EdTech and Girls Education in Low- and Middle-Income Countries: Which Intervention Types Have the Greatest Impact on Learning Outcomes for Girls?

Katy Jordan
klj33@cam.ac.uk
Faculty of Education
Cambridge, Cambridgeshire, UK

Christina Myers
c.myers@odi.org.uk
Overseas Development Institute
London, UK

ABSTRACT

Gender-based inequality in access to education is an issue of global concern. The use of educational technology is often cited as a potential way to help close educational gaps and promote girls' education. However, the existing evidence base in relation to girls' learning outcomes when using educational technology in low-income countries is limited. The evidence base was recently boosted by a study in which findings from classic educational development studies were revisited and disaggregated by gender [7]. In this paper, we present a secondary analysis of this dataset, focusing specifically on the educational technology-focused interventions, and sourcing additional data. The analysis comprises 35 interventions, reported across 15 publications, published between 2003 and 2019. We discuss the relative efficacy of different types of educational technology interventions by comparing effect sizes of learning outcomes for girls. The findings suggest that interventions which focus on distributing hardware alone have mixed - and sometimes negative - effects on learning outcomes for girls. The impact of software-focused interventions is more positive, particularly personalised learning applications. Furthermore, we consider characteristics of the studies included in the analysis, and identify gaps in the literature which will help shape research in this field in the future.

CCS CONCEPTS

• **Applied computing → Computer-assisted instruction**.

KEYWORDS

international development, educational technology, low- and middle-income countries, girls education, gender, equity

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1 INTRODUCTION

Globally, approximately 129 million girls were out of school as of 2019, and there are concerns that many will not return when schools reopen after the Covid-19 pandemic [20]. At the time of writing, only 49 percent of countries in the world have achieved gender parity in primary education, 42 percent in lower secondary education, and 24 percent in upper secondary education [31]. There is increasing interest in the potential to use educational technology (EdTech) at-scale within low-income contexts, with a view to helping to boost attainment [22] and progress toward Sustainable Development Goal 4: Quality Education [10]. There is a small but growing body of evidence illustrating that providing equitable and inclusive access to EdTech leads to greater levels of engagement for girls and women than their male counterparts [32], for reasons which are often context-dependent, such as compensating for gender-related educational beliefs and roles [27].

However, there is a risk that the use of EdTech can reinforce gender inequality as social inequalities are usually reflected in the way EdTech is designed, used, and implemented [6]. Multiple studies evidence a gender digital divide, as a result of cultural bias and gendered assumptions about girls' competence and enjoyment of technology often lead to girls having less access to EdTech [32]. It is therefore critical to consider the positive and negative impacts of EdTech in relation to girls education, before EdTech is used at-scale within an educational system, in order to help ensure that the integration of technology does not serve to exacerbate divides.

Despite a handful of studies highlighting the potential for EdTech to be used to support girls' education in LMICs, there is a distinct lack of robust evidence, as to-date rigorous evaluations have rarely explored differences based on gender. However, the dataset accompanying a recently published paper, 'What we learn about girls' education from interventions that do not focus on girls' [8] - has substantially boosted the evidence base available in relation to girls education in LMICs. The paper and dataset - which includes the newly-calculated effect size and standard errors for each study, specifically in relation to girls - have been openly published under a CC-NC licence. EdTech is not a specific focus of the paper, but the sample of studies compiled by Evans and Yuan includes some studies reporting EdTech-focused interventions. Discussion is limited to brief description of only the interventions which fall either in the top 10 most or least effective (notably, some EdTech interventions feature in both). There is therefore scope to use this dataset for novel analysis, focusing specifically on the data associated with EdTech interventions, to understand which types have the greatest impact on learning outcomes for girls.

2 METHOD

This paper presents a secondary analysis of part of the dataset compiled and published by Evans and Yuan [1], in order to investigate which types of EdTech interventions are associated with the greatest gains in learning outcomes for girls in LMICs. To this end, the research process consisted of four steps.

2.1 Step 1 - Data extraction

The original dataset included a total of 267 interventions across 175 papers [8]. It included a wide range of types of interventions aimed at improving access to education or educational outcomes in LMICs, and for which either data was already publicly-available disaggregated by gender, or that the authors of the original studies had provided when requested. The dataset was downloaded and screened for EdTech-related interventions, based on the descriptions given in the data table. 15 papers, reporting a total of 38 interventions (approximately 9 percent of the original dataset), were identified for potential inclusion, and collated into a spreadsheet.

2.2 Step 2 - Identifying supplementary data

Next, we searched for other studies which could supplement the evidence in the original dataset [8]. The studies included in three recent reviews related to the topic of girls education and EdTech were checked for potential inclusion [26, 29, 32]. The following selection criteria were applied: Involving an EdTech intervention; Undertaken in a LMIC; Report experimental or quasi-experimental research designs presenting quantitative findings in terms of learning outcomes, disaggregated by gender. Only one additional study was identified which was suitable: Pitchford et al. (2019) [27].

2.3 Step 3 - Categorising the interventions

While the original dataset contained some brief descriptive information about the interventions, EdTech was not a primary focus of the study [8], so the data required a new, EdTech-specific categorisation to be applied. To do so, the original texts of the studies were located and read. At this stage, one paper was discarded as on consulting the full text, it was found to not be EdTech-focused; non-EdTech intervention components of other studies were also removed. The following categorisation scheme emerged, with numbers in brackets indicating the number of papers and number of interventions falling within each category:

Hardware: Computers (2, 4); Interactive whiteboards (1, 1); One laptop per child (OLPC) (4, 7).

Software: Educational computer games (2, 2); Electronic worksheets (1, 2); Mulltimedia software packages (3, 7); Personalised adaptive learning (3, 6).

Other: Interactive learning tool (1, 3), Satellite instruction (1, 2).

2.4 Step 4 - Data analysis

The 15 publications which formed the final sample, and 35 interventions reported within them, are summarised in Table 1. The data – including effect sizes (Cohen's d), standard errors of d, and categorisation of EdTech intervention type - were imported into SPSS for comparison and analysis. Although this type of data would lend itself to potential meta-analysis, we did not conduct full statistical analyses due to high heterogeneity. This was noted by Evans and Yuan as a reason for not conducting full meta-analysis in their original paper, and heterogeneity was confirmed to be high within this sample. The sample overall and major subgroups (hardware and software) all demonstrate I^2 values over 75 percent I^2 = 0.96, 0.91 and 0.92, respectively) [11]. Nonetheless, comparisons can still be drawn based on relative trends within the data according to different categories of EdTech. To this end, we used descriptive statistics and visualised the data using forest plots.

3 RESULTS AND DISCUSSION

The majority of studies clearly fell into one of two main groups: whether the nature of EdTech use was primarily concerned with implementation of hardware (13 interventions, reported in five papers), or software (17 interventions, in nine papers).

Two papers, comprising five interventions, did not clearly sit within the hardware or software categories. The first focused on the use of an interactive learning tool - a 'PicTalk' machine - which combines both hardware, in the form of the machine itself, with interchangeable content through memory cartridges [9]. As such, it was not clear that this intervention could be unambiguously categorised as a hardware intervention. The second paper reports on two interventions broadcasting live lessons delivered remotely by teachers from a different location via satellite to children at schools in Ghana, as a way to ameliorate local teacher shortages [14]. Interaction with the teachers during live lessons was also possible, through computers and software also installed in classrooms as part of the intervention along with a suite of other hardware.

3.1 Hardware interventions

The hardware category comprised 13 interventions, reported across five publications. One paper (reporting three interventions) contributed to each the sub-types of computers [3], and interactive whiteboards [4]. The remaining studies focused on OLPC initiatives [5, 12, 28]. Effect sizes and confidence intervals for the hardware interventions are displayed as a forest plot in Figure 1.

The distribution of the effect sizes within the hardware category suggest that hardware alone is not an effective way to improve learning outcomes for girls. The average effect size across the group is close to zero. Furthermore, several of the interventions show negative effect sizes for girls' learning outcomes. There is no visible trend within this dataset to suggest that any one of the three subcategories is clearly better than another, and all groups include both positive and negative effects.

3.2 Software interventions

Overall, the collection of software-focused interventions suggests a more positive effect on girls' learning outcomes (Figure 2) than hardware interventions (Figure 1), although not all are positive. While the interventions were clearly software-focused, the subgroups were harder to define. Of the four sub-groups, the oldest studies present educational computer game software [1, 17]. Both report slight and very consistent positive effects; this is not coincidental, as both report slightly different evaluations of the same program in India, one difference-in-difference study design [17] and one randomised experiment [1]. Two further studies also included

Table 1: Overview of studies and interventions included in the final dataset for analysis. Each row represents one publication, which may report several interventions.

Authors	Year	Location	Category	Number of interventions	Learning outcomes reported
Linden et al.[18]	2003	India	Software: educational computer games	1	math and verbal outcomes combined
Banerjee et al. [1]	2007	India	Software: educational computer games	1	math and language outcomes pooled
He et al. [9]	2008	India	Other: interactive learning tool	3 (tool alone, and with activities)	English outcomes across two grades
Linden [25]	2008	India	Software: electronic worksheets	2 (in-school and out-of-school use)	math and English outcomes
Barrera-Osorio & Linden [3]	2009	Colombia	Hardware: computers	3	math, language, and aggregate test scores
Cristia et al. [5]	2010	Peru	Hardware: OLPC	3	outcomes in language, math, and a summary measure
Berlinski & Busso [4]	2013	Costa Rica	Hardware: computers; interactive whiteboards; OLPC	3	geometry outcomes
Humpage [12]	2013	Peru	Hardware: OLPC	2	math and verbal fluency outcomes
		Costa Rica	Software: multimedia software packages	4 (two different software packages)	oral language outcomes in two grades
Imbrogno [13]	2014	Mexico and Chile	Software: personalised adaptive learning	2 (one per country)	test scores
Sharma [28]	2014	Nepal	Hardware: OLPC	2	math and English outcomes
Lai et al. [16]	2015	China	Software: multimedia software packages	1	math outcomes
Mo et al. [24]	2015	China	Software: multimedia software packages	2	math outcomes from two grades
Johnston & Ksoll [14]	2017	Ghana	Other: satellite instruction	2	EGRA and EGMA outcomes
Muralidharan et al. [25]	2019	India	Software: personalised adaptive learning	2	math and Hindi outcomes
Pitchford et al. [27]	2019	Malawi	Software: personalised adaptive learning	2	math and reading outcomes

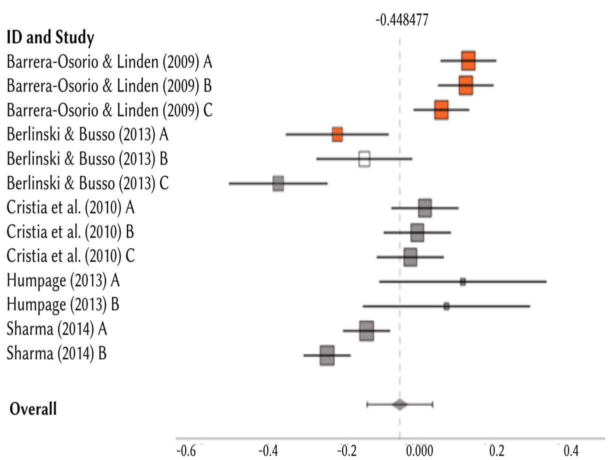

Figure 1: Forest plot illustrating effect sizes and confidence intervals for hardware-focused interventions. Orange denotes computers; white, interactive whiteboards; grey, OLPC.

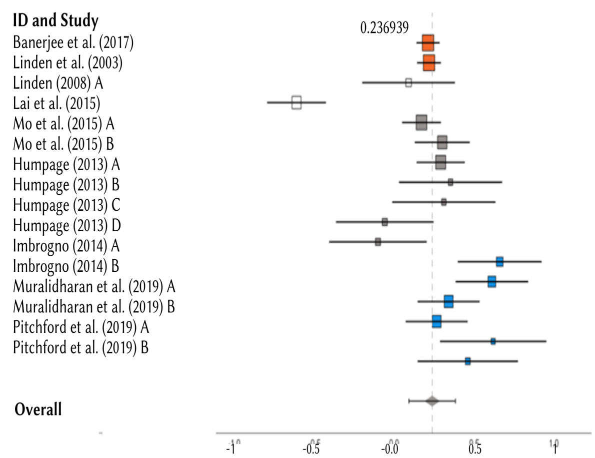

Figure 2: Forest plot illustrating effect sizes and confidence intervals for software-focused interventions. Orange denotes educational computer games; white, electronic worksheets; grey, multimedia software packages; blue, personalised adaptive learning applications.

educational computer games; however, in both instances the educational computer games were used in conjunction with instructional videos [16, 24]. As such, these interventions were placed into a category of 'multimedia software packages' (see below). However, the effects on girls' learning outcomes were remarkably similar across the four studies reporting educational computer games (with or without instructional videos), suggesting that this type of software can yield small but positive learning outcomes for girls.

Two interventions, reported in the same publication, sit within the electronic worksheets category [18]. Despite their technical similarity, the individual interventions demonstrate markedly different effects upon girls' learning outcomes. When used in the classroom as a substitute to activities with a teacher, a strongly negative effect was reported; while if used out-of-school in addition to formal schooling, the intervention had a small positive effect. This difference is not particular to the girls' learning outcomes, and was similarly observed in the original non-disaggregated data.

The 'multimedia software packages' category comprised a total of seven interventions, spanning three publications [12, 16, 24]. For the purposes of this classification, we defined multimedia software packages as software interventions which combined multiple elements of digital educational content, such as instructional videos, educational games, and quizzes, for example. As previously discussed, three of the interventions within this category used instructional videos in combination with educational computer games [16, 24], with similar results. The remaining four interventions in this category are sourced from a single publication, reporting two interventions each for two software packages (DynEd and Imagine Learning) [12]. The two software packages gave contrasting results; both DynEd interventions yielded positive results, while both Imagine Learning interventions had a negative impact [12]. The differences may be related to contrasting pedagogical designs in each software package [12].

The final sub-category within software interventions is 'personalised adaptive learning' (PAL). In common with the multimedia sub-category, the applications here often combine multiple types of digital educational content. However, applications within this category are distinct in that they additionally use some form of adapting the content to the learners' level. This sub-category includes six interventions, split across three publications [13, 25, 27]. It is notable that the three publications are relatively recent within the sample, which may reflect technical developments in relation to PAL. The data suggest that PAL is an effective way to support girls' learning outcomes, with the effect sizes of all six interventions in this category sitting above the average effect size for software interventions overall (Figure 2).

4 CONCLUSIONS

In this secondary analysis of a larger published dataset, which presented outcomes specifically in relation to girls' education [8], we have taken a closer look at EdTech-focused interventions. Two major distinct groups of interventions were identified; hardware-focused, and software-focused. Considering the distribution of effect sizes for girls' learning outcomes associated with each group, the data suggests that hardware interventions are less effective.

While it is often acknowledged that hardware in itself is unlikely to lead to positive impacts upon learning [7, 21] and may be a relatively poor investment [2], this data confirms this when focusing specifically on outcomes for girls. Furthermore, hardware-focused interventions alone can have a negative impact for girls, which is supported by qualitative findings [30]. This presents a dilemma which it is critical to be aware of and actively address at implementation, as without additional support, the overall effect may be to perpetuate or deepen gender divides in learning outcomes.

The analysis suggests that there is greater potential for software-based interventions to support girls' learning outcomes. In particular, PAL software - which adapts to the learners' level - shows relatively larger gains for girls compared to other forms of software. This reflects findings of a recent meta-analysis which highlighted the positive effects of PAL on learning outcomes in LMICs [19]. While it is important to caution that the sub-sample of PAL interventions here is small (six interventions), the average effect size is substantially larger (0.493) for girls compared to non-disaggregated data from PAL interventions in LMICs overall (0.18) [19].

In addition to examining the relative efficacy of different forms of EdTech interventions in terms of their impact on girls' learning outcomes, the characteristics of the sample of studies highlights areas and issues for future research. Above all, the sample underscores the need for data to be disaggregated by gender as standard practice when collecting data and reporting findings. None of the EdTech studies within the Evans and Yuan dataset reported on interventions which had been specifically tailored for girls; all were disaggregated by gender post-hoc. This issue was also demonstrated by the searches for additional studies, which only yielded one paper (reporting two interventions) with comparable data. This also reflects a methodological issue, in that the majority of papers included in recent girls' education and EdTech reviews [26, 29, 32] and screened for possible inclusion here did not report quantitative, learning outcome-focused research designs.

It would also be valuable to examine a wider range of learning outcomes, and consider in further detail the differences between using EdTech for different types of outcomes. The interventions in the sample are restricted to languages and math outcomes; while these topics are foundational, there may also be scope to examine other outcomes such as socio-emotional learning, or other effects beside learning gains. Math outcomes are measured most frequently within the sample, and may be greater; for example, within the software-based interventions, the average effect size for math interventions is twice that of languages interventions (0.427 and 0.204, respectively), suggesting that there is a need to focus on how teaching languages can be better supported through software.

There is also a gap in terms of the range of types of EdTech which gender-disaggregated data is available for. Studies which focus upon the use of phones and mobile devices are notably lacking; this medium has shown good potential for girls' education [15, 23, 33] but there is a need for robust evaluation. It would also be valuable to further characterise different types of interventions in terms of both the technology and the underlying pedagogy, as highlighted by the challenges in categorising increasingly complex software packages. Finally, while the studies included in this paper have been predominantly quantitative - to facilitate comparison of outcomes - there is further comparison of qualitative data, in order to explain the reasons behind the trends and place them in context.

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