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# Compensating the socioeconomic achievement gap with computer-assisted instruction

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1 Supporting Information file

## Abstract

**Background.** As educational digital technologies are increasingly being used in schools, past research left unanswered the question of these technologies' impact on the socioeconomic achievement gap even when equal access is guaranteed.

**Objectives.** The objectives of the present study are to examine whether and how the socioeconomic achievement gap can be reduced through the use of computer-assisted instruction (CAI).

**Methods.** We addressed this issue experimentally by comparing CAI to conventional teacher-led classroom instruction with more than eight hundred middle and high school students from disadvantaged and highly privileged socioeconomic backgrounds in a range of topics.

**Results and Conclusions.** Both disadvantaged and highly privileged students taught with CAI outperformed those taught with conventional instruction, thus maintaining the socioeconomic achievement gap constant. However, we also found that disadvantaged students receiving CAI performed as well as highly privileged students receiving conventional teacher-led instruction.

**Takeaways.** The positive effects associated with CAI may therefore help compensate the difficulties of students with a disadvantaged background, a still neglected possibility.

*164 words*

**Key words:** Socioeconomic achievement gap; Social inequalities; Socioeconomic status; Education; Computer-assisted instruction.

# Compensating the socioeconomic achievement gap with computer-assisted instruction

## Introduction

Despite a global increased access to schooling over the last 20 years, social inequality in education is still a worldwide issue hampering success of the less advantaged students (The United Nations Educational, Scientific and Cultural Organization -UNESCO Institute for Statistics, 2018, *One in Five Children, Adolescents and Youth is Out of School*). In their policy recommendations for education systems, the Organisation for Economic Co-operation and Development -OECD- reports have continuously encouraged educative strategies targeted to disadvantaged students (e.g., *Equity and Quality in Education. Supporting Disadvantaged Students and Schools*, 2012). This includes promoting student-centred forms of instructions that might be achieved via educational digital technologies (EDTechs). This promotion implies a reduction of the digital divide between disadvantaged and privileged students, an observable trend in the past decade. The 2009 Programme for International Student Assessment -PISA- report found that 15% of students in OECD countries did not have access to the internet at home, while in 2018 this proportion fell to 5% (OECD, 2019b, *PISA 2018 Results: Combined Executive Summaries, Volume I, II & III*). However, even a more equal access to EdTechs does not guarantee that their use change anything to the socioeconomic achievement gap, which at best may remain constant assuming that all students benefit from digital learning. The present study sought to investigate whether digital technologies, in particular Computer-Assisted Instruction (CAI), may help reduce the socioeconomic achievement gap.

## Statement of the problem

Considering social inequalities as a major challenge in education (OECD, 2019b), one may ask whether and how digital technologies modulates the socioeconomic achievement gap, that is, the gap in achievement between lower and higher socioeconomic background students. Socioeconomic status (SES) reflects students' access to financial, social, cultural and human-capital resources available to the family within its social position or rank in the social structure (American Psychological Association, 2020; OECD, 2019a, *PISA 2018: Insights and*

*Interpretations*”). SES is commonly measured with indicators combining various sources of information (e.g., educational level, occupation and family income, cf. Sirin, 2005). SES is thus a complex construct having determining consequences on important life outcomes including health, professional occupation and education: it is well-documented that low SES students perform less well academically than their privileged counterparts (Bourdieu & Passeron, 1990; for a recent review, see Farah, 2018). The latest PISA report (OECD, 2019a) showed that in 23 countries more than 1 out to 3 children from disadvantaged backgrounds do not reach the proficiency level in reading. On average across OECD countries, only 1 to 10 disadvantaged children have a reading score ranking within the first quartile. The chances to integrate high quality schools, that would allow disadvantaged children to develop their potential, are also considerably low (1 to 6 in average in 25 countries), whereas their chances to integrate a school with lack of resources are twice as high relative to their advantaged peers (in 46 countries). In countries as diverse as France, Germany, Hungary, Israel and Peru, the achievement gap severing the 10% most privileged from the 10% most disadvantaged students in reading is estimated at four years of delay in schooling. While students’ SES discrepancies account for 13% of the variance in reading and sciences scores on average across OECD countries, this coefficient reaches 20% in France with very slow improvements (-2%) since the 2006 PISA report (OECD, 2018, “*Education at a Glance 2018: OECD Indicators*”, 2019a).

## **Theoretical background and related work**

The socioeconomic achievement gap may be understood as an extension of the Matthew effect (Merton, 1968; Stanovich, 1986; Walberg & Tsai, 1983). Originally, the Matthew effect designed the mechanisms by which the most recognized scientists and higher institutions tend to maintain their dominance in the world of research and innovation and this framework had fruitful applications in education to understand individual differences in learning (Merton, 1968). Applied to the education context, the framework explained how children with initial slightly different advantages in reading (and other abilities) due to richer home environment progress faster and draw away from their less advantaged peers, thus steadily increasing the achievement gap over the schooling process (Stanovich, 1986; Walberg & Tsai, 1983). In relation to digital technologies, it reflects the virtuous circle in which highly performing students, in particular those who benefit from richer socioeconomic backgrounds, may use their

advanced knowledge or familiarity with technology available at home to benefit more from digital technologies in educational contexts (Mingo & Bracciale, 2018).

In support for this, Rodrigues and Biagi (2017) conducted correlational re-analysed the 2015 PISA report and included information- communication and technology (ICT)-related variable as moderators of the socioeconomic achievement gap. They found that among students that are the less likely to use digital technologies, increasing their use for educational purposes only benefits students of medium and high socio-economic status while having a negative effect on disadvantaged students' science scores, thus increasing the socioeconomic achievement gap.

Alternatively, it has been suggested that digital technologies might help reduce the achievement gap (Darling-Hammond et al., 2014; Rosen & Wolf, 2011). The general rationale is that personalized learning, which is made possible through digital technologies may foster one's learning potential through self-paced learning and individualized feedback tailored to one's needs (Sleeman & Brown, 1982; Walsh, 2011). CAI are particularly relevant in this respect. CAI refers to the instructional use of a computer to present virtual material (texts, videos, graphics, audios) through training methods such as problem-solving exercises and tutorials, that make an extensive use of feedback (Kulik, 2003). CAI is also part of a desire to personalize learning by adapting to the characteristics of the learner (Walsh, 2011). This customization is based on educational rules defining access to educational objects, which are either configured by the teacher or automatically (Root et al., 2018).

In support for a possible reduction of the SES achievement gap, a study by Roschelle et al. (2016) evaluated an intervention using ASSISTments (Heffernan, & Heffernan, 2014), an online homework CAI in a large cohort of seventh graders on mathematics compared to traditional homework practices and showed an increase in student's scores with a more pronounced benefit for low-prior achievement in mathematics. Importantly, the magnitude of the improvement was higher than the difference in academic score between students with high and low-SES, suggesting a possible compensation of the socioeconomic achievement gap.

A report by Darling-Hammond et al., 2014 documented that interactive technologies, such as those providing high levels of feedback, diagnosis of student's difficulties and detailed information about progress (such as CAI) were particularly efficient in helping at-risk students, for example by increasing the rate of successful state competency tests.

In the same vein, Rosen and Wolf (2011) provided equal access to digital technology at school to students with low socioeconomic background using the Time to Know digital teaching platform (a typical CAI, Walters et al., 2009) and compared this method to conventional

classroom instructions on Mathematics, Hebrew and English achievements. They found that instructions provided through the tool increased knowledge in the three domains relative to conventional instructions and narrowed the gap among students in terms of knowledge and skills.

However, although the latter two studies suggest actual benefits of CAI for low-SES students, they did not compare them to more advantaged peers, thus leaving open the question whether the achievement gap reduces or maintains constant with digital technologies. Indeed, improving low-SES students' skills does not mean that they would necessarily draw closer to their more privileged classmates if the benefits associated with CAI equivalent for high and low-SES students. CAI have shown to improve learning compared to conventional teacher-led instructions of about  $d = 0.30$  standard deviations, that is, an improvement from the 50<sup>th</sup> to the 62<sup>nd</sup> percentile (Kulik & Fletcher, 2016; VanLehn, 2011). However, it is still unclear whether the learning benefits associated with CAI vary depending on student's socioeconomic status or other individual characteristics (Higgins et al., 2012; Leroux et al., 2017).

Suggesting equivalent effects, a study by Lashley (2017) investigated the use of CAI in fourth grade low and middle-income pupils on mathematics and compared the instruction method to conventional teaching. They found that the CAI condition was associated with better academic performance outcomes relative to conventional teaching with equivalent effects for low- and middle-income pupils, thus maintaining the socioeconomic achievement gap constant (see also Hollingworth et al., 2008 for similar conclusions).

## **Research questions**

Whether the introduction of digital technologies may benefit some groups of students more than others has been debated (see Rodrigues & Biagi, 2017). However, given the inconsistent findings in past research, either suggesting an increase (Rodrigues & Biagi, 2017), a reduction (Roschelle et al., 2016) or a maintenance (Lashley, 2017) of the socioeconomic achievement gap with digital technologies, evidence is still lacking, especially regarding CAI. In the present study, we sought to answer the following research questions:

- 1) Is CAI beneficial for improving students' academic performance compared to conventional teacher-led instruction?
- 2) Is CAI capable to reduce the socioeconomic achievement gap?

Figure 1 about here

## Methods

### Setting

To answer these questions, we conducted the present study in public schools within the perimeter of the Auvergne region in France, over the four counties pertaining to the school district of Clermont-Ferrand. The sample included 806 middle and high school students, a fairly high sample size relative to experimental field studies in CAI research (Kulik & Fletcher, 2016). Figure 1 illustrates the experimental design that we used to examine whether the learning benefits of CAI can be found both in students with a high vs low SES and related consequences on the size of the classic socioeconomic achievement gap. Receiving either conventional teacher-led instruction or CAI, low and high SES students were exposed to topics related to Physics-Chemistry, Earth and Life Sciences, Technology and History-Geography during a time period varying from four to ten weeks. For each topic, students completed academic tests of prior knowledge (i.e., an assessment of knowledge level before instructional intervention) and learning outcomes (i.e., an assessment of knowledge acquired through intervention).

The knowledge tests' content and the base knowledge content of the instructional intervention were identical across experimental conditions. However, they differed from one topic to another. This aimed at reflecting the original lengths and complexity of the respective topics across disciplines and school levels, as they present in the official national educational programme, thus reflecting the different amount of factual knowledge and learning skills they encompass. We aimed at considering these particularities in the intervention content and durations and, accordingly, in how the knowledge tests were elaborated, which resulted in different metrics for the knowledge tests across topics. Therefore, to make the tests more statistically comparable, we converted all knowledge tests into Z scores (centred around 0 and scaled in standard deviation units) prior to analyses.

Random attribution to experimental conditions (i.e., conventional teacher-led vs CAI) was simply not feasible here since an optimal use of the CAI required essential material features such as an adequate internet connection, or a sufficient number of recent computers per student,



that were not necessarily available from one school to another. These are typical field constraints found in many large-scale studies (Bray et al., 2008), which is accentuated in studies focusing on digital learning given the unequal distribution of technological resources at the school level (for a few exceptions, see Fairlie & Loyalka, 2020). To remedy these constraints, we followed up-to-date recommendations (Castro-Schilo & Grimm, 2018; Xiao et al., 2017) and conducted multilevel modeling with a cautious control over a range of parameters allowing increasing validity through estimation bias reduction. In particular, we conducted preliminary analyses to examine pre-test imbalance in students' prior knowledge and socioeconomic status (Figure S1, Appendices). SES effects should be interpreted downward (e.g., the decrease in academic performance from highly privileged to disadvantageous backgrounds).

## Participants

An initial sample of 998 individuals participated in this study<sup>1</sup> representing students from disadvantaged and highly privileged backgrounds as defined by the French Ministry of Education (see below). Of them, 19% did not complete academic tests in at least one of the academic subjects, we therefore excluded them from analyses. The final sample size resulted in 806 middle and high school students ( $M_{\text{age}} = 14.75$ ,  $SD_{\text{age}} = 1.44$ ; 415 females). Out to 410 middle schoolers, 61% were in grade seven and 39% were in grade nine. All 396 high schoolers were in grade eleven. Within the final sample size (806), 52% were categorized as highly privileged students and 48% were disadvantaged students according to the nomenclature of professions and socio-professional categories (PCS) of the French Ministry of Education (see below, section on socioeconomic status). All participants were recruited in their usual school by the referent teacher participating in the study. 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 form several weeks before the study that they had to read and sign to allow their child to participate. The

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<sup>1</sup> The study is part of a larger research project which received an approval from Clermont Auvergne University's Ethics Committee in conformity with the French bioethical law (covering Psychology)

procedure was identical for legal adults (eleventh graders of 18 years or above), except that they signed the informed consent form themselves.

## **Material and procedure**

### ***Lesson plan implementation***

The CAI versions used for each subject and topic were evolved versions of a tool (Tactileo©) developed by Maskott©. These more sophisticated and dynamic versions were the product of a synergic work in which programmers integrated the material content provided by teachers while parametrizing the CAI in accordance with teachers and researcher's recommendations. For this study, we relied on the idea that technologies created or adapted by research teams and including teachers are more efficient for learning than those technologies either taken from the commercial market or those that merely used the technology as a delivery system (Moran et al., 2008). This is because the close collaboration between researchers and teachers ensures a more adequate alignment of the knowledge content and pedagogical resources with the school's curriculum and standards. Accordingly, the pedagogical content knowledge was taken from the National Educational Programme and was identical in both instruction methods (CAI and control). Approximately half the students (51.2%) received conventional/traditional instructions and the other half (49.8%) were taught using CAI.

For each topic taught through CAI, secondary education teachers, school inspectors, programmers and designers collaboratively transcribed the content knowledge of taken from the official French National Educational Programme into the system. The selection of the content knowledge was decided and supervised by state school inspectors representative of the disciplines involved and the implementation followed the typical training methods representative of the CAI literature including problem solving exercises (O'Neil et al., 2014), and tutoring modes (Kulik, 2003) embedded in narrative scenarios (Finnegan & Sinatra, 1991). For conventional instruction, the same topics were used but the instruction method was left at the discretion of the teacher, provided that it was teacher-led, using no digital technology.

Since our research project took place in authentic school settings, the level of participation of particular schools and referent teachers determined the enrolment of individual or group of students in one or more topics. More precisely, each school referent for the project (either the school principal or a teacher) had the possibility to propose one or more group of students. The number of participating groups (the usual classrooms) was determined by an internal agreement between the school referent, the school principal and teachers from different disciplines. In case several teachers from one school agreed in participating, the students enrolled in these teachers' usual classrooms received the intervention for the various subjects taught by these teachers, provided that the consent was given.

Based on the agreement between teachers and the school referent, approximately 60% of the students took a single course, and the remaining were enrolled in more than one discipline. An average score was calculated for students who took more than one discipline. All students assigned to the CAI condition were equipped with one tablet-computer per student and interacted with the CAI in their usual classrooms in presence of their teachers depending on the subject. The role of teachers was to introduce the topic and then to let their students learn on their own through interactions with the CAI and only intervene in case of problems or questions from students. Students were instructed not to collaborate with other students to maximize the time spent on their tablet computer.

### *Academic tests*

**Test of prior knowledge (T0) before intervention.** To determine CAI's efficacy on academic performance in Physics-Chemistry, Earth and Life Sciences, Technology and History-Geography, measures of prior knowledge were taken. These measures assessed contents from the National Educational Program acquired during the *previous* year, corresponding to the knowledge prerequisites for learning the content taught through intervention in each topic (see T1 measures below). They were used to provide a performance baseline aiming at controlling for initial individual differences in knowledge as well as to examine potential interactions with instructional methods. The tests of prior knowledge consisted in short-answer questions and multiple-choice questions. The scoring procedure was fully automatized by the online platform used for data collection, which considered several entries as valid for short-answer questions, allowing some tolerance for typos. This provided the raw data that was further analysed by the researchers. Students took the T0 at least two weeks before experimental interventions.

Both to maximize statistical power and to standardize tests scales, the T0 scores (from one to four scores, depending on students' enrolment in one or more than one discipline) were first converted into standardized Z-scores. Only then they were averaged for students who took more than one subject to form a composite pre-test performance score.

**Tests of knowledge (T1) after intervention.** As for T0, T1 measures also consisted in short-answer questions and multiple-choice questions focusing on relevant topics of the National Educational Program related to each subject. The scoring procedure was similar to that of T0 measures. In contrast with T0, T1 measures assessed contents that were taught during the *current* curriculum years (seventh, ninth and eleventh grades) through intervention with one of the two instructional methods (control or CAI). In middle school, the topics were “Mass and volume” in Physics-Chemistry, “Climate” in Earth and Life Sciences, “Material structure” in Technology, “The world since 1945: independence and the construction of new states” in History-Geography). In high school, the topics were “Movement (Newtonian mechanics) in sport practice” in Physics-Chemistry, “The nature of the living” in Earth and Life Sciences, and “The enlargement of the world (15th - 16th centuries)” in History-Geography. Technology was not represented in high school. More details about the National Educational Program in France is available in the Appendix 4 in the online Supporting Information file. These topics corresponded to the base content knowledge taught through the two instructional methods (CAI vs conventional instruction). Tests of current knowledge differed from one subject to another and were not identical to pre-test knowledge tests to avoid test-retest mnemonic biases (Zhou & Cao, 2020) but more importantly, because they did not focus on the same content base knowledge (T0 tests assessed knowledge prerequisites acquired during the previous year). Students took the T1 approximately two weeks after the intervention. As for the prior knowledge tests, students' available T1 scores were first converted into standardized Z scores. Only then they were averaged for students who took more than one subject to form a composite post-test performance score.

### ***Socioeconomic status***

In France, a commonly used indicator of SES (established by the French National Institute for Statistical and Economic Studies or INSEE) is the nomenclature of people's professions and socio-professional categories (PCS) (INSEE, 2018). The PCS index provides a classification of the population based on a synthesis of occupational status, hierarchical position

and economic status. This index can be further categorized into four categories, using a previous nomenclature proposed in 1982 (INSEE, 2018) that correspond to increasing levels of social standing, ranging from disadvantaged background, middle class, privileged background and highly privileged background.

In the present study, to clarify the role of SES and related achievement gap we used only the extremes categories (i.e., 1 and 4) of the 1982's classification, corresponding to disadvantageous and highly privileged backgrounds. There were three reasons for that. First, the difference in terms of family income and years of education is often subtle between two adjacent PCS categories using the four indicators nomenclature (INSEE, 2018), making it difficult to provide a clear-cut SES distinction. Second, category 2 (middle class) was disproportionately large compared to the other categories, preventing a well-balanced sample in each SES categories if collapsing the four 1982's levels into low (1+2) and high SES (3+4). By comparing disadvantaged students (low SES) versus highly privileged students (high SES), our objective was to simplify analyses and result interpretability by using these two categories as a dummy variable in the multilevel models while keeping well-balanced sample sizes. SES effects in the results section should be interpreted downward (e.g., as SES decreased from highly privileged to disadvantageous backgrounds, it decreased academic performance). We were also interested in classes and school SES. To assess whether students' SES was accounted for by differences in classes and schools' SES (i.e., contextual effects), we averaged student's SES within their classrooms and schools and used these variables as predictors in the analyses.

## **Statistical analyses**

We used multilevel modelling to fit 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 source of variance (Fidell et al., 2007). To date, there is no clear consensus on how to determine adequate power and sample size when the data structure is more than two levels (Kerkhoff & Nussbeck, 2019). Therefore, we relied on recommendations from McNiesh and Stapelton (2016) to include more than 30 units at level two to ensure unbiased fixed effects and variance component parameters. Complying with this recommendation, data from the present study comprised 110 classes at level two. As an attempt to transpose this recommendation at level three, but faced with the great difficulty to find a large number of schools, 20 of them were included at level three. The objective was to examine the effects of CAI and

socioeconomic status on newly learned materials (after experimental intervention with CAI or teacher-led instruction), controlling for prior knowledge and contextual effects of prior knowledge and socioeconomic status (effects -at Level 1- resulting from student's belonging to certain classes -at Level 2-, or schools -at Level 3- which average performance vary from one to another, impacting student's individual academic performance). We first conducted two preliminary analysis assessing possible pre-test imbalance of prior knowledge (the main covariate) and socioeconomic status (as the first independent variable) in the modalities of the second independent variable (experimental interventions, CAI or conventional teacher-led instruction). After identifying a very small imbalance (less than one percent of variance explained, 0.7%) for prior knowledge, we used multilevel modelling with a mean centring approach to correct for any (small) non-equivalence in the two experimental conditions, as recommended in case of non-randomized trials, that are common in large field studies due to field constrains (Xiao et al., 2017). Then we compared a null model that contained only the intercept for current knowledge as fixed effect and the random effects for classes -Level 2- and schools -Level 3- in addition to the residuals effects at the student level -Level 1. The null model was compared to a series of models incremented with main effects, contextual effects and interactions in a step-by-step fashion. We conducted all statistical analyses with the R software version 4.0.1 (R Core Team, 2013) and used the CAR (Fox, 2019) and lme4 (Bates et al., 2015) packages respectively for the preliminary analyses and subsequent multilevel models.

## Results

The preliminary analyses revealed non-significant group differences in socioeconomic status,  $\chi^2(1) = 1.97, p = .16$ , but an imbalance at pre-test for prior knowledge,  $F(1, 804) = 5.30, p = .02, \eta^2p = .007$ . However, the effect size was extremely small, with less than one percent (0.7%) of explained variance, and was easily dealt with the subsequent statistical procedure fixing the covariates at their grand-mean (Castro-Schilo & Grimm, 2018; Xiao et al., 2017). Then, prior knowledge and SES were entered as covariates and fixed at their grand mean in subsequent multilevel analyses. This procedure allowed to obtain bias-free estimates of instructional methods' effects on learning outcomes.

Next, we computed a series of multilevel models that distinguished students' individual effects of prior knowledge and SES on academic performance (Model "1") from class (Models "a" and "c") and school-related (Models "b" and "d") contextual effects, that is, effects resulting from

students' belonging to a given class or school. All models were compared to a null model (Model “0”) that only included the random intercept for test of current knowledge (T1). Finally, we tested two interaction models (Model “ia” and “ib”) examining whether prior knowledge and SES moderated CAI effects. Two models fitted the data equally well (see Table 1). The two models (Model “1” and Model “a”) comprised main effects of instructional method, prior achievement, and SES whereas Model “a” additionally comprised the class contextual effect of prior knowledge on learning outcomes. The fact that Model “a” was of equal utility as Model “1” indicated the presence of class contextual effects of prior knowledge in addition to individual effects, meaning that part of the variance in the between-students prior knowledge impact on learning outcomes was accounted for by between-classes differences in prior knowledge. As both models showed equal utility, we focused on the more explanatory one (Model “a”), took account of the class contextual effect of prior knowledge and isolated it from true individual effects in subsequent interaction models. Both interaction Models (“ia” and “ib”) underperformed Model “a” as shown by higher Akaike and Bayesian Information Criteria values and non-significant interaction effects ( $ps > .405$ ). This finding indicates that CAI benefits (detailed below) were stable across prior knowledge and socioeconomic levels. In other words, CAI boosted performance in all students but the gap remained constant across disadvantaged and highly privileged students.

The regression coefficients for socioeconomic ( $\beta = -.21, p = .001$ ) and CAI effects ( $\beta = +.23, p = .007$ ) reported in Model “a” were approximately similar in magnitude although pointing to opposite directions. More precisely, the negative coefficient of  $\beta = -.21$  describing SES effects on academic performance indicates that students from disadvantaged backgrounds underperformed their highly privileged peers of about 0.21 standard deviations. Transposing this score to Grade-Points Average (out of 5 points), this corresponds to a significant socioeconomic-related performance gap of about 0.15 points. If the threshold for university admissions is set at 3/5, our data suggest that socioeconomic status effects would virtually prevent around 6% of the 12<sup>th</sup> graders to enter into higher education, which represents nearly 24’000 students in France (Ministère de l’Enseignement supérieur, de la Recherche et de l’Innovation - French Ministry of Education-, 2018) and 210’000 in the US (NCES, 2018). In contrast, the positive coefficient of  $\beta = +.23$  describing CAI benefits on academic performance indicates that students receiving CAI outperformed those who receiving conventional teacher-led instruction of about 0.23 standard deviations. If we apply a similar transposition to Grade-Points Average, this corresponds to a significant improvement of about 0.17 out of 5 points, elevating an average student from the 50<sup>th</sup> to the 64<sup>th</sup> percentile, which replicates the data

reported in Kulik and Fletcher (2016). Again, if the threshold for university admissions is set at 3/5, our data suggest that CAI would virtually help a similar percentage of around 6% of the 12<sup>th</sup> graders to pursue higher education.

Table 1 about here

We further tested the hypothesis that CAI targeted to low SES students might “compensate” the negative SES effects on academic performance. To do so, we compared highly privileged students receiving conventional instructions (i.e., the control group) to disadvantaged students receiving CAI, and tested SES effects once more in a new model (Model “2”). Depicted in Figure 2 and Table 2, results of Model “2” revealed that SES effects were no longer significant, yielding comparable academic performance between highly privileged and disadvantaged students.

Figure 2 about here

Table 2 about here

As Model “2” contained only half the sample size ( $n = 382$ ) due to the exclusion of highly privileged students receiving CAI and disadvantaged students receiving conventional instruction, we ensured SES and CAI effects observed in Model “a” ( $N = 806$ ) were stable with comparable sample sizes. To this end, we examined SES effects in the conventional instructions control group (Model “e”,  $n = 401$ ) and the CAI group (Model “f”,  $n = 405$ ) separately, and examined CAI effects in highly privileged students (Model “g”,  $n = 417$ ) and disadvantaged students (Model “h”,  $n = 389$ ) separately. As shown in Figure 3 and Table 1, SES effects were significant in both experimental conditions, and so were CAI effects separate SES groups.

Figure 3 about here



## Discussion

The present findings shed light on several important points. First, by indicating CAI benefits in students regardless of their SES, our data reveal a still overlooked possibility in research on the benefits of digital technologies for education. Again, whether the introduction of technologies such as CAI may benefit some groups of students more than others (e.g., low- and high-SES students) has been debated (see Rodrigues & Biagi, 2017), but the paucity of empirical research focusing specifically on students' socioeconomic background and other characteristics left this issue unanswered and controversial. Barley et al. (2002), for example, argued that the potential of technologies to change a teacher-centred model to a more student-centred instruction approach may be of special benefit to students at risk of dropping-out, those with a low socioeconomic background and other disadvantaged students. Favoring this assumption is the fact that the use of CAI makes possible to adjust the level of difficulty and learning speed to the capabilities of disadvantaged students (Falck et al, 2015), and to connect academic learning to real-life situations through the use of images, videos and sounds. We agree that the use of CAI may help individualize learning, which combined with its non-judgmental feedback, may increase students' autonomy and engagement. However, the few studies in this area offered mixed evidence. Rodrigues and Biagi's (2017) correlational reanalyses of PISA data even suggested that the use of digital technologies for educational purposes only benefits students of medium and high SES, at least among students who are the less likely to use digital technologies at home. Our research provides evidence that both high and low SES students may benefit from technologies such as CAI (Hollingworth et al., 2008; Lashley, 2017). Of course, learning benefits associated with CAI regardless of students' SES do not mean that the highly desirable practices developed through traditional teacher-led instruction are not essential or efficient. Instead, it means that students reasoning and planning alone with CAI may also be a valuable option at certain points in students' learning process, implying the possibility for teachers to alternate conventional instruction and CAI. This strategy may also help teachers to manage the heterogeneity of their class—a topic of major importance in educational research—without trying to reduce it to preserve its full potential (Decristan et al., 2017). CAI may also reduce teachers' workload for the benefit of personalized learning, and should be thought as an additional assistance for teachers (Bulman & Fairlie, 2016).

Second, our findings indicate that the positive impact of digital technologies such as CAI do not necessarily change the magnitude of the socioeconomic achievement gap, even when the disadvantaged students' performance benefit from this use. The size of CAI benefits

in our research being similar in both high- and low-SES students, the socioeconomic achievement gap indeed remained unchanged under CAI, compared with the control group receiving traditional teacher-led instruction condition. The gap was displaced upward under CAI compared with conventional instruction, but its magnitude was similar in both conditions. The use of CAI may, in theory, help to reduce the socioeconomic achievement gap, but our findings indicate that this reduction is unlikely when the use of CAI facilitates learning in both groups of students, a neglected possibility so far (for a review, see Rodrigues and Biagi, 2017). This conclusion does not contradict the widespread idea of an increase of the socioeconomic achievement gap favouring the most privileged students in the event of unequal access to CAI. Providing all students with the opportunity to access and use technologies such as CAI is the first step to reducing the digital divide and related socioeconomic achievement gap, as also pointed out by many organizations around the world (e.g., European Commission, 2013). As also noted by Isomaki and Kuronen (2013) and Rizk and Davies (2021), the reduction of this gap also implies the reduction of distinct digital inequalities related to students' autonomy of use, skills, social support, motivation, engagement and attitudes. Although our research was not designed to address these complementary issues, it indicates at least that with an equal access to digital technologies such as CAI at the school level (which does not speak about CAI accessibility at home), the socioeconomic achievement gap does not necessarily increase. This is good news since the adoption of digital technologies such as CAI may persist and thus be used more intensively than before in combination with more traditional methods.

Third, and perhaps more importantly, we found evidence that the disadvantaged students receiving CAI can reach similar performance levels to those shown by their highly privileged counterparts receiving conventional instruction. This finding strengthens the importance of varying and targeting teaching methods depending on students' socioeconomic characteristics to allow disadvantaged students to maximize their learning potential and chances to access to higher education, as also strongly recommended by international organisations (OECD, 2012; 2019b). This learning gain in the lower SES students under CAI also strengthens the importance of making digital technologies accessible to all students. However, technological accessibility alone does not guarantee learning benefits. In our research, the CAI was carefully elaborated based on teacher's expertise so that digital technology was deliberately constrained by pedagogy rather than the opposite. At the condition that technology truly serves pedagogy, a more intense use of CAI in disadvantaged students may increase their academic chances. Targeting CAI to these students more than to their highly privileged counterparts might be an effective way to reduce the socioeconomic achievement gap, again assuming equal accessibility

to digital learning, appropriate education-based tools, and sufficient or appropriate autonomy of use, skills, social support, motivation, engagement and attitudes.

One may argue that targeting lower SES more than high SES students with CAI would be unfair, as it would not provide the same treatment to all students. However, this solution would help compensate for the higher SES students' considerable and continuous advantage over their lower SES counterparts in their access to knowledge, a gap that not only pre-exists to—but maintains through—schooling (Bourdieu & Passeron, 1990; OECD, 2018; 2019a). Ironically, this advantage may persist with an equal, seemingly “fair” treatment, as indicated here by the intact socioeconomic achievement gap that we found under CAI. Hence the interest of considering differential treatment to a certain extent, to help the most disadvantaged students to realize their true potential if not to reach their more advantaged counterparts—as in the present study—and to allow teachers to correct at least partially performance inequalities of socioeconomic origin. Although reducing these inequalities in education is still a major challenge, this objective should obviously not lead to depriving the advantaged students of methods likely to further increase their academic performance. Rather, it is about finding the optimal balance between CAI and conventional instruction depending on students' socioeconomic background. A balanced approach to learning in which disadvantaged students intermingle work with CAI and work under traditional materials a bit more than their more advantaged counterparts might be optimal (i.e., the possibility for disadvantaged students to be deliberately more exposed to CAI than their more advantaged counterparts at least at some points of the learning process). Deciding when digital technology-based intervention may supplement traditional learning in classrooms is a critical issue for teachers working with the general student population (Bulman & Fairlie, 2016; Fairlie & Loyalka, 2020). The present findings suggest adding to the question "when" the question "for which categories of students" technology-based education can supplement traditional education, both of these questions being necessary to reduce the socioeconomic achievement gap.

## **Limitations**

A limitation of the present study concerns its non-randomized, quasi-experimental design. Random attribution to experimental conditions was not feasible here given the unequal distribution of technological resources at the school level. Although we agree that randomized trials are gold standard in intervention research, recent studies lead toward considering

additional points. First, randomized studies do not systematically guarantee balance in all observed covariates if cluster design differs substantially between control and experimental condition, or if there are important between or/and within differences in sample size at pre and/or post-test (Xiao et al., 2017). Second, even in the case of absent pre-existing differences in a randomized sample, the relationship between pre- and post-test might vary substantially from one condition to another, which might also bias estimates (Castro-Schilo & Grimm, 2018). According to Xiao et al.'s (2017) conclusions, an ANCOVA approach using multilevel modelling (MLM) is always preferred in both non-randomized and randomized designs, as divergence in estimates related to experimental design tend to decrease under MLM.

Our research also leaves open the question of the processes underlying the learning gains associated with CAI. Although CAI produced similar gains for students regardless of their SES, one cannot exclude that the underlying processes may not be strictly identical in the two groups. For example, there is evidence that benefiting from working times outside the potentially evaluative pressure of their peers and/or teachers facilitates learning among disadvantaged students (Monteil & Huguet, 1999; Huguet & Kuyper, 2017). Such working times can easily be achieved by using technologies such as CAI, which indeed may remove at least temporarily the threat of receiving negative judgments and experiencing unfavourable social comparisons that may seriously damage students' academic self-concept and learning. Although the more advantaged students may also experience this threat when working in very selective academic environments (Huguet et al., 2009), the private dimension of CAI may be of particular interest for their disadvantaged counterparts. CAI also enables students to go back and forth on a specific information whenever they want, repetitions that, when combined with appropriate feedback and hints, may lead to a variety of positive outcomes (higher perception of control, enjoyment and curiosity, higher performance and lower anxiety (Huguet et al., 2001; Loderer et al., 2018; Parker & Lepper, 1992; Pekrun & Perry, 2014). More generally, further studies should disentangle between the role of task-related features (e.g., aesthetics, playfulness, navigational nature) and student-related factors (e.g., self-competence beliefs, emotions, see Lajoie et al., 2019; Loderer et al., 2018), which may help understand what exactly drives CAI learning benefits in students with different socioeconomic backgrounds. This is also a necessary step to improve the use of technology-rich learning environments and maximize their benefits for all students.

## **Conclusion**

**The present study investigated the status of the socioeconomic (SES) achievement gap in the context of digital technologies using an experimental approach comparing computer-assisted instruction (CAI) to conventional teacher-led classroom instruction. We found that the difference in academic performance between disadvantaged and highly privileged students remained constant when both SES groups learned with CAI compared to conventional instruction. Furthermore, the disadvantaged students taught with CAI performed equally well as their highly privileged counterparts taught with conventional instruction. This shows the potential benefits of CAI to reduce socioeconomic inequalities at school by bringing low SES students to a higher performance level. The present findings can reasonably be taken as evidence that this reduction is possible at the condition of targeting the disadvantaged students more often with CAI through possible combinations of instructional methods tailored to students' SES background.**

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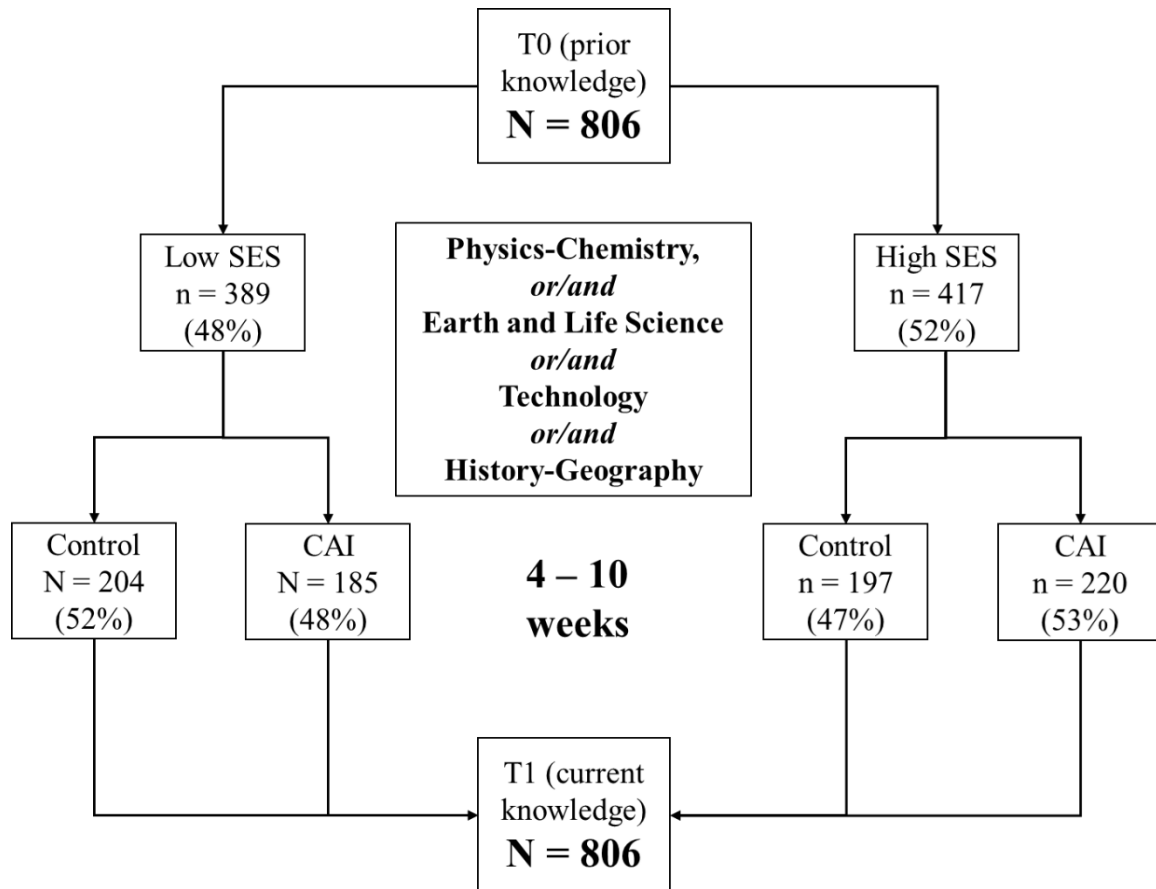
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### **Data Citations**

1. Chevalère, J., Cazenave, L., Berthon, M., Martinez, R., Mazenod, V., Borion, M.-C., Pailler, D., Rocher, N., Cadet, R., Lenne, C., Maïonchi-Pino, N., & Huguet, P. (2020). *CAI\_SES*, <https://doi.org/10.17605/OSF.IO/XEGQZ>.

## Figures and Tables

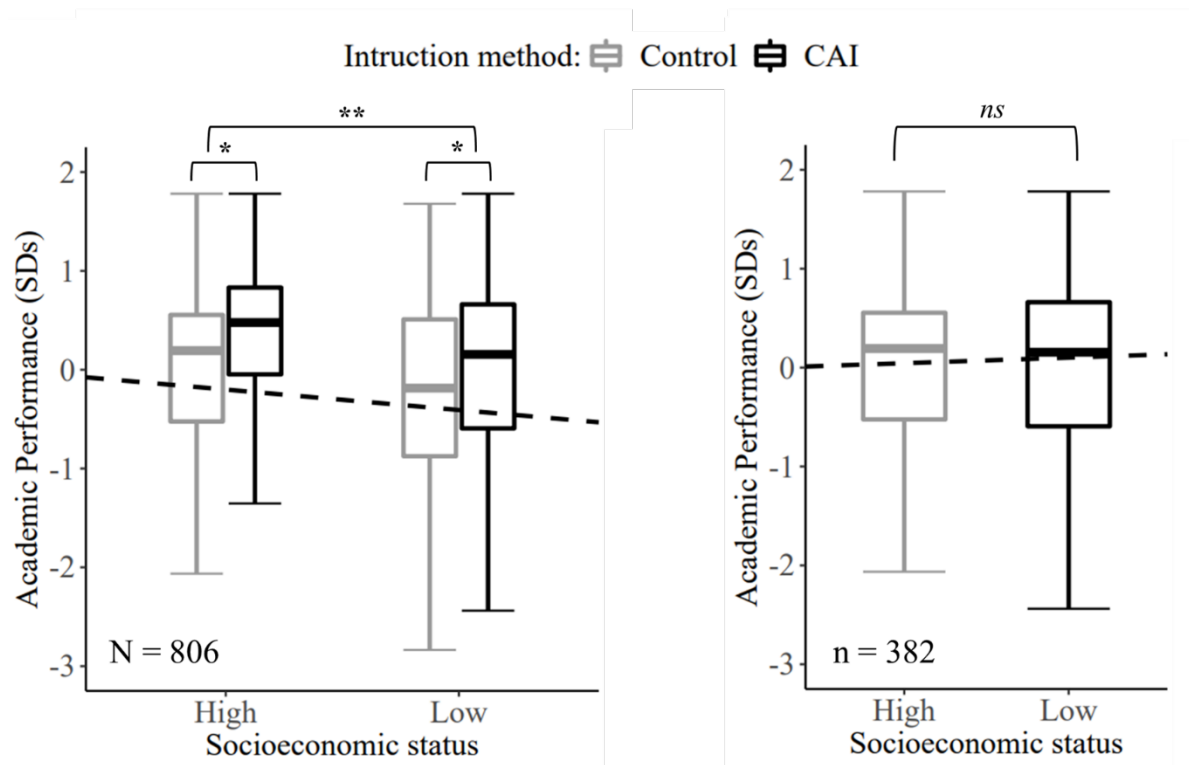


**Figure 1.** The experimental design of the present study. The pedagogical material and academic tests metrics in Physics-Chemistry, Earth and Life Sciences, Technology and History-Geography were collaboratively elaborated by teams of teachers from each discipline. All data were collected in real classroom environments via an online platform dedicated to the present research, including demographics and academic tests.

**Table 1.** Random intercept multilevel models testing contextual effects, main effects and interaction.

| n students = 806, n classes = 110,<br>n schools = 20 | Model 0 |            | Model a           |                     | Model b    |             | Model c    |             | Model d    |             | Model 1    |             | Model ia   |             | Model ib   |             |
|--|---------|------------|-------------------|---------------------|------------|-------------|------------|-------------|------------|-------------|------------|-------------|------------|-------------|------------|-------------|
|  | E       | 95% CI     | E                 | 95% CI              | E          | 95% CI      | E          | 95% CI      | E          | 95% CI      | E          | 95% CI      | E          | 95% CI      | E          | 95% CI      |
| <b>Fixed Effects</b>                                 |         |            |                   |                     |            |             |            |             |            |             |            |             |            |             |            |             |
| <i>Student Level</i>                                 |         |            |                   |                     |            |             |            |             |            |             |            |             |            |             | 28         |             |
| Intercept  | -.02    | [-.13;.09] | <b>.006</b>       | <b>[-.08;.08]</b>   | .006       | [-.08;.08]  | .006       | [-.10;.09]  | .003       | [-.08;.08]  | .006       | [-.08;.08]  | .003       | [-.08;.07]  | .005       | [-.08;.09]  |
| T0   |         |            | <b>.31***</b>     | <b> [.26;.39]</b>   | .34***     | [.29;.41]   | .34***     | [.30;.41]   | .34***     | [.29;.41]   | .34***     | [.29;.42]   | .31***     | [.25;.39]   | .31***     | [.26;.39]   |
| SES  |         |            | <b>-.21**</b>     | <b> [-.32;-.06]</b> | -.24***    | [-.36;-.10] | -.21**     | [-.30;-.06] | -.21**     | [-.33;-.07] | -.22***    | [-.34;-.08] | -.21**     | [-.32;-.05] | -.21**     | [-.32;-.07] |
| <i>Class level</i>                                   |         |            |                   |                     |            |             |            |             |            |             |            |             |            |             |            |             |
| Contextual T0  |         |            | <b>.24*</b>       | <b> [.06;.43]</b>   |            |             |            |             |            |             |            |             | .24**      | [.05;.44]   | .24**      | [.07;.46]   |
| Contextual SES                                       |         |            |                   |                     | .13        | [-.23;.42]  |            |             |            |             |            |             |            |             |            |             |
| <i>School Level</i>                                  |         |            |                   |                     |            |             |            |             |            |             |            |             |            |             |            |             |
| CAI  |         |            | <b>.23**</b>      | <b> [.08;.39]</b>   | .26**      | [.09;.45]   | .22*       | [.04;.39]   | .26**      | [.08;.43]   | .25**      | [.09;.41]   | .23**      | [.07;.40]   | .23**      | [.06;.40]   |
| Contextual T0  |         |            |                   |                     |            |             | .27        | [-.21;.90]  |            |             |            |             |            |             |            |             |
| Contextual SES                                       |         |            |                   |                     |            |             |            |             | -.09       | [-.56;.41]  |            |             |            |             |            |             |
| <i>Cross Level Interactions</i>                      |         |            |                   |                     |            |             |            |             |            |             |            |             |            |             |            |             |
| CAI x T0   |         |            |                   |                     |            |             |            |             |            |             |            |             | .05        | [-.07;.18]  |            |             |
| CAI x SES  |         |            |                   |                     |            |             |            |             |            |             |            |             |            |             | -.03       | [-.30;.18]  |
| <b>Random Effects</b>                                |         |            |                   |                     |            |             |            |             |            |             |            |             |            |             |            |             |
| <i>Residual variance (also ICC)</i>                  |         |            |                   |                     |            |             |            |             |            |             |            |             |            |             |            |             |
| Student Level (SD)                                   | .83     | (.92)      | <b>.72</b>        | <b>(.85)</b>        | .72        | (.85)       | .72        | (.85)       | .72        | (.85)       | .72        | (.85)       | .72        | (.85)       | .72        | (.85)       |
| Class Level (SD)                                     | .12     | (.35)      | <b>.07</b>        | <b>(.27)</b>        | .08        | (.28)       | .08        | (.28)       | .08        | (.28)       | .08        | (.28)       | .07        | (.27)       | .07        | (.27)       |
| School Level (SD)                                    | .02     | (.15)      | <b>.00</b>        | <b>(.00)</b>        | .00        | (.00)       | .00        | (.00)       | .00        | (.00)       | .00        | (.00)       | .00        | (.00)       | .00        | (.00)       |
| Log Likelihood                                       | -1113.4 |            | <b>-1041.1</b>    |                     | -1043.9    |             | -1043.8    |             | -1044.2    |             | -1044.3    |             | -1040.7    |             | -1041.0    |             |
| Akaike information criterion                         | 2234.9  |            | <b>2098.1</b>     |                     | 2103.9     |             | 2103.6     |             | 2104.4     |             | 2102.5     |             | 2099.4     |             | 2100.1     |             |
| Bayesian information criterion                       | 2253.7  |            | <b>2135.7</b>     |                     | 2141.4     |             | 2141.1     |             | 2141.9     |             | 2135.4     |             | 2141.7     |             | 2142.3     |             |
| X <sup>2</sup> (df)                                  | -       |            | <b>144.74 (4)</b> |                     | 138.99 (4) |             | 139.33 (4) |             | 138.49 (4) |             | 138.36 (3) |             | 145.43 (5) |             | 144.79 (5) |             |
| p  | -       |            | <b>&lt;.001</b>   |                     | <.001      |             | <.001      |             | <.001      |             | <.001      |             | <.001      |             | <.001      |             |

Note. 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; † = marginal at  $p < .08$ ; \* = significant at  $p < .05$ ; \*\* = at  $p < .01$ ; \*\*\* = at  $p < .001$ . Model “0” (null model) was the reference for comparison with all other models. Model comparison was based on a combination of fit indicators, namely, X<sup>2</sup>p, Akaike information criterion and Bayesian information criterion values. The model with the lowest Akaike and Bayesian information criteria values along with a significant X<sup>2</sup>p indicated best fit for the data and thus, was preferred. The Akaike information criterion value indicated that Model “1” best fitted the data while the Bayesian information criterion value (penalizing for model complexity) indicated a better fit for Model “a”.



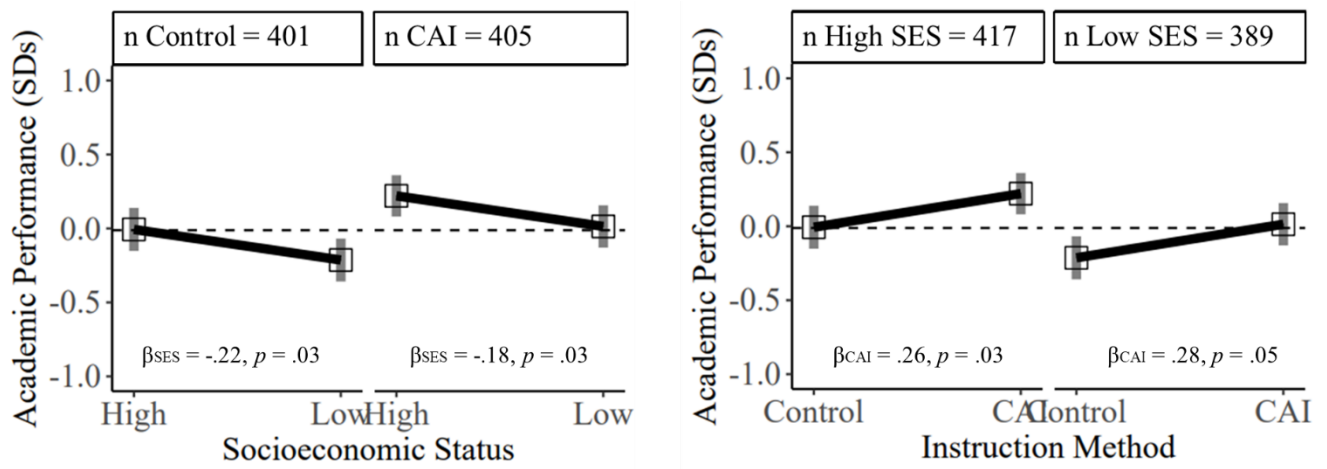
Note. Control = conventional teacher-led instruction; CAI = computer assisted instruction; SDs = standard deviations. \*\* = significant at  $p < .01$ ; \* = significant at  $p < .05$ ; *ns* = non-significant,  $p = .590$ . The dashed lines represent socioeconomic effects on academic performance. The non-significant  $p$  value in the right panel represents the socioeconomic status effects on academic performance reported in Table 2.

**Figure 2.** Boxplots for the negative SES effects (left panel, Model “a”) on academic performance compensated by CAI targeted to low SES students (right panel, Model “2”).

**Table 2.** Multilevel statistics for Model 2

| n students = 382, n classes = 98, n schools = 20 |                   |                    |                         |                     |           |           |           |        |        |        |
|--|-------------------|--------------------|-------------------------|---------------------|-----------|-----------|-----------|--------|--------|--------|
| Fixed Effects                                    |                   |                    |                         | Random Effects      |           |           | LL        | AIC    | BIC    |        |
| Student  |                   | Class              |                         | Residual (also ICC) |           |           |           |        |        |        |
| Intercept  | T0                | SES                | Contextual T0           | Student             | Class     | School    |           |        |        |        |
| Model 2  | -.01 [-.10 ; .79] | .35*** [.24 ; .47] | <b>.06 [-.17 ; .26]</b> | .21 [-.05 ; .46]    | .81 (.90) | .04 (.20) | .00 (.00) | -510.6 | 1035.3 | 1062.9 |

Note. T0 = test of prior knowledge; SES = socioeconomic status; ICC = intra-class correlation coefficient; LL = log likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion; \*\*\* = significant at  $p < .001$ . Values in bold represent the non-significant effect of socioeconomic status on academic performance after compensation by positive computer-assisted instruction effects, exact  $p$  value available in Figure 2's note.



**Figure 3.** SES effects in control and CAI conditions and CAI effects in low and high SES students (error bars represent 95% confidence intervals).

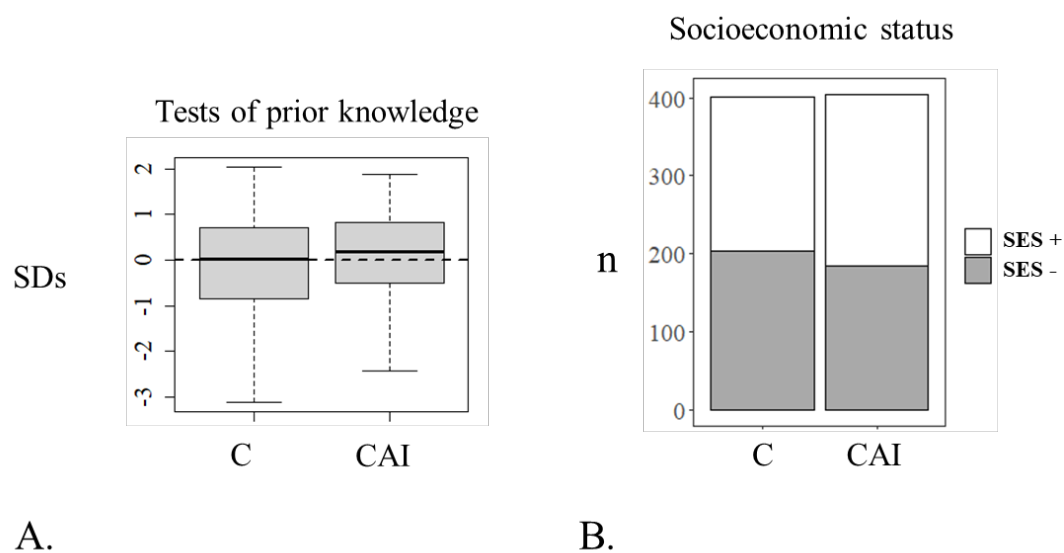


## Appendices

For

### “Compensating the socioeconomic achievement gap with computer-assisted instruction”

Includes Figure S1



Note. C = conventional teacher-led instruction; CAI = computer assisted instruction; SES+ = high socioeconomic background; SES- = low socioeconomic background. SDs = standard deviations; n = sample size. The horizontal dashed line represents the grand mean.

**Figure S1.** Pre-test imbalance analysis for measures of prior knowledge (A) and socioeconomic status (B).

# Supporting information

For

## “Compensating the socioeconomic achievement gap with computer-assisted instruction”

Chevalère J., Cazenave, L., Berthon, M., Martinez, R., Mazenod, V., Borion, M.C., Pailler, D., Rocher, N.,  
Cadet, R., C. Lenne, C., Maïonchi-Pino, N., & Huguet, P.

Includes: Appendix\_1\_SuppInfo, Appendix\_2\_SuppInfo, Appendix\_3\_SuppInfo, Appendix\_4\_SuppInfo

**Appendix\_1\_SuppInfo. Example of a problem-solving exercise (a.) and feedback (b.) within a narrative scenario.** The narrative scenario is entitled “Banana Jones and the crystal statuette” and is used in middle school Physics-Chemistry CAI.

a.

Quels instruments peuvent-être utilisés pour mesurer le volume ?  
Déplace chaque étiquette dans la case correspondante du tableau.

Un thermomètre  
Une éprouvette graduée  
Un bécner  
Un verre à pied non gradué  
Une seringue  
Une pipette  
Une balance électronique  
Un chronomètre  
Un verre doseur

Instruments permettant de mesurer un volume  
Instruments ne permettant pas de mesurer un volume

e.P3C MODULE 2 - Banana Jones et la statuette de cristal (15 décembre 2019)

b.

Quels instruments peuvent-être utilisés pour mesurer le volume ?  
Déplace chaque étiquette dans la case correspondante du tableau.

Instruments permettant de mesurer un volume  
Instruments ne permettant pas de mesurer un volume

Essaie encore. Tu peux t'aider des indications d'unités qui sont notées sur les appareils.

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
<https://faceduresourcesets.blob.core.windows.net/quiz-thumbnail/49752f5aa9b49529ebdd57a7e9d946e.png>

*Note.* Students are instructed to sort the instruments as measures of volume by placing them in the corresponding category. In panel b. the student received a negative feedback and a hint. The narrative scenario invites students to solve a series of problems that would help Banana Jones solve the mystery of the crystal statuette.

**Appendix\_2\_SuppInfo. Example of a scaffolding approach (a. to h.) with a virtual tutor middle school Physics-Chemistry CAI.** The approach guides student in understanding the notion of volume in relation to a measuring cylinder. The step-by-step problem-solving is contextualized within the Banana Jones and the crystal statuette narrative scenario.

a.

*On veut déterminer la valeur d'une division, c'est-à-dire que l'on cherche le volume compris entre deux petites graduations ou encore comment est graduée l'éprouvette (de 0,5 mL en 0,5 mL; 2mL en 2mL...).*



Selon toi, sur l'éprouvette de ta paillasse, 1 division représente un volume de ...  
(N'oublie pas d'écrire l'unité)

10 mL

Ah la la!

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*Note.* The student receives a negative feedback

b.



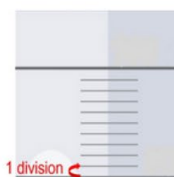
**Äie!** Soit tu as mal noté l'unité (mL et non pas ml) soit tu as mal compté !

*Voici une méthode rigoureuse qui te permettra de déterminer la valeur d'une division sans te tromper!*

*Note.* The virtual tutor helps the student by proposing a method to solve the problem.

c.

Combien comptes-tu de divisions sur ton éprouvette entre 30 et 50 mL? (indique simplement un nombre)



Entrez votre réponse...



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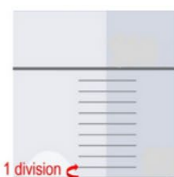
MODULE 2 - Banana Jones et la statuette de cristal (15 décembre 2019)



Note. The method is proposed.

d.

Combien comptes-tu de divisions sur ton éprouvette entre 30 et 50 mL? (indique simplement un nombre)



10

Ouif!



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Note. The student solves the first step and received a positive feedback.

e.



Bien vu!

Le volume  $V$  compris entre  
30 et 50 mL est  
 $V = 50 \text{ mL} - 30 \text{ mL} = 20 \text{ mL}$ .

Note. The virtual tutor gives a hint

f.

50 mL

Choisis et place les bonnes étiquettes pour calculer le volume d'une division

10 mL

2 divisions


1 division

30 mL

$$V(1\text{division}) = \frac{20\text{ mL}}{10\text{ divisions}}$$

Note. The proposed method continues with a second step.

g.




*Bravo, tu as compris et ce n'était pas si simple!  
Effectivement, il faut effectuer le calcul suivant :*

$$V(1\text{division}) = \frac{\text{Volume entre 30 et 50 mL}}{\text{Nombre de divisions entre 30 et 50 mL}} = \frac{20\text{ mL}}{10\text{ divisions}}$$

Note. The student receives a positive feedback confirming her correct answer with a short explanation.

h.

*On veut déterminer la valeur d'une division, c'est-à-dire que l'on cherche le volume compris entre deux petites graduations ou encore comment est graduée l'éprouvette (de 0,5 mL en 0,5 mL; 2mL en 2mL...).*



Selon toi, sur l'éprouvette de ta paille, 1 division représente un volume de ...  
(N'oublie pas d'écrire l'unité)

2 mL

Bravo!



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MODULE 2 - Banana Jones et la statuette de cristal (15 décembre 2019)



Note. The student is presented again with the first question, she answers correctly and receives a positive feedback.

**Appendix\_3\_SuppInfo.** The knowledge post-test in middle Physics-Chemistry on the topic “mass and volume”. In French language.

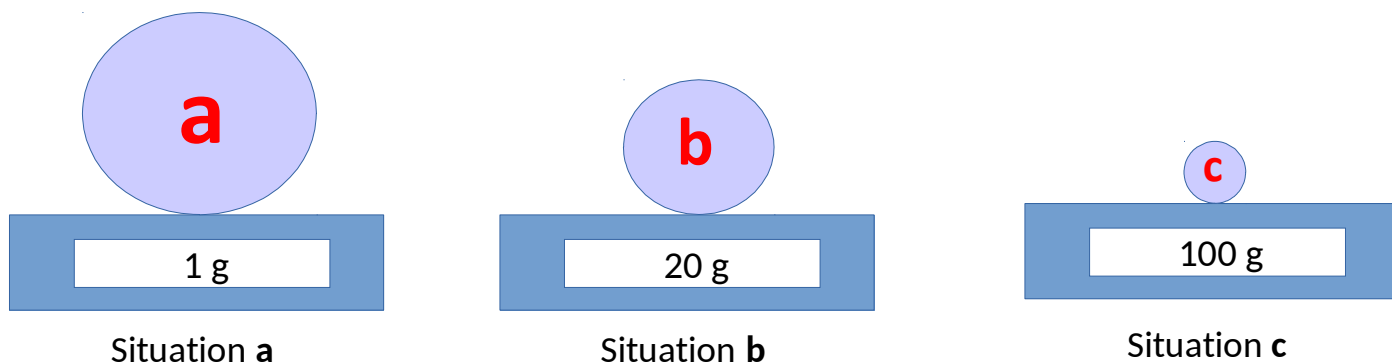
## Evaluation sommative de Physique-Chimie, groupe collège

### Distinction entre masse et volume

#### Objectifs de compétences et de connaissances visés au cours de la séquence :

- Savoir définir la masse et le volume.
- Savoir mesurer une masse et un volume d'un liquide et d'un solide.
- Connaitre le vocabulaire des appareils de mesure, les unités.
- Savoir convertir sur des unités courantes de masse et de volume.
- Savoir utiliser les connaissances et compétences de masse et volume dans une situation complexe (communication, expérimentale, élaboration et mise en place d'un protocole, ...) : densité, proportionnalité entre masse et volume pour une substance donnée (masse volumique).

#### 1. On considère les trois situations suivantes :



a Quel est l'objet le plus lourd ?

- a       b       c

b Quel est l'objet le plus gros ?

- a       b       c

c Quel est l'objet ayant la masse la plus importante ?

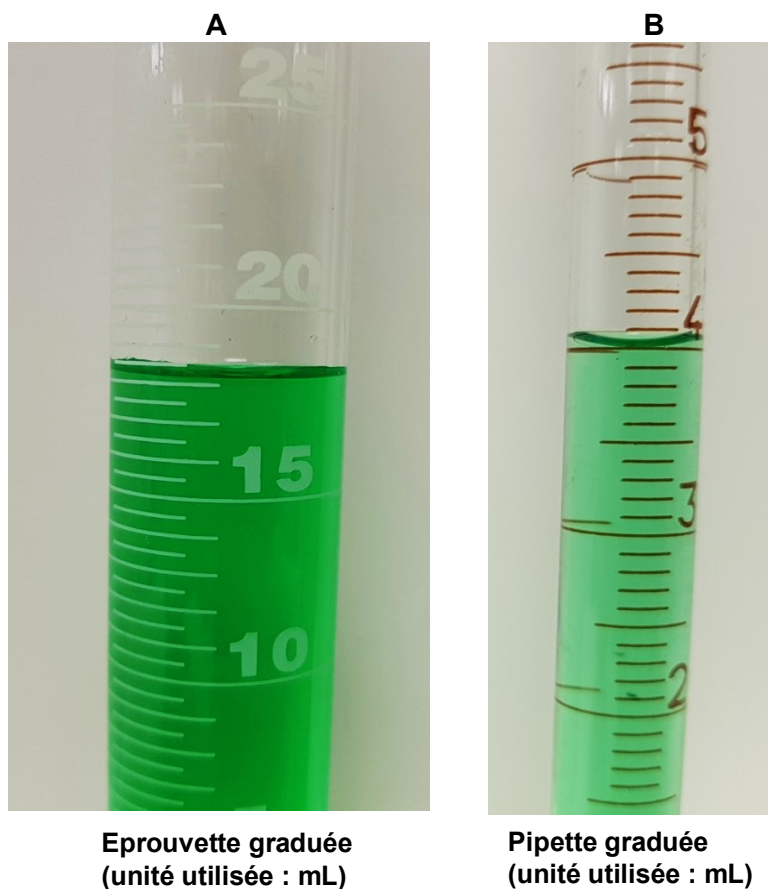
- a       b       c

d Quel est l'objet ayant le plus grand volume ?

- a       b       c



2. On verse un liquide vert dans une éprouvette (A) et une pipette (B).



a Que mesure l'élève en utilisant ces récipients ?

- La masse de liquide     
  le volume de liquide     
  la température du liquide

b Quel est le nom donné par les scientifiques à la forme que prend la surface libre du liquide ?

- le ménisque     
  la courbe     
  le creux     
  la vague

c Quelle est la valeur de la mesure pour l'éprouvette A ?

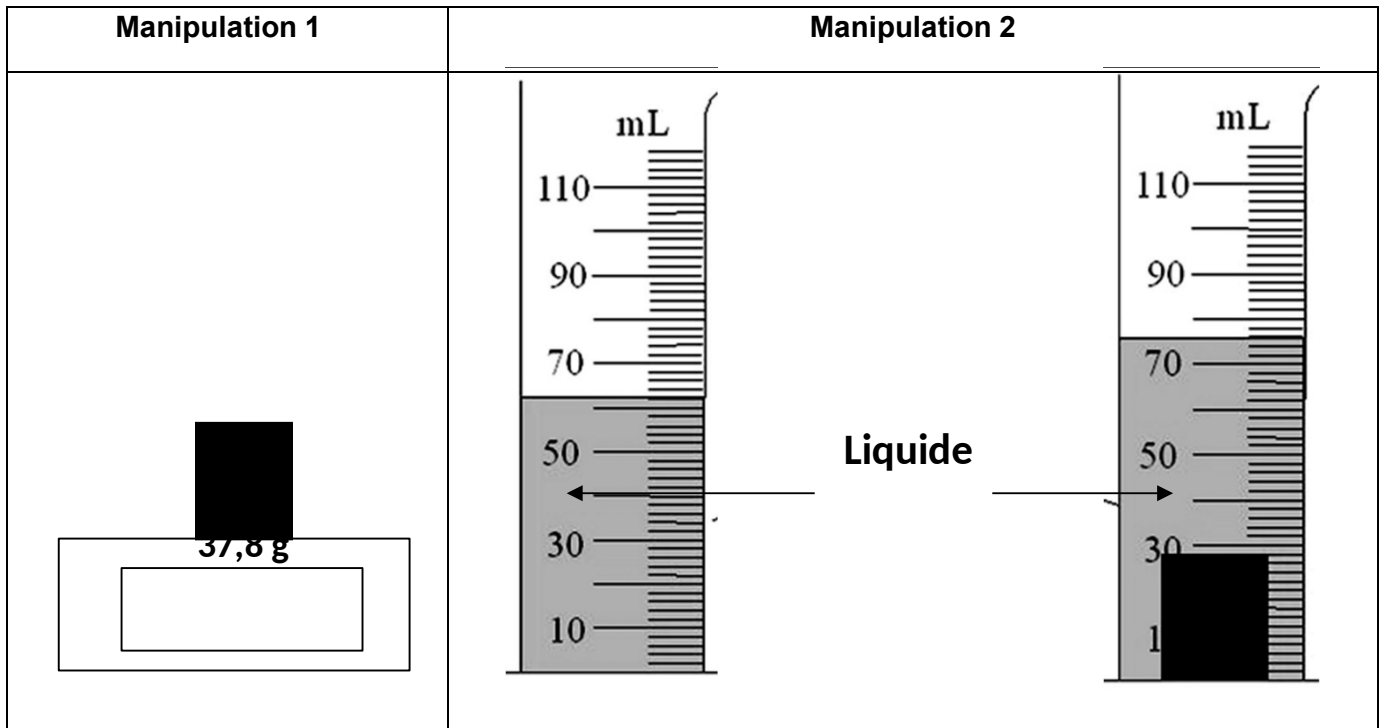
- 18,5 mL     
  21 g     
  19 mL     
  18 mL     
  21 mL

d Quelle est la valeur de la mesure pour la pipette B ?

- 4,1 mL     
  34 g     
  4 mL     
  4,2 mL     
  4,1g

3. Un élève réalise deux manipulations sur un échantillon de métal représenté par le cube noir.

Voici les schémas de ses manipulations :



a L'élève réalise la manipulation 1 pour mesurer :

- la masse de l'échantillon de métal.
- le volume de l'échantillon de métal.
- la température de l'échantillon de métal.

b L'élève réalise la manipulation 2 pour mesurer :

- la masse de l'échantillon de métal.
- le volume de l'échantillon de métal.
- la température de l'échantillon de métal.

c Quelle est la valeur du volume de l'échantillon de métal ?

- 37,8 g     
  62 mL     
  28 mL     
  76 mL     
  14 mL



#### 4. Un élève souhaite mesurer la masse de lait contenu dans un verre.

a Quel appareil doit-il utiliser ?

- une balance                       une éprouvette                       un thermomètre.

b L'élève réalise différentes étapes.

A toi de les mettre dans l'ordre en mettant « 1 » pour la 1<sup>ère</sup> étape puis « 2 » puis etc.





| Etape   | Ordre de l'étape |
|---|------------------|
| L'élève lit l'indication sur l'écran de l'appareil. |                  |
| L'élève allume l'appareil.                          |                  |
| L'élève appuie sur le bouton TARE de l'appareil.    |                  |
| L'élève vide le lait dans le récipient.             |                  |
| L'élève place un bécher vide sur l'appareil.        |                  |

c L'élève lit sur l'appareil un nombre égal à 85.

D'après vous en quelle unité est exprimée cette mesure. Attention à bien rester cohérent avec la quantité de matière possible que peut contenir un verre.

- 85 kg                       85 g                       85 mL                       85L

5. Complète le tableau : pour chaque matériau, coche la bonne proposition flotte sur l'eau ou coule dans l'eau.

| Matériau  | Densité | Flotte sur l'eau | Coule dans l'eau |
|---|---------|------------------|------------------|
| <b>Fer</b><br>     | 7,87    |                  |                  |
| <b>Liège</b><br>   | 0,26    |                  |                  |
| <b>Sapin</b><br>  | 0,42    |                  |                  |
| <b>Verre</b><br> | 2,5     |                  |                  |

6. Lydie, une élève, a devant elle une bouteille contenant un liquide incolore non identifié. Elle souhaite savoir si ce liquide est de l'eau ou pas. Malheureusement, elle ne possède pas de sulfate de cuivre anhydre pour tester ce liquide. Elle décide donc de déterminer la masse d'un litre de ce liquide.

a Quelle est la masse d'un litre d'eau dans les conditions usuelles de notre environnement ?

- 10 kg       1 g       1 kg       1000 mL

b Dans le laboratoire, Lydie a à sa disposition une balance électronique, une éprouvette graduée de 100 mL et la bouteille contenant le liquide inconnu. Elle pèse la masse de 50 mL de ce liquide et trouve 42 g.

Quelle est la masse d'un litre de ce liquide inconnu ?

- 840 kg       0,84 kg       420 kg       0,42 g

c En t'aidant du tableau ci-dessous, identifie ce liquide. Il s'agit de :

- alcool méthylique       essence       éthanol       huile       sapin       glycérol

| Substances à 20 °C | Masse d'1L de substance (en kg) |
|--------------------|---------------------------------|
| sapin              | 0,42                            |
| alcool méthylique  | 0,79                            |
| essence            | 0,84                            |
| éthanol (alcool)   | 0,87                            |
| huile              | 0,92                            |
| glycérol           | 1,26                            |

**Appendix\_4\_SuppInfo.** The content of the National Educational Program for each discipline in middle and high school (Physics-Chemistry, Earth and Life Sciences, History-Geography and Technology). Note that Technology was not represented in high school in the present study.

*Middle School:*

-Physics-Chemistry

<https://eduscol.education.fr/296/physique-chimie-cycle-4>

-Earth and Life Sciences

<https://eduscol.education.fr/293/sciences-de-la-vie-et-de-la-terre-cycle-4>

-Technology

<https://eduscol.education.fr/282/technologie-cycle-4>

-History-Geography

<https://eduscol.education.fr/298/histoire-geographie-cycle-4>

*High School:*

-Physics-Chemistry

<https://eduscol.education.fr/1648/programmes-et-ressources-en-physique-chimie-voie-gt>

-Earth and Life Sciences

<https://eduscol.education.fr/1664/programmes-et-ressources-en-sciences-de-la-vie-et-de-la-terre-voie-gt>

-History-Geography

<https://eduscol.education.fr/1667/programmes-et-ressources-en-histoire-geographie-voie-gt>