our tool (such as hints, feedback, and explanations following failures) may have been too limited to provide comprehensive and tailored support, at least not more effectively than conventional classroom instruction. Indeed, the design of the tool is crucial for effectively addressing the heterogeneous needs of students (Biswas et al., 2016; Sottolare, 2015).

CAI tools can be broadly categorized into two levels of sophistication: Intelligent Tutoring Systems (ITS) and more traditional tools (Kulik & Fletcher, 2016). ITSs are highly sophisticated and flexible, utilizing artificial intelligence algorithms capable of adapting both upwardly and downwardly to meet students' needs (Graesser et al., 2018). In contrast, traditional tools are more rigid and straightforward, offering a narrower range of possible instructional sequences. As noted by Graesser et al. (2018), a sophisticated ITS can be so finely

tuned that tutorial interactions on a given topic may result in unique sequences for individual students, whereas, in traditional CAI, the majority of students receive similar sequences. Past research has shown that ITSs are associated with higher learning gains compared to simpler CAIs (Kulik & Fletcher, 2016). Our tool was definitely closer to the traditional CAI approach than to ITSs. It included short-answered questions and multiple-choice questions and provided a few predefined hints in case of failure (usually around three hints available on request by students after a failure on a given item, see Appendix A), but it may have been limited in the depth of its scaffolding support beyond that level. Our findings underscore the importance of design sophistication in effectively scaffolding students cognitively, beyond simply allowing them to self-pace their learning and receive individual feedback.

The main finding of the present study concerns the validation of our second hypothesis: that students with a lower ASC learn more effectively with CAI than with conventional classroom instruction, compared to their counterparts with better self-perceptions. Although the duration of the intervention (three weeks) falls within the range of two to six weeks, a period typically associated with the novelty effect for students interacting with technology (Rodrigues et al., 2022), the current pattern of results is unlikely to be explained by this factor. If novelty were the primary driver of CAI benefits, one would expect all students unfamiliar with CAI to benefit, not specifically those with lower ASC. Furthermore, since the CAI benefits were observed in students with lower ASC rather than in those with lower prior knowledge, it is challenging to attribute the larger learning gains in students with lower ASC to more effective cognitive scaffolding in the CAI group. If that were the case, students with lower prior knowledge, like those with lower ASC, would also have demonstrated larger learning gains. Instead, our findings suggest that students using CAI, regardless of their ability levels, might improve their learning of new material when they feel incompetent in the subject matter. The

mechanisms behind this effect remain unclear. Our proposed explanation is that the private space offered by CAI plays a significant role. Low ASC is thought to result from past experiences of failure, made accessible through social comparison with classmates and related feelings of inferiority (Fang et al., 2018; Monteil & Huguet, 2013). By decreasing the visibility of others' performances, the digital environment may reduce the accessibility of such negative experiences or feelings, thereby decreasing students' tendency to internalize them and promoting a more favorable mindset for learning (Combette et al., 2023; Goudeau & Cimpian, 2021).

#### **RQs 4 & 5 – CAI Disrupted the Influence of ASC on Subsequent (Current) Performance.**

An interesting finding consistent with the social-cognitive account is that ASC was no longer predictive of subsequent academic performance in the CAI group, whereas it positively impacted performance in the conventional classroom instruction group. Since the relationship between prior (T0) and current academic performance (T1) was found to be invariant across conditions, this supports the interpretation that anonymity, rather than enhanced instructional structure, benefited learning in the CAI group—at least in our study, which used a relatively simple CAI. Students in the CAI group might have been more likely to adopt a growth mindset during the intervention, as CAI made them less susceptible to social comparison processes. In contrast, the significant relationship between ASC and current academic performance in the conventional classroom group could suggest that students were more likely to adopt a fixed mindset, driven by their past perceived failures or feelings of inferiority, and acted accordingly during the learning intervention.

Interestingly, the disrupted influence of ASC on subsequent performance in the CAI group suggests that not only less confident students but also their more confident counterparts

were affected. This raises concerns about potentially damaging consequences of providing a private space for learning. While it may benefit low-confidence students, it could also penalize highly confident students who benefit from downward social comparisons (Groothof et al., 2007; Smith, 2000), possibly depriving them of a drive to learn (Wang et al., 2023b). If this is the case, then providing a private learning space (e.g., through digital technology) may induce ambivalent effects, warranting further investigation in future studies.

### **The Role of Sex and Socioeconomic Status in Relation to CAI, ASC, and Academic Performance**

Although students' sex and SES were not the central focus but were used as control variables in the present study, a few considerations can nevertheless be made regarding their impact. Firstly, the absence of a significant difference between girls and boys in academic performance allows us to generalize our findings across the entire sample without needing to account for psychosocial interpretations of gender effects, such as stereotype threat on academic performance or academic aspirations, which are often reported in disciplines more sensitive to these effects, like science, technology, engineering, and mathematics (Lewis & Michalak, 2019, for a meta-analysis). The lack of a gender effect in history-geography is consistent with recent surveys conducted in the UK (Plaister, 2021) and in France (Chabanon & Jouvenceau, 2022), both of which showing that history-geography is among the subjects where the proportion of girls and boys is most balanced.

Secondly, regarding SES, our data align with previous research showing small to moderate effects of SES on academic performance (Chevalère et al., 2023b; Liu et al., 2019; Sirin, 2005; White, 1982). Interestingly, the fact that CAI benefits were apparent only among students with a low ASC, even after controlling for SES, suggests that students with high SES

are not immune to the effects of social comparison (Fang et al., 2018). These students may benefit from CAI just like their less advantaged peers, despite their typically better academic performance. Although the differential effects of CAI based on SES were not directly investigated in our study, previous data from over 2,300 students across 8 school subjects in middle and high school have already shown that CAI had similarly positive effects for students of both low and high SES (Chevalère et al., 2022). This brought students of low SES using CAI to the same academic level as their more advantaged peers who learned without CAI (ibid.). These findings suggest that, despite the persistence of a digital divide in terms of information and communication technology skills across different SES groups (Passaretta & Gil-Hernandez, 2023), providing equal access to CAI at the school level (regardless of accessibility at home) ensures that the SES achievement gap does not widen but instead remains constant while shifting upwards under CAI relative to conventional instruction.

### **Limitations and Future Work**

Despite our findings supporting a social-cognitive account over more classic cognitive accounts to explain CAI effects on learning, they are limited in several ways. A major limitation is the absence of a quantified frequency of social comparison episodes at pretest, which is the main factor purportedly influencing ASC. Additionally, quantifying the relative frequency of social comparisons during the learning intervention would have provided clearer evidence that CAI indeed reduces these episodes compared to conventional classroom instruction. Another limitation is the lack of a post-test measure of ASC, which would have been useful in clarifying the protective effects of CAI, under the assumption that CAI might boost ASC post-intervention by reducing the accessibility of failure-related and inferiority-related thoughts. Addressing

these limitations in future research would provide more robust evidence for the social-cognitive account.

Another limitation concerns the self-developed nature of the knowledge tests, which are known to inflate effect sizes compared to standardized tests (Kulik & Fletcher, 2016). The slight differences observed between T0 and T1 mean scores may be attributable to their non-standardized nature. Moreover, our findings cannot be generalized beyond the specific context of 10th-grade history-geography in France. The topic taught, ‘The Enlargement of the World,’ or the broader subject of history-geography, may hold particular societal importance, possibly amplifying the impact of ASC on subsequent performance and the effects of social comparison. Finally, we must also consider that the use of computers in schools is constantly evolving (Bocognano, 2021), as is the use of other technologies such as mobile devices (Dong et al., 2024). These changes may have implications for the novelty effect, the effectiveness of CAI, as well as for students’ motivation and digital competencies. Our sample reflects a specific point in time and may not be generalizable to future generations of students. Future research is needed to generalize our findings across more diverse school subjects and student populations, taking into account the rapid evolution of digital technologies in education.

## **Theoretical and Practical Implications**

To our knowledge, this is the first study to show that a digital technology may causally disrupt the influence of ASC on subsequent performance. This finding has both theoretical and practical implications. Theoretically, it contributes to our understanding of the causal relationships between self-perceptions and academic performance by reinforcing the view that the learning environment context (Kulakow, 2020; Yokoyama, 2019), and especially the social context (Wang, 2009), plays a crucial role in modulating the strength of these relationships. Furthermore, the present study offers an opportunity to rethink the nature of CAI benefits. This could lead to new research questions, such as how do cognitive and social-cognitive accounts interact to affect students' learning outcomes? Would the effects of highly sophisticated ITSs remain stable if students' progress were made visible to others?

Practically, this study suggests that the determinism of perceived incompetence is not fixed and that certain methods may be effective in promoting the perceived malleability of competence among students (e.g., Combette et al., 2023), particularly those who are prone to self-deprecation. However, as previously mentioned, it also raises a cautionary note regarding new methods based on digital technologies—such as the potential to reduce the influence of social comparison—that may not be universally beneficial for all students. While some students might benefit from such technologies, others might be disadvantaged, presenting new practical challenges in how to strategically use CAI technologies in the classroom (Chevalère, 2022).

## **Conclusion**

Considering CAI as influencing social-cognitive learning processes may open new research avenues on the strategic use of digital private and public learning spaces based on



students' levels of self-confidence, much like how current digital technologies adapt to students' cognitive characteristics. The possibility that CAI might enhance learning by mitigating the effects of perceived incompetence could be especially beneficial for students who are negatively impacted by in-class group dynamics. However, it is essential not to overlook the potentially harmful consequences of isolating students through the unconsidered use of these private digital spaces. One of the key challenges for the future will undoubtedly be to find the optimal balance between private human-machine interaction and public engagement. This balance is crucial for maximizing both the assimilation of knowledge and the development of oral expression, debating skills, and critical thinking.

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**Ethics approval.** The study is part of a larger research project which received an approval from the Clermont Auvergne University Ethics Committee (number IRBO0011540-2018-08) in conformity with the French bioethical law (covering Psychology). The study complies with APA ethical standards in the treatment of the human sample.

**Consent.** The recruitment process was overseen by an established collaboration between a school and Clermont-Auvergne University. For underaged participants, the parents or legal guardian received a written informed consent five months before the study which they had to read and sign to allow their child to participate. The procedure was identical for legal adults (tenth graders of 18 years or above), except that they signed the informed consent form themselves.

**Data.** The dataset ‘data\_CAI\_ASC’ and the R syntax supporting the findings of this study are available in the OSF repository [<https://doi.org/10.17605/OSF.IO/JSW4Q>].

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### **Supplementary Information**

A Digital Safe Space for Learning: How Computer-Assisted Instruction Supports Students  
with Lower Academic Self-Concept

Supplementary Information include: Appendices A, B, and C

## Appendix A. Illustration of the First Learning Sequence with Computer-Assisted Instruction

### Text A.1

#### *Characteristics of the First Learning Sequence*

Title. **'Séance 1 : I- Christophe Colomb et la « découverte » de l'Amérique'**

Duration. 3 hours

Notions Worked On. Contact, discovery, conquest, exchanges, evangelisation, America, enlargement of the world

### Fig. A.1

*Summary of a 'Learning Module' Presenting a Piece of Content Knowledge*

Module Comprendre : biographie de Christophe Colomb		
Activité élève	Documents d'appui	
Acquérir des repères temporels et spatiaux à partir de la consultation libre d'une frise et d'un site interactif	Éléments de repérage temporels (frise)  Infographie interactive « France TV Educations » : <i>L'Histoire des Grandes Découvertes avec les explorateurs des XVe et XVIe siècles</i>	



Fig. A.2 to A.5

## Screenshots of the Interactive Environment Within a 'Learning Module'

Fig. A.2

## Instruction to Read a Text

Lisez attentivement le texte

### Les erreurs lumineuses de Colomb

Une série d'erreurs de calcul et une observation négligée... c'est à ce prix que Christophe Colomb a posé le pied en Amérique ! Grâce au journal de bord du navigateur, vous pouvez savoir tout après tout son départ.

Quel de nous pour approcher un héros aussi jacobin que Christophe Colomb que de lire les textes qu'il nous a laissés ? Certes, le journal de bord dans lequel il offre aux Rois Catholiques Isabelle de Castille et Ferdinand d'Aragon, le récit de son premier voyage ne nous est pas connu directement... forgé à cet effet... mais un passage par les géométries montre que le chemin en zigzag du Colomb de Las Cañas a respecté dans son ensemble les angles des terres. Tous deux ont également des raisons de ses trois voyages suivants et de nombreuses lettres, notamment à son commanditaire royal.

A l'ère Colomb, c'est aussi l'honneur d'une rupture que l'on découvre dans une date fautive à peine au sein même des modes de pensée présents au Moyen Âge. Carrien on le verra dans les siècles suivants, Christophe Colomb est d'abord un empereur médiéval, guidé par le Livre des merveilles de Marco Polo. De fait, sa première expédition doit être une préface auprès du Grand Khan elle nous jette les, dans l'esprit de le traverser au christophe et de parler ainsi l'indication chrétienne dont les souverains hispaniques se sont faits les champions en envoyant Colomb aux Indes et en espérant le gain de leurs royaumes en 1492.

#### LA CERTITUDE QUE LA TERRE EST RONDE

Colomb et les équipages de ses trois caravelles quittent le port andalou de Palos le 3 août 1492. Leur projet : rejoindre les Indes, mais pas en contournant l'Asie comme le font les Portugais, mais en naviguant cap vers l'est. Le 6 septembre, ils rejoignent des terres inconnues en abordant les Caraïbes. Pourtant, l'importance de se savoir perdu au milieu d'espaces océaniques immenses et immensités ne se traduit guère dans le journal de bord. Bien au contraire, quelques jours à peine après leur départ, les navigateurs accusaient les Indes qui confirmaient leur sensation d'être à proximité d'un ou de terres qui seraient se plonger sans cesse.

À plusieurs reprises, l'équipage demande que l'on mette le cap plus au sud afin d'atteindre un lieu proche ; mais Colomb résista presque jusqu'au bout et maintint le cap vers les Indes qu'il croit à portée de main. Malgré les moments de doute et de lassitude, la certitude offre un permanent gain du sud et l'usage d'un monde où la mer est plus de chose amant permis à Colomb de toucher effectivement terre, le 12 octobre 1492.

CLASSE, CSST, LE JAPON

COMPRENDRE : "Les erreurs lumineuses de Colomb" par Jérôme Bouchet

Fig. A.3

## Example of a Multiple-Choice Question

"guidé par le Livre des merveilles de Marco Polo"

« Pour l'indication de l'existence des Indes, ce ne seraient ni raisons ni mathématiques ni suppositions ; ce qui précisément s'est accompli est ce qu'il faut dire. »

« Sans estimer la circonférence de la Terre pour savoir qu'il survenait l'étendue des terres européennes »

« Pour l'indication de l'existence des Indes, ce ne seraient ni raisons ni mathématiques ni suppositions ; ce qui précisément s'est accompli est ce qu'il faut dire. »

Article de Jérôme Bouchet, L'Esprit, n° 793, juillet-août 2016, pp.60 à 67

**Dans cet article, l'auteur présente les grandes erreurs commises par Christophe Colomb.**

**Consigne : Sélectionnez les réponses correspondant aux erreurs de Colomb.**

COMPRENDRE : "Les erreurs lumineuses de Colomb" par Jérôme Bouchet

Fig. A.4

## Example of an Incorrect Answer and Feedback

The screenshot displays a learning interface with the following elements:

- Question:** "qu'elle est la zone des nouvelles de Marco Polo?"
- Answer:** "Sous-équateur la croissance de la terre suit surtout qu'il y a une relation des terres asiatiques"
- Feedback:** "Pour l'exécution de l'emprise des Indes, ce ne seraient ni raisons mathématiques ni magiques, ni qui généralement s'est accompli en ce qu'il est arrivé."
- Feedback Status:** A red speech bubble labeled "Bonne réponse" is positioned above the feedback text.
- Footer:** Includes the "maskott" logo, the text "COMPRENDRE 'Les erreurs géographiques de Colomb' par Jérôme Bouchier", and navigation icons.


**Fig. A.5**  
*Example of a Correct Answer and Feedback*

The screenshot displays a learning interface with the following elements:

- Question:** "qu'elle est la zone des nouvelles de Marco Polo?"
- Answer:** "Sous-équateur la croissance de la terre suit surtout qu'il y a une relation des terres asiatiques"
- Feedback:** "Pour l'exécution de l'emprise des Indes, ce ne seraient ni raisons mathématiques ni magiques, ni qui généralement s'est accompli en ce qu'il est arrivé."
- Feedback Status:** A green speech bubble labeled "Mauvaise réponse" is positioned above the feedback text.
- Footer:** Includes the "maskott" logo, the text "COMPRENDRE 'Les erreurs géographiques de Colomb' par Jérôme Bouchier", and navigation icons.

**Fig. A.6**

*Summary of a 'Training Module' Focusing on Students' 'Analysis and Explanation Skills'*

<b>Module s'entraîner : biographie de Christophe Colomb</b>		
<b>Activité élève</b>	<b>Documents d'appui</b>	
travailler la méthode de l'analyse de documents en histoire.  <b>c. analyser / expliquer : analyser et expliquer le document à l'aide de vos connaissances personnelles</b>	Extraits du journal de bord de Christophe Colomb. Cité dans Christophe Colomb, <i>journal de bord (1492-1493)</i> , Michel Balard, Imprimerie Nationale, 2003	

**Fig. A.7 to A.10**

*Screenshots of the Interactive Environment Within the Same 'Training Module'*

**Fig. A.7**

*Instruction to Watch a Video and Take a Problem-Solving Exercise*



**Analyser / Expliquer - les conditions du voyage**

**Consigne : Visionner la vidéo pendant 4 minutes 29 secondes et déplacer les étiquettes dans le groupe correspondant.**

Le journal de bord de Christophe Colomb raconte que la durée de la traversée a été longue (2 mois et quelques jours) et que les conditions ont été difficiles (eau).

À l'issue de cet exercice, vous pourrez accéder à des ressources complémentaires.


IC | 111111111111 | Analyser / Expliquer : le journal de bord de Christophe Colomb
>

**Fig. A.8**  
*Example of an Incorrect Answer Allowing for Hint Solicitation*

The screenshot shows a learning interface with a question at the top: "Le journal de bord de Christophe Colomb mentionne que la durée de la traversée a été longue (2 mois et quelques jours) et que les conditions ont été difficiles mais: ...". Below the question are three columns of incorrect answer options: "Dieu, et le retour vers le continent natal", "Les Espagnols ont découvert de nouveaux territoires au contact des populations locales", and "Les navigateurs utilisaient des cartes marines précises". Below these are three more columns of incorrect options: "Christophe Colomb a pu profiter d'avancées technologiques...", "... mais a dû faire face à des conditions qui étaient difficiles.", and "Affirmations fausses...". A red banner at the bottom right says "Prenez le temps de bien visionner la vidéo. N'hésitez pas à prendre des notes." The interface includes a logo for "maskott" and navigation icons.

**Fig. A.9**  
*Example of Hint Delivery on Request*

This screenshot shows the same learning interface as Fig. A.8, but with a hint window open. The hint window is titled "Indice" and contains the text: "De l'Indice : l'Indice de la traversée mentionne que la durée de la traversée a été longue (2 mois et quelques jours) et que les conditions ont été difficiles mais: ...". Below the text is a circular diagram with a compass rose and a globe. A red banner at the bottom right says "Vous n'avez pas répondu ou la réponse est incorrecte, voulez-vous continuer?". The interface includes a logo for "maskott" and navigation icons.

**Fig. A.10**  
*Example of a Correct Answer and Feedback*

**Consigne : Visionner la vidéo pendant 4 minutes 29 secondes et déplacer les étiquettes dans le groupe correspondant.**

Le journal de bord de Christophe Colomb rappelle que la durée de la traversée a été longue (2 mois et quelques jours) et que les conditions ont été difficiles mais :

Il n'apparait pas d'élément expliquant les difficultés rencontrées ;  
 Il n'est pas tout à fait possible de voyager à grande vitesse.  
 La vidéo doit vous permettre d'y répondre.

Christopher Colomb a pu profiter d'avancées technologiques... / ...mais a dû faire face à des conditions qui restent difficiles / Affirmation fautive...

Les Portugais et les Espagnols ont pu profiter de la boussole importée par les arabes / Les gouvernails ont été améliorés / Les navires fabriqués par les Portugais et les Espagnols pouvaient "prendre la mer"

Les navires utilisés sont des caravelles lourdes, lentes et petites / L'eau et la nourriture se conservent mal

Les Arabes ont inventé la boussole / Les Espagnols ont beaucoup appris au contact des marchands chinois.

maskott (C) ICF/INRAH - Analyse / Explication : le journal de bord de Christophe Colomb

## Text A.2

### *Detailed List of Hints and Expected Answers Within the Same 'Training Module'*

#### **'1. Analyser / expliquer - les conditions du voyage.**

**Visionner la vidéo pendant 4 minutes 29 secondes et déplacer les étiquettes dans le groupe correspondant.**

**[7 étiquettes à classer dans 3 colonnes]**

**[indice 1 : La colonne un comporte trois bonnes réponses... /**

**Indice 2 : "En Chine,(...) l'aiguille (de la boussole) montrait non pas le nord mais le sud, par égard pour l'empereur, car il fallait respectueusement tourner le dos à la Grande Ourse, résidence du « souverain d'en haut » dont il était le représentant sur la Terre. À la fin du XIe siècle, en mer de Chine et dans l'océan Indien, les pilotes chinois, arabes et persans s'orientaient aussi parfois grâce à l'aiguille aimantée lorsqu'un ciel exceptionnellement couvert leur masquait les étoiles."**

**Indice 3 : La caravelle, une avancée technologique qui permet de naviguer sur tous les océans.]**

**Colonne 1 : Les Portugais et les Espagnols ont pu profiter de la boussole importée par les arabes / Les gouvernails ont été améliorés / Les navires fabriqués par les Portugais et les Espagnols pouvaient "prendre la mer"**

**Colonne 2 : Les navires utilisés sont des caravelles lourdes, lentes et petites /L'eau et la nourriture se conservent mal**

**Colonne 3 : Les Arabes ont inventé la boussole /Les Espagnols ont beaucoup appris au contact des marchands chinois.'**

*Note.* Hints and expected correct answers are highlighted in orange and green respectively. Instructions are in black bold font.

## **Appendix B. Details of the Statistical Analyses**

### **Text B.1**

We conducted all statistical analyses using R software version 4.1.2 (R Core Team, 2022). The nlme R package version 3.1.162 (Pinheiro et al., 2023) was used to conduct a random intercept model to account for the hierarchical structure of the data (i.e., students - Level 1 - nested in classes - Level 2 - and classes nested in schools - Level 3) and to control for their respective sources of variance on current knowledge (T1) (Fidell et al., 2007). To date, there is no clear consensus on how to determine adequate power and sample size when the data structure has more than two levels (Kerkhoff & Nussbeck, 2019). Therefore, we followed McNiesh and Stapleton's (2016) recommendation of having at least 30 units at Level 2 to ensure accurate variance estimates. Given the great difficulty in obtaining such a large number of classes and, *a fortiori*, schools, only 24 classes in 7 high schools participated. However, the focus of this study is not on the variance components, but on the fixed effects at the student level, where Level 1 data is most relevant. At this level, we meet McNeish and Stapleton's (2016) recommendation of having more than 5 observations per cluster (class) for accurate Level 1 fixed-effect estimates.

The required sample size at the lowest level (student level, Level 1) was determined a priori through a power analysis ( $1-\beta = .80$ ,  $\alpha = .05$ ) conducted using the R package InteractionPower 0.2.1 (Baranger et al., 2023). The minimum sample size ( $N \geq 341$ ) was calculated based on the interaction (Instruction Method \* ASC) addressing Hypothesis 2, where input parameters (Pearson's correlations between dependent and independent variables and between independent variables) were derived from converting effect sizes for CAI effects on

academic performance ( $d = .30$ , VanLehn, 2011) and ASC's impact on subsequent academic performance ( $\beta = .14$ , Marsh and O'Mara, 2008) into Pearson's correlation coefficients. Due to the unavailability of prior correlation coefficients between CAI and ASC, as well as between their interaction term with academic performance, a starting value of  $r = .15$  (relatively small magnitude) was used. Subsequently, an *a posteriori* power analysis using InteractionPower was conducted after data collection to adjust the parameters by entering the final sample size ( $N = 389$ ) and the observed Pearson correlation coefficients (available in Appendix C, Table C.2). The *a posteriori* power analysis revealed an actual power of  $1 - \beta = .87$  for detecting the IM (Instruction Method) \* ASC interaction effect.

The statistical analyses modeled the effects of the two instructional methods on students' academic performance in the current knowledge test (the study's dependent variable) after two weeks of intervention, while also considering the influence of initial ASC levels and prior knowledge in history-geography. The analyses controlled for students' sex and SES. This approach allowed for the simultaneous investigation of the study's two main objectives: the effectiveness of CAI and the underlying mechanisms, while accounting for the hierarchical structure of the data organized into student (Level 1), class (Level 2), and school (Level 3) levels. We employed a three-step procedure to investigate the research questions.

In the first step, we conducted preliminary analyses to assess possible pre-test imbalances in the study variables, specifically the main predictors of interest (ASC and prior knowledge) and the covariates (sex, and SES), across the instructional methods (CAI and conventional classroom instruction). This step utilized the CAR R package version 3.1.2 (Fox & Weisberg, 2019). The between-participant variance of current academic performance (T1) was larger in the CAI group ( $\sigma^2_{CAI} = 1.86$ ) compared to the control group ( $\sigma^2_{Control} = 1.05$ ),  $F = 1.40$ ,  $p = .020$ . Consequently, in all subsequent multilevel models, we controlled for this

variance heterogeneity in the estimated effects of instructional methods on T1 by specifying a group-related heterogeneous variance structure using the nlme R package.

The preliminary analyses also investigated the potential presence of contextual effects on current academic performance (T1) at the class and school levels using a random intercept model. This step ensured that the influence of a given Level 1 variable on students' current academic performance (T1) was not attributed to global variations of that variable across classes and schools (Branum-Martin et al., 2010; Chevalère et al., 2021; Christ et al., 2014). For instance, two students from different classes may show similar performances even though one is the weakest student in their class and the other is the best in another class, which could lead to variations in the magnitude of the ASC-academic performance relationships at the student level. To address this, in Model<sub>Cntx</sub>, we averaged each Level 1 variable at the classroom and school levels and used these averages as predictors along with the main effects. If a contextual effect was detected in Model<sub>Cntx</sub>, it was retained in further analyses.

In the second step, we addressed the first three hypotheses of the present study using a random intercept model (Model 1). The model allowed current academic performance (T1) to vary across classes (Level 2) and schools (Level 3). We included the main effects of instructional methods (Hypothesis 1), ASC, the Instruction Method \* T0 (Hypothesis 2), and the Instruction Method \* ASC interaction terms (Hypothesis 3). With prior knowledge entered as a covariate in Model 1, *learning* was represented by the residual score on the posttest knowledge test (T1) after accounting for the influence of the pretest knowledge test (T0) (Xiao et al., 2019). Students' sex and SES were also included as covariates in the model. Since all students were recruited in their 10th grade and consequently had similar ages ( $SD_{Age} = 0.47$ ), age was not included as a covariate.



As the third and final step, we conducted additional analyses to explore the role of CAI in disrupting the influence of ASC (Hypothesis 4) and prior knowledge (Hypothesis 5) on subsequent/current academic performance by comparing the strength of the associations between ASC and T1, and between T0 and T1, in the control and experimental groups. For this, we performed path analyses using the R package ‘lavaan’ (Rosseel et al., 2012) version 0.6.16, modeling these relationships separately for the CAI and control groups. The magnitude of the ASC → T1 and T0 → T1 links were compared across groups using a Wald test (Klopp, 2019) while controlling for students’ sex and SES. The relationship between ASC and T0 was also examined and was expected to remain consistent across groups.

All model parameters for the multilevel analyses and path analyses (steps 1, 2, and 3) were estimated using maximum likelihood estimation, and 95% confidence intervals were generated using bootstrapping (5,000 resamples) and percentile methods (Efron & Tibshirani, 1993). These analyses were conducted using the R packages nlraa version 1.1 (Miguez, 2022) and lavaan (Rosseel et al., 2012) version 0.6.16 for the multilevel and path analyses, respectively.

## **Appendix C. Results of the Preliminary Analysis**

### **Text C.1**

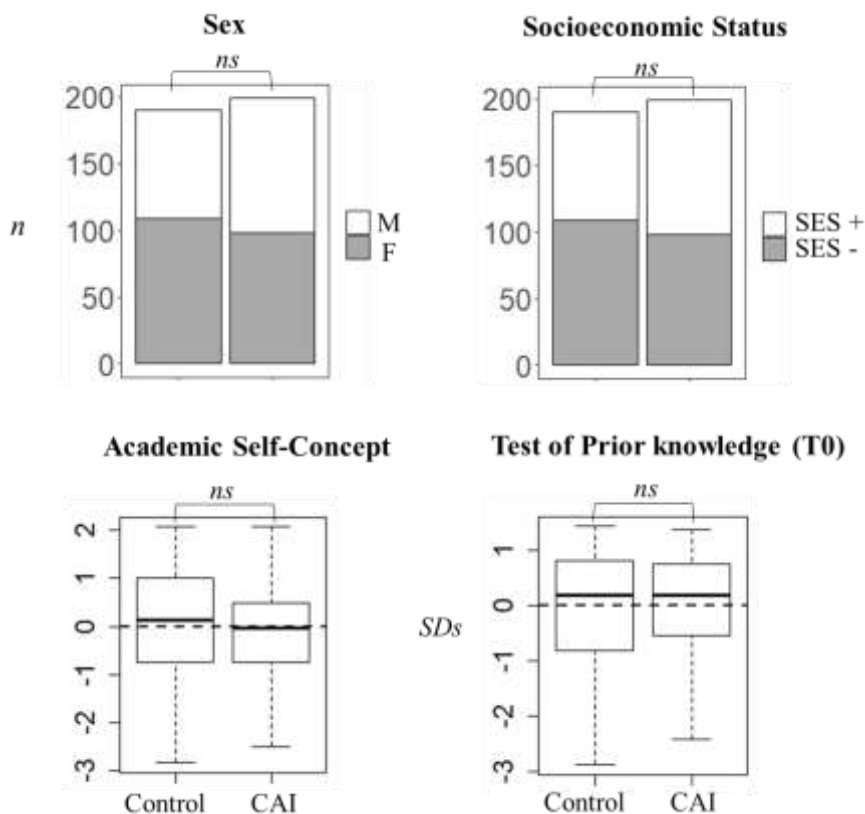
The preliminary analyses focused on: a) potential pretest group imbalances in the study variables, b) potential contextual effects on the study variables, and c) the relationships between the study variables.

### *Analyses of Pre-test Group-Related Imbalance*

As shown in Fig. C.1, the preliminary analyses revealed non-significant group-related pretest differences in participants' sex,  $\chi^2(1) = 2.34, p = .13$ , socioeconomic status,  $\chi^2(1) = 2.87, p = .09$ , ASC,  $F(1, 387) = 2.25, p = .14$ , and prior knowledge  $F < 1$ .

**Fig. C.1**

*Preliminary Analysis of Group Imbalance at Pretest in for the Study Variables*



*Note.* CAI = computer-assisted instruction; Control = Conventional classroom instruction; M = males; F = females; SES+ = high socioeconomic background; SES- = low socioeconomic background. Horizontal dashed lines represent the grand mean.

**Text C.2***Class and School Contextual Effects of Study Variables*

Next, we investigated the presence of potential contextual effects on current academic performance at the class and school levels for all study variables. As shown in Table C.1, the non-significant contextual effects,  $\gamma_s \leq -.52$ ,  $ps \geq .075$ , in the present sample, students' current academic performance was not biased by classes or schools with different proportions in terms of sex, prior knowledge, SES or ASC.

**Table C.1**

*Contextual Effects of the Study Variables at the Class and School Levels on the Test of Current Knowledge (T1)*

<i>n</i> students = 389, <i>n</i> classes = 24, <i>n</i> schools = 7	Model <sub>Cntx</sub>	
	<i>E</i>	95% CI
<b>Fixed Effects</b>		
<i>Student Level</i>		
Intercept	.002	[-.09; .09]
Sex	-.03	[-.13; .06]
SES	-.09 <sup>t1</sup>	[-.18; -.002]
T0	.22***	[.13; .31]
ASC	.10*	[.002; .20]
<i>Class level</i>		
Contextual Sex	-.52 <sup>t2</sup>	[-.94; -.09]
Contextual SES	-.11	[-.90; .49]
Contextual T0	.33	[-.13; .69]
Contextual ASC	-.20	[-.73; .40]
<i>School Level</i>		
Contextual Sex	-.36	[-1.06; .39]
Contextual SES	-.24	[-1.03; .66]
Contextual T0	-.88	[-2.45; .82]
Contextual ASC	.79	[-.03; 1.49]
<b>Random Effects</b>		
<i>Residual variance (also ICC)</i>		
Student Level	.84	-
Class Level	.04	-
School Level	.00	-
Log Likelihood	-513.17	-
AIC	1060.34	-
BIC	1127.73	-

*Note.* <sup>t1</sup>  $p = .062$ ; <sup>t2</sup>  $p = .075$ ; \*  $p < .05$ ; \*\*\*  $p < .001$ ; T0 = test of prior knowledge; SES = socioeconomic status; CAI = computer assisted instruction (effect); E = estimate; CI = confidence interval; SD = standard deviation; df = degrees of freedom; ICC = intraclass correlation coefficient; AIC = Akaike information criterion; BIC = Bayesian information criterion.

### **Text C.3**

#### *Description of the Relationships Among Study Variables*

We examine the relationship between sex, SES, prior knowledge (T0), SES, ASC, instruction methods and current academic performance (T1), and the Instruction Method \* T0 and Instruction Method \* ASC interaction terms using Pearson correlational analyses shown in Table C.2. Sex was unrelated to other variables, ( $rs \leq |.08|$ ,  $ps \geq .10$ ). Students with a lower SES were associated with a lower prior knowledge, ASC and current academic performance ( $rs \geq -.10$ ,  $ps \leq .049$ ) but it was unrelated to experimental conditions,  $r = -.09$ ,  $p = .07$ . Students with a higher prior knowledge also showed a higher ASC and current academic performance,  $rs \geq .21$ ,  $ps < .001$ , but it was unrelated to experimental conditions,  $r = -.02$ ,  $p = .71$ . Student with a higher ASC also showed a higher current academic performance,  $rs \geq .21$ ,  $ps < .001$ . The correlational analyses failed to find an association between experimental conditions and current academic performance,  $r = .07$ ,  $p = .20$ , which is not incompatible with moderation effects with other variables. The Instruction Method \* T0 interaction term was only associated with the Instruction Method \* ASC interaction term,  $r = .22$ ,  $p < .001$ . Finally, the Instruction Method \* ASC interaction term was significantly associated with ASC  $r = -.11$ ,  $p = .024$  and current academic performance  $r = -.15$ ,  $p = .003$ .

### **Table C.2**

#### *Pearson's Correlations for the Study Variables*

	1. Sex	2. SES	3. T0	4. ASC	5. IM	6. T1	7. IM*T0	8. IM*ASC
1.	-	-.08	.01	-.08	-.08	-.08	-.02	-.04
2.		-	-.10*	-.20***	-.09	-.16***	-.01	.01
3.			-	.21***	-.02	.28***	-.01	-.04
4.				-	-.08	.21***	-.04	-.11*
5.					-	.07	.00	.00
6.						-	-.07	-.15**
7.								.22***
8.								-

Note. \*  $p < .05$ ; \*\*  $p < .01$ ; \*\*\*  $p < .001$ ; T0 = test of prior knowledge; T1=test of current knowledge; SES = socioeconomic status; ASC = academic self-concept; IM = instruction method

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