The Construction and Verification of Early childhood Personalized Education Path Based on Artificial Intelligence

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Abstract

Early childhood education (ece) is foundational to lifelong learning & development, but traditional pedagogy uses a "one size fits all" method that can't account for the different ways kids grow, like their interests and how fast they learn. This paper addresses this issue with an innovative system to build personalized learning paths with AI that has been proved valid. Main thing we're looking at revolves around designing an AI that puts together a dynamic learner profile, a bunch of structured materials, and a good recommendation system all together. Learner profile module. Learner profile gathers an individual's ability, and their engagement by carrying out interactive assessments and constantly tracking. The content repository comprises modular learning activities tagged with rich metadata - difficulty level and prerequisite skills are just two components of it. AI engine uses a hybrid algorithm, mixing collaborative filtering and a knowledge graph, to create an ever-changing order of those activities, thus providing a perfect, personal learning journey for every child. In order to verify the effectiveness of this model, a 12-week quasi-experiment was carried out by choosing 60 kindergarten children for the experiment, the experimental group which used the AI-based platform and the control group which used non-personalized digital curriculum. From the statistical results we can see that the learning outcome of experimental group is significantly better than that of control group, especially concerning numeracy and solving problems. Moreover, engagement metrics like task completion rates and time-on-task were notably better for kids on the personal path. These results show how powerful AI might be in making better, more fun, and fair learning places for kids in ECE, which could lead to a whole new way of teaching each student differently.

Keywords

Personalized learning, artificial intelligence, early childhood education, learning path, educational technology, validation, adaptive learning.

1. Introduction

Early childhood education (ECE) is a very important part of human developing, it makes a solid foundation for our future study and good life. The skills of thinking, being with others, and understanding feelings start from this time. the encounters and exchanges a child will go through during these years of development can very much shape one's attitude on education. But most ECE settings are structured around a single standardized educational curriculum being delivered in the same way to a group of children with highly varied abilities, interests, and developmental maturity. And this traditional model is scalable but can't actually meet the unique learning journey of each child. Long ago, developmental psychology stated that kids would move through the stages of thinking at different velocities and in various ways. When the static curriculum isn't able to match up with the inherent variation found in children, it can bring about suboptimal outcomes, some kids falling behind on account of not getting the required support at their foundational stage and others becoming bored because there's no mental engagement involved in the learning process[1]. The notion of personalized learning comes about as an extremely strong counter-narrative to one such as this, and it promotes instruction as well as what goes into that process that is specifically customized to fit the unique needs of every single learner. Though the premises of personalized learning might be highly regarded, its actualization in the ECE context has often been hampered by the considerable logistical and cognitive burdens imposed on educators, unable to practically handcraft and administer dozens of distinct learning journeys at the same time[2]. It's within those contexts that AI comes in as something of a change-making possibility. With the computing capacity of AI, we can analyze a large amount of learner data at an instant and make decisions based on data so as to adjust the teaching experience in real time, making learning experience personalizable at scale which is unthinkable before. In this paper, a system of ai for the construction of personalized learning paths for young children is detailed from the point of view of its design, implementation and validation based on empirical evidence. Our main goal is to prove that the way we've taken an adaptive, AI-powered angle can make it a lot better for students' learning results and getting them more interested in what they're learning with digital tools that don't personalize themselves. In the following sections, I will provide an introduction to the theoretical background of the model, introduce the model architecture, give a brief description about the way we validate our model, and share, explain the results of our experiment, finally conclude this research with its implication and future direction.

2. Theoretical Foundations and Related Work

To create an effective personalized learning system for young kids, we need to build on the ideas about how children grow up and get smarter, as well as look at new ideas from the people who teach them in school and online. basal theories like the four stages of cognitive development by Jean Piaget or by concept such as the Zone of Proximate Development (ZPD) developed through an exploration in Lev Vygotsky; According to Piaget's idea, kids build information via their surroundings and move along certain developmental periods, which signifies that what has to be learnt should match a little one's brain skill level right now. Vygotsky's Zone of Proximal Development (ZPD) — that is, the area where a learner can do something by themselves and the area where they can do it with help — stands out. A real personalized system would want to stay always within each child's ZPD giving them something neither to bore with being too easy, nor to frustrate with being too hard, but just right to grow[3]. Our AI modeling our concept of the ZPD by constantly checking how a child is doing and then chooses the next task to give which builds off what they already know and still provides some support when learning something new. A wider field of AI in Education (AIEd) has lots of history on this, from old smart teachers on a computer (ITs) to newer things that change what you learn as you go. They have succeeded for these systems, mostly in higher ed and where a particular domain is well defined – math, computer science. But then there is the application in ECE, which brings new problems. Children under 10 need play-based activities that are very visual, but not full of text. And since they have some noisier (i.e., less replicable) and context dependent developmental data, Our work extends the principles of AIEd, but specifically for this younger crowd. We are designing interaction paradigms that will be intuitive for kids who haven't learned to read and we've got a content repository of interactive games and stories rather than problem sets. There has been a recent start to researching AI in ECE, and most research done right now is in robotic tutors or tablet apps with little adaptability.

3. Construction of the AI-Based Personalized Learning Path Model

The structure of our artificial intelligence (AI) - based personalized learning system contains three major and interrelated core parts, which includes the dynamic learner profile module, modular content library, the AI recommendation engine. This unified structure is meant to build up a responsive education ecosystem that is always adjusting: Dynamic Learner Profile Module is the thinking basis of the system which is responsible for development and upgradation of comprehensive, growing profile of every kid. It starts with an initial on-boarding phase, during which the child plays through a series of specially calibrated diagnostics games to get a basic idea of baseline competencies in areas like numeracy, spatial reasoning. and pre–literacy skills without it seeming like a proper test. Then, as the child plays around on the platform, the module passively records the time it took to complete a given task, the number of tries, whether they used a hint or help feature and how often they were successful. Behavioral data and the result of the begin assessment is then concatenated into vectors which will represent the child and his current knowledge as it stands, what he may be confused about or how she seems to like to learn (maybe he likes more Animal themed verses Vehicle Themed). This profile is also not static, the profile will be updated in real time with every session the system has with the learner making sure the system understands the learner correctly all the time[4].

Second, the Modular Content Repository, this is the system's curriculum library It's not a monolithic course but rather a granular learning activity database. an interactive story, a puzzle, a matching game or a short animated video can be considered each a single Learning Object. And most importantly, each object has been carefully tagged with a large amount of metadata. This metadata contains the basic learning goal for the child(e.g. identifying the number '7'), the level of difficulty on a fine-grained scale (e.g., 0.3), a list of the skills necessary for engaging with the activity(e.g. being able to count to 5), and the content format. And thus, with this structured and metadata-driven manner, it allows the A.I. engine to be aware of the pedagogical worth and context of each piece. modularity means flexibile means can makes lots of different combination and make unique learning sequence through modularity out of different tasks. This is in stark contrast to linear, pre-scripted curricula, which provides the building block for true personalization, an AI can pick whatever tools makes the most sense for the pedagogical point that they want to achieve at the moment.

Heart of the System: AI Recommendation Engine - The smart part of our system, what brings it all together. This engine is employing a combined algorithmic manner to bring together a student's profile together with the actual content. Examines the child's dynamic profile to determine the edges to the ZPD – concepts adjacent to what they currently master. Laying out possible next steps for a learner's journey, an engine with a knowledge graph made out of the content repo's prereq metadata For example, if the profile shows that the learner knows Single digit addition, the next topics for him would be Double digit addition (no carrying) and subtraction. To pick out the particular activity of many suitable choices, the engine adopts a form of collaboration, where it learns in a soft way by mimicking how other like learners interact.

4. Experimental Design and Validation Methodology

To test the efficacy of our AI-driven personalized learning model, we ran a 12 week quasi-experiment with a pre-test/post-test control-group design. The main goal was to compare the learning gains and level of engagement of children using our adaptive system with those who used a non-adaptive digital learning platform. The study was conducted on 60 kindergarten students between 4 and 5 years old who belong to only one urban pre-school school. The children were randomly divided into 2 groups, a first group with 30 children that used the AI-personalized learning platform (the experimental group) and a second group of same number of participants (30 children) that used a high-quality, but linear, non-personal digital curriculum for the same subject areas (control group). to ensure that the groups were comparable when they entered into the experimental study, we collected the demographic information and there was no significantly different mean age, gender distribution, as shown in Table 1: Study procedures is good. During the prior week of intervention, all 60 of the participants were administered a standardized pre-test. This test, created with the help of ECE experts, contains a series of one-on-one tablet tests. It looks at two areas, which we will call Baseline 1 and Baseline 2.Numeracy (e.g, Number Recognition, counting, simple additions), Problem Solving (e.g., Pattern Completion, Logical Puzzles)[5].

5. Results and Analysis

The data collected after the 12 - week period is analyzed and there is a ton of evidence supporting the AI personalize model. The first demographic data evaluation table (Table 1) shows that the two participants are quite similar after they are randomly selected, which means there are no obvious disparities before the experiment in terms of age and gender. This proves the internal validity of our research.

Table 1. Participant Demographics.

Group	N	Mean Age (Years)	Standard Deviation	Male	Female
Experimental	30	4.6	0.45	16	14
Control	30	4.7	0.51	15	15

With the main investigation about learning effectiveness, it's concerned the differences of gain scores from pre- and post-test. As shown in Table 2, in terms of developmental gains, we can see improvements for both groups over the 12 weeks and that is expected for this phase. But it was not the same on the scale. As for the experimental group that used AI-personalized platform, they had much greater improvement in both Numeracy and Problem-Solving. An independent samples t - test showed that the mean gain score on the Numeracy subscale of the experimental group $M = 8.43$, $SD = 2.15$ was significantly higher as compared to the control group $M = 4.12$, $SD = 1.98$, $t(58) = 8.21$, $p < .001$ Similarly significant results were obtained for the Problem-Solving domain as well, with the Experimental group's gain ($M=7.91$, $SD = 2.40$) exceeding the Control group's ($M = 3.88$, $SD = 2.05$) by quite quite a wide margin, $t(58) = 7.03$, $p < .001$ This key discovery points towards the fact that it seems the adaptive AI system that customizes the lesson plan to every child's specific needs and tempo is a whole lot better at promoting the development of brain skills as compared to having a one-size-fits-all digital method.

Table 2. Comparison of Pre-test and Post-test Mean Scores and Gains.

Domain	Group	Pre-test Mean (SD)	Post-test Mean (SD)	Mean Gain Score (SD)
Numeracy	Experimental	10.21 (2.8)	18.64 (3.5)	8.43 (2.15)
	Control	10.35 (2.6)	14.47 (3.1)	4.12 (1.98)
Problem-Solving	Experimental	9.88 (3.1)	17.79 (3.9)	7.91 (2.40)
	Control	9.95 (2.9)	13.83 (3.4)	3.88 (2.05)

In addition to the achievements, learners' engagement is also a signifier as to whether it was a good educational experience or not. The data shown in Table 3 clearly shows that there is great distinction in the engagement of both groups. Children in the experimental group averaged more activities accomplished by far and sustained a better success rate on their first tries. This shows that the AI system could be operating inside the ZPD of the child, so it could provide just enough challenge, which encouraged the child to persist and get good at it. On the other hand, the control group, faced with a set curriculum, may have had tasks that were either so low as to be easily finished quickly but without much effort, or so high that they failed or abandoned them. The greater average session duration of the experimental group is also an indication that the personalized content was much more intriguing and kept the children engaged throughout, an important thing to consider within the setting of early childcare.

Table 3. Analysis of Learning Engagement

Metric	Experimental Group	Control Group	p-value
Avg. Activities Completed per Session	8.2	5.6	< .01
Avg. First-Attempt Success Rate	85%	68%	< .001
Avg. Session Duration (Minutes)	18.5	15.2	< .01

In order to explore the reason of success for the experimental group more, we examined whether there was any correlation between the adaptivity of the AI and the learning outcomes of the students in the experimental groups. As seen in Table 4 we used to classify students according to how many times the AI engine changed the difficulty level of their learning paths by increasing or decreasing the difficulty level of the task. A strong positive correlation ($r=0.76$, $p<.001$) was also observed between the number of adaptive adjustments made by the system, and the overall student's learning gain (Numeracy + Problem solving) This is very useful, because it gives us proof that the act of personalizing itself makes learning happen. children for whome the system had to calibrate the difficulty many times were the ones who improved the most. which means the system managed to recognize and react to their own learning requirements, giving them aid when they had trouble and furthering them when they were prepared for a change, so that their development could be made to benefit the most from the system.

Table 4. Correlation Between System Adaptivity and Learning Gains (Experimental Group, N=30).

Student Category	Number of Adaptive Adjustments	Mean Total Learning Gain
Low Adaptivity (<15 adjustments)	10	12.5
Medium Adaptivity (15-30 adjustments)	12	16.8
High Adaptivity (>30 adjustments)	8	21.3
Correlation (Adjustments vs. Gain)	r = 0.76

6. Conclusion and Future Directions

To build up and prove a personalized learning course plan for little kids that relies on artificial intelligence, this study was carried out with the intention to solve the weaknesses contained in normal, one-form-fits-all ways of teaching. We have very supportive evidence from the model. And out research yields the primary finding that an adaptive-learning setup sustained by AI gives off a great deal more upgrades of foundational cognitive capabilities just like numeracy and resolving difficult problems compared to an exceptional however no personal one digital curriculum did. In addition, the increased engagement, such as higher completion rates and longer periods of focus, further imply that personalization not only increases learning but also makes it more positive and motivating. We found a strong correlation between how often the AI adapts and how much students learn. This directly supports our main idea—what drives the faster learning is actually the act of continuously adjusting based on data. These results have huge meaning for the future of early childhood education, they point to a way we might achieve a long-imagined ideal of customized instruction for lots of kids. For educators, these kinds of systems could also become co-pilots with deep insight into student progress and the automation of task differentiation free them to give more socio-emotional support.

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