Towards dynamically monitoring computer-assisted instruction to reduce educational inequality

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ABSTRACT

Educational inequality may entail not only socioeconomic disparities, but also cognitive-affective disparities across students. Considering the pervasive socio-contextual factors inherent to classroom environments affecting students’ self-confidence and learning – e.g., stereotype threats linked to low cognitive abilities or disadvantaged socioeconomic backgrounds – I envision the possibility to administer and monitor computer-assisted instruction dynamically to fit individual learner needs as a way to minimise, when needed, the influence of contextual factors and enhance self-perceptions to better help students cope with other classmates in group settings. This approach, which represents a neglected possibility so far, may be of interest for researchers and teachers in their daily practice and may stimulate the debate on educational inequality.

Among the current challenges of the 21st century in relation to education, inequality is often acknowledged as a major issue in worldwide surveys (OECD, 2012, 2019). Educational inequality arises from a complex interplay of factors located at different levels of analysis according to Doise and Mapstone’s (Doise & Mapstone, 1986) framework, from intra-individual (e.g., disparities in cognitive abilities and self-representations) and inter-individual (e.g., influence of social comparisons) to positional (e.g., disparities in socioeconomic status) and cultural factors (e.g., country-specific ideologies and cultures). While acknowledging this complexity, I emphasise the specific contributions of socioeconomic disparities and cognitive variability to education inequality, as they show a non-negligible relationship around $r = .30$ (Piccolo et al., 2016; Von Stumm & Plomin, 2015). Although dissociable, one explanation for this relation suggests that increased deprivation of vital and cultural resources with increased poverty gradually affects mental health and the maturation of cognitive functions (language, executive functions, memory and general intelligence, Farah, 2018; Herrmann & Guadagno, 1997; Lawson & Farah, 2017; Schwab & Lew-Williams, 2016).

To reduce educational inequality, digitalised learning tools have been put forward in response to challenges related to class size and heterogeneity as a way to prevent the most vulnerable students from being left behind. This is because Computer-Assisted Instruction (CAI) technologies associated with even simple interaction mechanisms
(i.e., feedback, hints and scaffolding problems) offer an efficient alternative to human tutoring (Kulik & Fletcher, 2016), a praised one-to-one method of teaching in contrast to large classroom instruction, which does come at a cost that is not always – if not rarely – affordable in the ordinary educational curriculum, even in developed countries.

In this direction, well-financed digitalised education programmes have been deployed on a large scale, some of them resulting in complete failure, especially when lacking independent research evidence while giving too much power to fully-automatised artificial teaching algorithms (Boninger et al., 2020).

However, there are reasons to believe that when used intelligently and monitored by human teachers (Baker, 2016), evidence-based CAI may reduce inequality through targeted instruction to more vulnerable students. After showing that the benefits of CAI shifted the socioeconomic achievement gap upward, yet maintained it at a constant when used in students from different socioeconomic backgrounds, Chevalère et al. (2021a) compared disadvantaged students learning through CAI to their highly privileged peers receiving teacher-led, in-group direct instruction. The comparison showed that the negative socioeconomic effect was compensated and abolished by the positive CAI effects, thus reducing discrepancies in performance. These encouraging results invite researchers to consider differential treatment to a certain extent, to help the most disadvantaged students reach their full potential and allow teachers to at least partially correct performance inequalities of socioeconomic origin and contribute to reducing the socioeconomic achievement gap.

Inequality in education is not just a social issue, but concerns also students’ wide variability in cognitive abilities. Previous work showing greater CAI benefits in students with higher working memory capacity (Chevalère et al., 2021b) warns about possible increases in inequality at school, which raise ethical concerns regarding the dissemination of innovative forms of individualised pedagogy. Indeed, as improving learning should not be to the detriment of equality, researchers and teachers should consider a flexible use of CAI. For example, to prevent inequalities from widening, one may use the benefits of CAI preferably in students with lower cognitive abilities and more parsimoniously in larger audiences. Such an approach might help counteract the Matthew effect (Stanovich, 1986), here understood as the process by which students with initial slight advantages in cognitive abilities progress faster and draw away from their less advantaged peers, thus steadily increasing the achievement gap over the schooling process. In addition, a more intensive use of CAI in students with lower socioeconomic status might balance out the disproportionate attendance rate of privileged students at private tutoring (Guill & Lintorf, 2019), the by-product effects of which increase the achievement gap even more (Choi, 2012).

As illustrated in Figure 1, variable degrees of CAI intervention could be delivered in proportion to other instruction methods, such as in-group instruction, with the idea being to search for an optimal balance tailored to student’s needs, in line with an individualised pedagogy approach. In-group instruction here refers to face-to-face activities involving at least a few students in a physical or virtual environment, open to social comparison. This includes teacher-led large and small classroom instruction as well as collaborative tasks among students, such as inquiry-based activities.
I argue that individual support should be restricted neither to the sole provision of artificial tutoring agents, nor to the sole provision of in-group instructional methods, but that future pedagogical practices should consider an in-between strategy by finding the optimal adaptive ratio of in-group and individualised instruction assisted with digital technology for each student. Here, I stress the importance of contextual factors inherent to traditional in-group instruction, especially through social comparison bias (Huguet & Monteil, 2013) and stereotype threat (Croizet et al., 2004), that affect students’ self-efficacy and academic performance, often at the expense of the most vulnerable students (Wiederkehr et al., 2015). This does not mean that the highly desirable practices developed through traditional in-group 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 their learning process, implying the possibility for teachers to alternate conventional instruction and CAI. For instance, a more intense use of digital technologies such as those providing private feedback might boost self-efficacy and confidence in students who are most at risk of dropping out of school and prevent these students from suffering the pervasive effects of negative in-class social comparisons.

Of course, many contextual considerations are at play when carrying this out, such as students’ motivation in regulating themselves when using the technology, or the availability of technology at home, to mention just a few, which are difficult to predict. Nevertheless, some propositions may help teachers and researchers willing to search for the aforementioned optimal balance. Propositions can be distinguished in terms of vulnerability diagnostics and intervention monitoring. With respect to diagnostics, three levels of assessment may be used as a framework to identify a student’s vulnerability and/or momentary difficulties. At the top level, a trait-vulnerability index may combine assessments from a set of critical and easily measurable domains, such as – but not limited to – cognitive ability (e.g., working memory (WM) task), self-representation (e.g.,

![Figure 1. Schematic illustration of the dynamic balance between computer-assisted individualised instruction and in-group instruction.](image-url)
a global self-esteem questionnaire) and socioeconomic status (e.g., parents’ occupational status). At an intermediate level, a state-vulnerability index may moderate the trait index for the duration of a particular course, by considering a student’s achievement level (e.g., grade) in the discipline related to the intended topic, and a self-efficacy assessment on the topic. At the lowest level, a situation appraisal might be more indicative of momentary difficulties that students encounter regarding specific aspects of the course.

Based on the diagnostic tools, the monitoring of CAI in proportion to in-group instruction may also leverage a few dimensions, namely the duration, sequencing and frequency of the CAI sessions. For duration and sequencing, the trait- and state-vulnerability indices might be useful. For example, a student from a disadvantaged background with an average WM capacity and self-esteem (traits), who is not doing well in the discipline related to the topic and is not expecting to perform well (states), might benefit from spending more time interacting with the CAI compared to a middle-class student with average levels of WM capacity and self-esteem (traits) who does quite well in the same discipline (state). Because early exposure to in-group instruction may hinder the ability of the student in the former case to adequately engage in the learning process, as the knowledge gap is made visible in the classroom (Huguet & Monteil, 2013), early exposure to CAI might be better suited. After benefitting from an early CAI intervention, that student with heightened self-confidence might be in a better position to confront others’ perspectives, think in front of others and develop collaboration and debating skills, all of which represent an important part of the educational process.

For frequency, a situation appraisal could be more useful. Adjustments of the CAI intervention could be tailored to the difficulty students experience momentarily over the course of a lesson – such as those based on concepts a student struggles with – to maximise the chance that all students are provided with similar levels of comprehension. For example, a privileged student with average cognitive abilities (traits), relatively high grades and high efficacy expectations for the intended topic (states) may benefit from short and sporadic CAI sessions near the end of the course to focus on parts of the lesson she did not fully understand – or was inattentive to – when exposed by the teacher. This procedure may help ensure that this student is presented with all the material, which can be doubled-checked by means of responsive interactions with the computer.

The weight of different levels in the diagnostic tools and the dynamic monitoring of CAI is subject to discussion and needs a deeper elaboration and empirical evaluation. Nevertheless, even at this embryonic stage, these few insights about how to dynamically monitor digitalised individual pedagogy and in-group pedagogy may stimulate the debate onto new avenues with the aim of reducing school inequality.

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