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Learner Agency in Personalised Content Recommendation: Investigating Its Impact in Kenyan Pre-Primary Education

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Abstract. There is a lack of understanding regarding how pre-primary learners exercise their agency in their learning processes when interacting with AI-powered digital personalised learning (DPL) tools. This study aims to address the gap by investigating the interaction between pre-primary learners' agency and a DPL tool in a Kenyan classroom setting. A total of 76,479 pre-primary learners participated in a two-month experiment, where each learner was randomly assigned to two partitions. Learners in the control partition followed the learning content designated by an algorithm within an adaptive DPL tool. In the experimental partition, learners received two additional learning units to choose from as well as the default content unit. Learning outcomes were assessed through six summative test units measuring literacy and numeracy skills. The results revealed that learners who were provided with a choice scored significantly higher in four out of the six test units. This study highlights the potential that pre-primary learners can exercise some degree of agency and direct their own learning within a structured set of choices provided by a DPL tool. Future research is needed for a comprehensive understanding of pre-primary learner agency.

Keywords: Learner agency, digital personalised learning, human-AI collaboration, pre-primary education, content recommendation, low- and middle-income country

1 Introduction

The application of AI in education can benefit learners in a variety of areas, such as increasing engagement, providing personalised learning experiences, offering timely feedback, and ultimately improving learning outcomes [18]. Digital personalised learning (DPL), which is often powered by AI, has demonstrated positive effects on learning outcomes, by tailoring content to students' characteristics and learning needs [15, 19]. However, there is a potential concern that the automation inherent in DPL might reduce human autonomy in the learning process [8].

To ensure a beneficial integration of DPL in educational environments, it is important to maintain a balance between DPL automation and learner agency [14]. Learner agency refers to the degree of freedom and control that learners have to make choices, exert influence, and take responsibilities for their learning when interacting with AI-powered learning systems [13,14]. It has been identified as a key feature to promote learner engagement, motivation, and effective learning [1, 6]. Identifying the optimal moments and methods for integrating learner agency into DPL is challenging but essential for its effective deployment and to unleash its full potential [17].

Providing learners with choices in learning paths, content, and pace, is considered as an important feature of DPL, as it may enhance learner agency and motivate them through their learning processes [1, 16]. A key strategy for activating learner agency involves enabling learners to navigate freely through learning content, such as instructional videos and game levels, rather than confining them to a fixed sequence of materials [9, 13]. However, it is worth noting that unrestricted freedom in determining learning paths does not necessarily lead to improved learning outcomes [13]. Therefore, careful design and rigorous investigation of learner agency should be conducted to gauge the degree of agency that effectively enhances learning within the Artificial Intelligence in Education (AIED) field.

The majority of agency research focuses on post-primary learners, from lower secondary level up to university. However, understanding early-grade learners' agency in the AIED field plays a key role in incorporating their perspectives into the design and implementation of educational technologies, including who makes the choice, what options are available to them, and the context in which choices occur [3]. [4] emphasised the importance of examining how young learners engage with AI-powered content recommender systems, considering factors such as their age and developmental readiness. This suggests a notable gap in our understanding of how agency is expressed when pre-primary learners are interacting with AI-powered learning environments.

Although not specifically within the AIED field, studies have shown that early-grade learners have the ability to manifest agency in their learning. In traditional classroom settings, these early-grade learners recognise the need to actively engage in their learning, and understand how various pedagogical activities can facilitate or hinder agency among diverse learners [11,12]. Listening to pre-primary learners is crucial because their perspectives can help construct learning environments that provide meaningful opportunities for them to make decisions about their education [11]. Building on this foundation, this current study investigated how pre-primary learners interact with and make choices about learning content recommended by a DPL system.

1.1 Contributions

This study contributes to the literature on integrating agency within DPL systems by providing learners opportunities to select learning content from a collection of algorithm-generated choices. The study has a particular focus on how pre-primary learners exercise this described agency in a DPL tool within a low- and middle-income country (LMIC). The research informs the AIED community about the plausible, scalable implementation of DPL in typical school systems, taking into consideration learner agency in determining their own learning paths. The main research question addressed in the paper is: What's the impact of providing learners with choices in DPL on pre-primary numeracy and literacy outcomes in Kenya?

2 Method

2.1 EIDU DPL tool

EIDU is a classroom-based intervention in government run schools, providing digitised structured pedagogy resources for teachers and DPL literacy and numeracy gamified learning exercises for students, which are curriculum aligned. The software is accessed through low-cost android devices with each learner having an account linked to their class. There are one to two devices per class, with teachers setting up a dedicated table in the classroom for learners to engage individually with the devices for 5-minute sessions. This can be during regular classroom instruction or during break times. After a learner finished a session the next learner's profile appears to facilitate peer to peer handover without any teacher involvement. Over the study period, learners engaged with the device for an average of 30 minutes per week. EIDU is aligned with the Kenyan curriculum in domains (literacy and numeracy), strands (e.g., Classification), and substrands (e.g., Matching & Grouping) and all content has been approved by the Kenyan Institute for Curriculum Development (KICD). Teachers select which area of the curriculum they want their learners to focus on prior to providing them with the device. EIDU's personalisation system then selects a content unit (a predefined game made up of 3 to 4 exercises) for a given learner based on that learner's performance history.

2.2 Personalisation

The adaptive feature of the DPL tool is achieved by providing a sequence of learning content that tailors to learners' performance. A learner's historical binary outcome on previous content units (successful or non-successful completion) is provided as a sequence to a Long Short-Term Memory (LSTM) neural network, similar to the deep knowledge tracing model described by [10]. Given the low-connectivity environment, the model needs to be available locally on devices through TensorFlow Lite (https://www.tensorflow.org/lite).

For every available content unit in the teacher selected area, the model takes the learner history at time t, then predicts performance at t+1, and then simulates the learner's knowledge state at t+2 given this predicted performance. Knowledge state is defined as the average predicted success rate on the vector of available content units in a teacher-selected area. The content unit expected to provide the largest increase in knowledge state at t+2, taking into account probability of completion at t+1, is then selected as the next optimal unit for a learner.

As part of their product development process EIDU runs A/B tests on new features to explore impacts on learning outcomes. Since the method described above returns a ranked list of content units for a given area, it is an arbitrary decision to provide the learner with only one unit. To explore whether providing learners with a greater degree of agency in selecting content would be beneficial, this study implemented an A/B test in the EIDU platform. In one partition, learners were shown a thumbnail preview of the top three units the personalisation algorithm expected to have the greatest impact, while in the other partition the default of only displaying a single unit, also with a thumbnail preview, was maintained.

2.3 Data collection and sampling

Prior to releasing any A/B test EIDU went through a development process where teachers were first consulted in discussion groups, prototypes are provided to individual teachers and learners. If feedback was positive, there was a release to a small group of dedicated Beta testing schools, who provided extensive feedback. Once the feature was deemed safe to release, schools where teachers and local government authorities have provided EIDU with digital gatekeeper consent at sign-up were included in the A/B test. This test lasted from August 28 to October 27, 2023. A total of 76,479 pre-primary learners participated. Learners were assigned into the two partitions using simple randomisation. All personal identifying data is always encrypted locally on devices with anonymised usage data being uploaded to EIDU servers when an internet connection is available. A data-sharing protocol was established to facilitate sharing of anonymised data for this study.

2.4 Summative assessment

As learners engaged with the learning units, they were occasionally provided with dedicated assessment units instead of learning units. There were six assessment units used to evaluate this A/B test: initial sound identification, letter sounds, number discrimination, number identification, word sounds, word sounds Swahili. These assessment units are digitised versions of established assessment batteries such as EGMA, EGRA or MELQO [5]. Learners engage with no more than one assessment unit per day. This routine of continuous assessment creates longitudinal learning data which can be used to evaluate the impact of feature changes through A/B testing. Summative assessment scores were calculated based on the correctness – as the percentage of correctly answered items over the total number of items within a test unit. The possible range of the score was from 0 to 1.

2.5 Data cleaning

Duplicated data points were removed before any in-depth check of the dataset. Data was excluded where an assessment was tagged as having ended through consecutive timeouts. This happens when a learner has either disengaged with the content and stopped touching the screen, or a teacher has removed the device mid-assessment without ending it. This represents approximately 0.1% of total assessments, so has negligible impact on analysis. The assessment outcomes that were larger than 1 were removed as these are generated due to data errors. The cleaning process resulted in a total of

288,339 assessment outcomes the default partition and 280,435 outcomes in the strand Choice partition. The latest assessment for each learner in each test unit type was selected resulting in 194,751 assessment outcomes in the default partition and 203,169 outcomes in the Choice partition. The loss of information is justified in this initial analysis to avoid unbalanced repeated measures being present as part of this initial analysis.

2.6 Analysis

Descriptive statistics, including the mean and standard deviation, were calculated on the correctness of summative assessment for each test unit. To understand how learners interact with the available choices, we computed the percentage of time a learner selected what would be the default option, which is the unit the personalisation model considered optimal. The primary objective was to ascertain whether the intervention—characterised by learner autonomy in content selection—significantly impacted educational outcomes in a government-run school setting.

In the context of our study, where assessments are undertaken sporadically across time, we opted for an ANOVA model after filtering for only the latest result per learner and per test unit. This choice was to ensure a robust evaluation of group differences taking into account the longitudinal nature of our data, where learners engaged with assessment units across different time points during the A/B test. Levene's test for equality of variances was performed to assess the assumption of homoscedasticity across groups, yielding a statistic of $F = 7.85$, $p = .005$. ANOVA is robust to the homogeneity assumption when group sizes are large and similar [2]. Secondary analysis using a regression model examined the impact of choice on learning outcomes by using the percentage of default option selections as a predictor for each test unit. This analysis was performed for the choice partition only.

3 Results

The descriptive statistics in Table 1 show that on average learners have low scores across all assessments, apart from Initial Sound Identification and Number Discrimination. This could be representative of general low levels of learning outcomes in this context but could also be due to higher levels of disengagement with digital assessments [5]. Learners in the Choice partition score marginally higher than learners in the Default partition in all test units apart from in Number Discrimination. Across both partitions there were at least 30,000 learners who completed each test unit type.

Our ANOVA analysis (Table 2) reveals that learners in the choice partition scored significantly higher in all test units apart from Number Discrimination and Word Sounds Swahili. This suggests that providing learners with increased agency in this pre-primary context did lead to higher learning outcomes in specific numeracy and literacy domains.

Our secondary analysis explored how the degree of agency impacted assessment outcomes in the Choice partition only. On average, learners selected the default choice 35% (SD 15%) of the time when offered with other options in literacy-related content. In contrast, for numeracy-related content, the default choice was selected 32% (SD

15%) of the time. This frequency of default choice per learner was added as a variable to the analysis. This suggests choosing the default option significantly and positively predicted the score of all test units (Table 2). This implies that although increasing agency in the choice partition led to higher overall outcomes it may be beneficial to restrict this choice further in future A/B tests for example by only providing 2 rather than 3 choices.

Table 1. Descriptive statistics of assessment score and sample size per partition per test unit

Test unit name	Assessment score Mean (SD)		Learner count	
	Default	Choice	Default	Choice
Initial Sound Identification	0.474 (0.313)	0.480 (0.315)	31513	30084
Letter Sounds	0.246 (0.171)	0.253 (0.173)	33843	32139
Number Discrimination	0.524 (0.249)	0.522 (0.249)	35856	34685
Number Identification	0.231 (0.262)	0.241 (0.266)	34788	33648
Word Sounds	0.273 (0.198)	0.278 (0.201)	33569	32123
Word Sounds Swahili	0.201 (0.169)	0.202 (0.172)	33600	32072

Table 2. Regression coefficients on group comparisons and agency effects per test item

	Group comparison	**Choice partition only**
Test unit name	Paritition_id (coefficient)	Agency (content related) (coefficient)
Initial Sound Identification	.006**	.127***
Letter Sounds Short	.006***	.046***
Number Discrimination	-.002	.112***
Number Identification	.010***	.117***
Word Sounds Short	.005**	.061***
Word Sounds Swahili	.002	.085***

Note: ** $p < .05$, *** $p < .001$

4 Discussion and Future Work

This study investigated how providing pre-primary learners with an increased choice in sequencing their learning experience versus a restricted AI-powered sequence impacted learning outcomes. The results showed that providing learners with increased agency significantly improved learners' scores in numeracy and literacy domains compared with the learners who followed the system-generated learning content. This is in line with previous research from [7] showing positive effects of DPL on literacy and numeracy development. Importantly though this work enhances these findings by exploring how learners even at a young age can effectively act as humans-in-the-loop when it comes to AI systems. The fact that high use of the default option was associated with higher learning outcomes despite the primary results finding agency increased learning outcomes, suggests that a more restricted number of choices may be beneficial.

Although the study shows promising results in increasing agency of learners in digital spaces in the Kenyan pre-primary context, a few limitations exist that offer directions for future research. In particular, why certain content units were chosen by learners over others or how the expected gain in knowledge state across different choices modulated the effectiveness of learner agency. Exploring what other strategies foster learner agency could also provide insights for how DPL systems can be optimised to benefit learners [3].

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