# The Impact of Different Personalisation Algorithms on Literacy and Numeracy in Kenyan Pre-primary Education:
## A Comparative Study of Summative and Formative Assessments Results


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## INTRODUCTION

Evidence indicates that digital personalised learning (DPL) can have a positive impact on learning outcomes. An important research area of personalisation is to sequence learning content to actively engage learners (Diwan et al., 2023) and/or increase knowledge acquisition (Major et al., 2021). Research suggests that content sequencing powered by personalisation algorithms can outperform the sequence set by experts (Chau et al., 2018).

This paper contributes to research on DPL in that (1) we implemented and compared two personalisation algorithms (optimising engagement vs. score), evaluated against a default expert-curated sequence to assess learning effectiveness, and (2) the study was conducted in an under-researched context, i.e., a low- and middle-income country (LMIC; Kenya). The impact of three different content sequencing methods deployed on the EIDU DPL tool are investigated, by comparing the effects on three learning metrics: summative assessment, curriculum progress, and formative assessment.

## RESEARCH QUESTION

**What is the impact of personalisation (Engagement vs Score vs Expert-Curated Sequence) on learning for Kenyan pre-primary learners?**

## METHODS

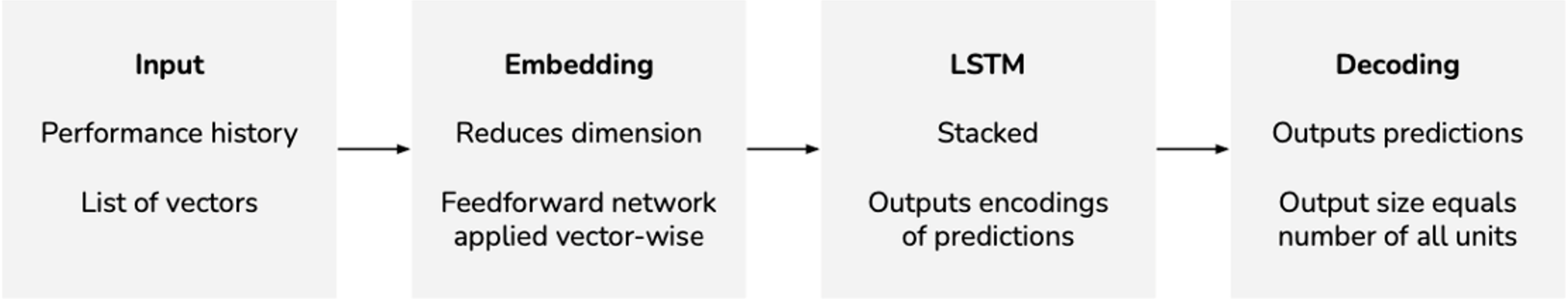
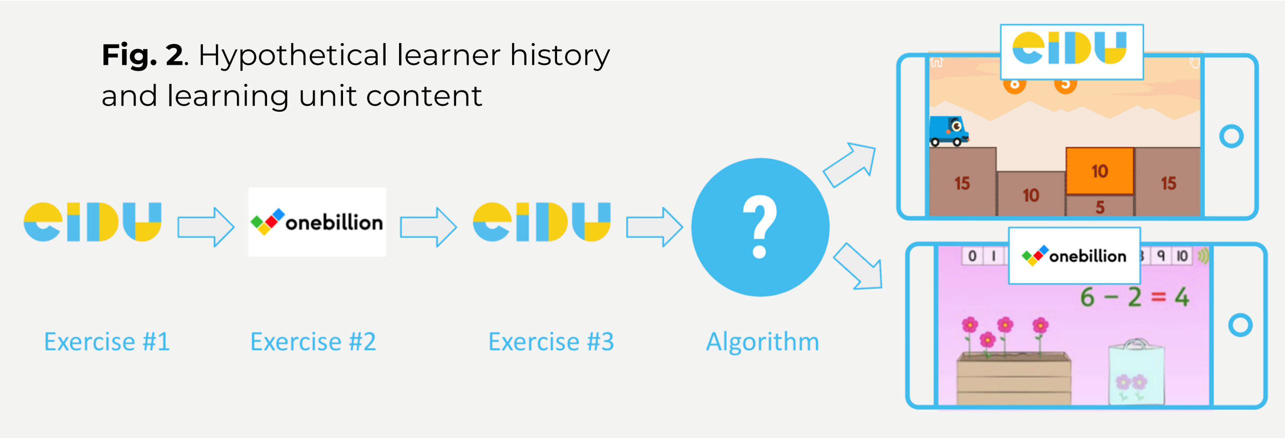
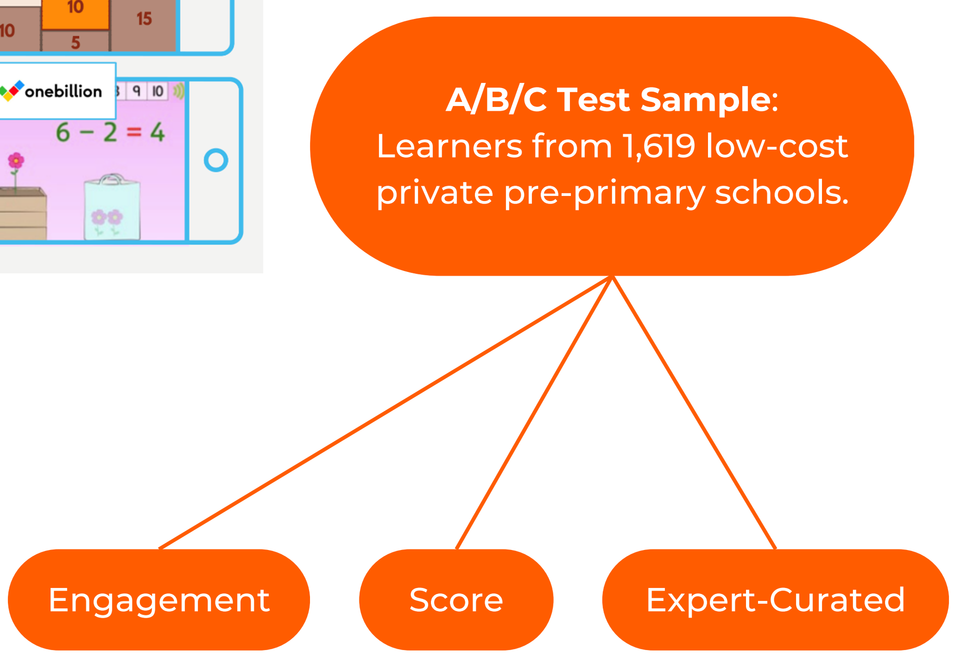



**Fig. 1.** Predictive models' architecture

**The EIDU DPL platform runs on low-cost Android devices. Learning units align with the Kenyan curriculum in domains (numeracy and literacy) and strands (e.g., classification).**

**Fig. 2.** Hypothetical learner history and learning unit content




- An A/B/C test was conducted over three weeks in July 2023 in Nairobi, Kenya.
- Institutional and teacher gatekeeper consent was sought by EIDU.
- The post-test sample was 6,479 learners from 1,509 classes.
- The pre-test data were selected from learners who used EIDU in June 2023, by matching anonymised IDs in the post-test data.
- The pre-test sample consisted of 5,884 learners from 1,177 classes.

## RESULTS

### SUMMATIVE ASSESSMENT

**1,661 learners** completed the summative assessment **in the Engagement partition, 1,702 in the Score partition**, and **1,640 in the expert-curated sequence** group. Possible score range was 0 to 1 for each assessment unit. Scores were averaged across all test units and aggregated to overall scores for literacy and numeracy.

ANOVA tests **did not reveal significant group differences** for **pre-test** **literacy** learning ($F(2,4106) = 2.96$, $p = .052$) and **numeracy** learning ($F(2,1906) = .11$, $p = .89$). Similarly, **post-test** analysis **did not show any group difference** in **literacy** ($F(2,4361) = .96$, $p = .38$) and **numeracy** ($F(2,2186) = .58$, $p = .56$).

### CURRICULUM PROGRESS

**No differences** were found in **total usage** between partitions ($F(2,6488) = 2.00$, $p = .13$; *Table 1*).

There were **significant differences** in the **number of unique learning units completed** ($F(2,6488) = 1509.58$, $p < .001$; *Fig. 3*).

**Engagement** partition progressed through most number of learning units *(Table 1)*.

**Table 1: Curriculum Progress: Usage and Number of unique learning units completed.**

| | Total duration (in minutes) | Average progress (*Mean*) |
|---|---|---|
| Engagement | 96.73 | 21.6 |
| Score | 99.73 | 8.2 |
| Expert-curated sequence | 103.74 | 18.5 |

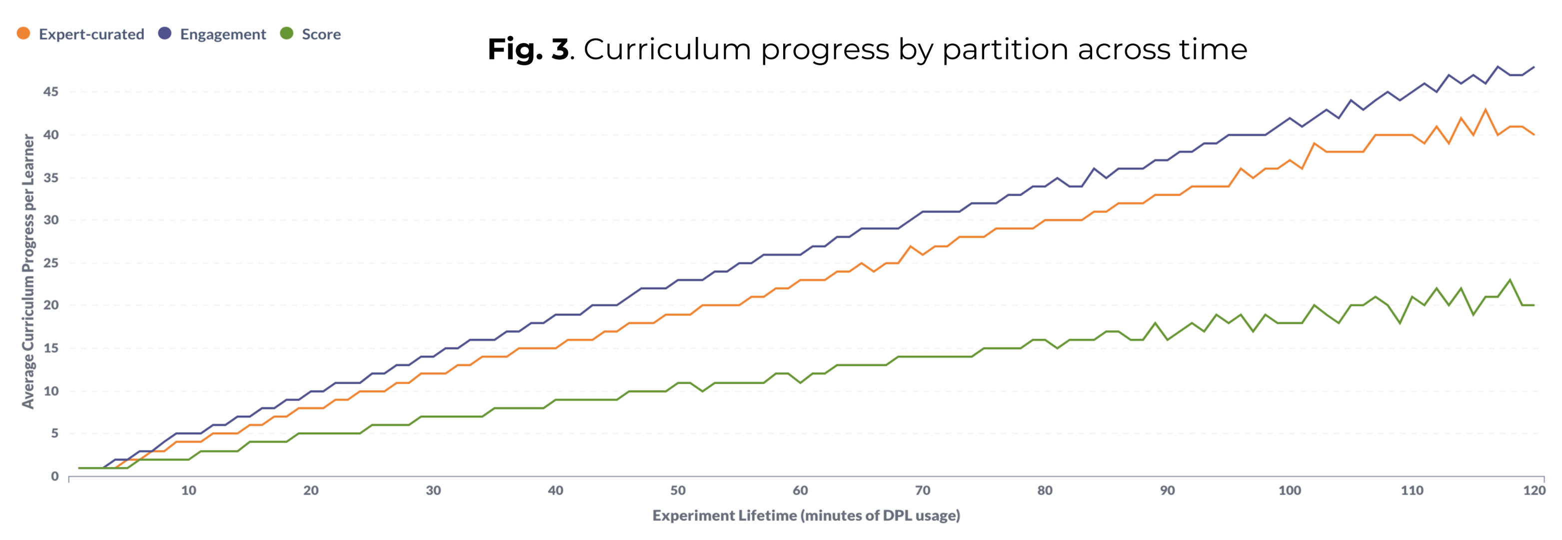



**Fig. 3**. Curriculum progress by partition across time

### FORMATIVE ASSESSMENT

**Table 2: Post hoc Tukey test for group comparisons**

| Partition | Eg vs. Expert Mean (SE) | Score vs. Expert Mean (SE) | Eg vs. Score Mean (SE) |
|---|---|---|---|
| Classification | .033 (.004) *** | .044 (.004) *** | -.011 (.003) ** |
| Listening | .028 (.007) *** | -.068 (.007) *** | .096 (.006) *** |
| Measurement | .056 (.008) *** | .042 (.008) *** | .014 (.009) |
| Numbers | -.044 (.008) *** | -.162 (.008) *** | .119 (.009) *** |
| Phonological awareness | -.017 (.007) | -.022 (.007) ** | .006 (.007) |
| Reading | -.013 (.008) | -.117 (.008) *** | -.104 (.007) *** |
| Speaking | .043 (.007) *** | -.034 (.007) *** | .076 (.006) *** |
| Writing | -.001 (.001) | -.005 (.001) *** | .006 (.001) *** |

Note: ** $p < .01$, *** $p < .001$. Eg = Engagement, Score = Score partition, Expert = expert-curated

In total, **6,371 learners participated across all three partitions:** 2,089 Engagement, 2,117 Score, and 2,165 expert-curated. Learners collectively played 216 common learning units across 8 strands.

**Different sequencing impacted learning outcomes in different ways depending on the learning strand** - *Table 2* outlines this variation according to learning strands (e.g., classification, listening, etc.) (In *Table 2*, Eg = Engagement).

## DISCUSSION

This work contributes to a deeper understanding of how low-cost DPL benefits literacy and numeracy learning for pre-primary learners in LMICs. The **findings demonstrate varied effects of different content sequencing algorithms on specific learning content.** Personalisation had **no impact on the summative assessment, but may affect learning pathways** (e.g., Engagement partition went through learning units faster) and improve certain content learning.

**Future research** should focus on **investigating and identifying algorithms that are more beneficial for pre-primary learners in LMICs,** taking into account the specific subject matter. Further investigation is needed to pinpoint the **exact effects of content sequencing algorithms**, by comparing different LSTM-based algorithm designs.

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