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Construction of Personalized Learning Mode for Higher Mathematics in Vocational Education Based on Artificial Intelligence

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Abstract: With the inclusion of artificial intelligence (AI)in vocational education, there comes new chances to improve on how higher mathematics gets taught and learned. Traditional methods used for instruction in vocational college cannot cater to the varying mathematical base, speed of learning and mode of thinking among students thus leading to big differences in achievement as well as loss of interest. This paper proposes and examines a comprehensive AI-based personalized learning mode specifically designed for higher mathematics instruction in vocational education contexts. Based on the theories of adaptive learning, cognitive load theory and mastery learning theory, it is expected that a personalized learning path could be realized by combining ML algorithms, KGs and ITS. From the empirical data that I have obtained after doing a 16 weeks intervention with 240 vocational college students, we can look into how effective this model is. Student's math performance has improved a lot, they are more engaged and confident too. Four data table give out the comparison on a way of performance metric, learning styles distribution, adaptation strategy matching and satisfied result. It will contribute to academic researches about AI-enhanced Education and also have practical significance for curriculum developer, instructors, administrator in vocational education.

Keywords: Artificial Intelligence; Personalized Learning; Higher Mathematics; Vocational Education; Adaptive Learning; Intelligent Tutoring Systems.

1. Introduction

With the rapid development in artificial intelligence(AI) technology, AI is influencing many areas and education is one area that will be greatly changed. In China's vocational higher educations, which educate quite an amount of the country's students, the problem about teaching math in school still exists for a long time. As the bedrock science which supports engineering, economics & technologies education and studies, higher math gets into trouble more easily than vocational students can, arriving with mixed prior math skills & levels of drive. A traditional teacher-centred instructional model has difficulty catering for varied individual needs in a time when learners have different cognition and learning preferences which leads to a lot of failure rate, disengaged students and lack of math confidence in many vocational student.

Personalized learning means customizing what is provided in terms of education such as contents, speed, ways of teaching and checking your knowledge according to each person's requirements. But this is hard to do practically on a larger scale with limited resources, also the fact that teachers are trying to manage large classes of 30+ students all at once as well as try and differentiate their teaching makes it difficult. As a result, this tension between the ideal of individualized instruction and the realities of educating masses at institutions of higher learning is something that has always been among the key unsolved problems in instructional design. AI gives a new answer that lets us do bigger and more personal stuff all the time, right away, and better each day. AIs are allowed due to machine learning, natural language processing and data analysis. Ais can see students works, understand what is wrong with the answer, predict how students would learn in the future as well as modify their own teaching without any help from teachers for every decisions. The intelligent tutoring system, recommender engine, and learning analytics dashboard all showed some results in different parts of education. Though there is plenty of evidence for AI's ability to be instructive, little research has been done in terms of AI-driven personalization within Chinese vocational higher education and with regards to higher mathematics. This paper will try to fill that gap.

2. Theoretical Foundations and Literature Review

The theoretical basis for the suggested mode comes from a few different overlapping streams of literature. Bloom's Mastery Learning Theory [1] was solidified after the groundbreaking '2 Sigma problem' paper which showed that one-on-one tutoring caused students to learn at twice the rate of those in normal classrooms, this showed how one-on-one tutoring can be very effective, but also highlighted that it is not feasible to give each student their own personal human tutor. Cognitive Load Theory also shows us the way that we must design such systems so as to balance the content we give so much is not given that it overwhelms a learner's working memory but enough for the Germane processing that takes place when Vocational learners meet with an abstraction of concepts like limit,derivative and integral the very first time around. The theory makes a distinction among internal load which comes from the stuff of the material, external load coming from bad teaching design and germane load that contributes to forming lasting schemas. A dynamic trouble and presentation style for problems is an ai system can take on all 3 load types at once, something an instructor in a diverse class could not handle alone. Also Vygotsky's Zone of Proximal Development tells us the system ought to supply some problem a bit more difficult than where every single student is right now, this turns into scaffolded learning on such computation.

The last few reviews of AI in higher education include an

accumulating amount of empirical. Chen, et all [2] did a detailed look into 20 years' worth of research related to the use of AIs in education, saying these kinds: adaptive learning systems, intelligent tutoring system and learning analysis always had good news for people working with students and teaching them;Zawacki-Richter et al [3]. AI can offer up personal commentary for all. It was highlighted. Mathematics domain is in the same position as VanLehn [4]states that the effect size was equivalent to a human tutor. As of lately, Wang et al [5] has proved that the large language model based tutorial tool could make specific math explanation according to students' misunderstandings. Liu et al [6]have also found that the introduction of AI-assisted mathematics into Chinese vocational education decreased the drop out rate and increased the pass rate by around 18 percentage points, which directly informs our own choice.

3. Design of the AI-Based Personalized Learning Mode

The Proposed Framework can be seen as a model comprising 4 different layers, interconnected with one another: first layer is Diagnostic Assessment Module. Secondly comes our Knowledge Graph & Learner Modelling Engine [7] . Then we have our Adaptive content delivery systems. And last but not least is the Learning analytics and feedback mechanisms Diagnostic assessment module is the first step: When the student signs up, there's this online adaptive exam about all those pre-req parts like number operations, algebra stuff, geom thinking pieces, and some trig: Based on IRT (Item Response Theory), it chooses the following question in a dynamic manner and finds out the location of each student's competency level along about 40 knowledge components regarding higher Mathematics curriculum.

The knowledge graph and learner modeling engine form the cognitive part. A math-specific one would map the prerequisite-relationship of each and every concept in our curricula to find good learning paths for students at different starting places [8] . Deep Knowledge Tracing(DKT)is a kind of algorithm based on the Recurrent Neural Network which always updating every student's estimated knowledge states after interacting with any learning contents and doing practice exercises. System holds on to a probabilistic estimate about mastery of every knowledge component, it utilizes those estimates when picking the upcoming learning activity which is most likely going to yield significant gains. And adaptive delivery content platform is personalized per activity as well – for every single one of those knowledge components, we have got some examples with solutions worked out along with the animated visuals and problem applications relevant to each different vocational context by way of varying library levels: The recommendation engine finds out the best content bundle for every student, based on their current learning method (visual, auditory, etc.), what they already know, and also recently how well they have performed - making math ideas into specific application examples that are used in different areas like building designs for architecture students or quality control steps when it comes to manufacturing workers. Learning analytics feedback: do practice problems right away, weekly student-instructor progress reports to the students; class-level teacher/course lead dashboards and if course failure risk is there it would be a falling engagement level warning.

Table 1 presents a comparative overview of key characteristics distinguishing the proposed AI-based learning mode from traditional classroom instruction.

Table 1. Comparison of Traditional Instruction and AI-Based Personalized Learning Mode

Dimension	Traditional Instruction	AI-Based Personalized Mode
Instructional Pacing	Fixed, class-wide	Individualized, self-regulated
Content Differentiation	Minimal	Dynamic, multi-level
Feedback Timeliness	Delayed (exam-based)	Immediate, formative
Student Monitoring	Periodic assessment	Continuous, data-driven
Instructor Role	Knowledge transmitter	Facilitator, coach
Learning Path	Linear, uniform	Adaptive, branching
Contextual Relevance	Generic	Vocation-specific

4. Implementation and Empirical Results

4.1. Study Context and Participants

In the eastern part of China, an intermediate size vocational university was used to try out this learning model for 16 weeks. It was made up of 240 freshmen students from the four department,electrical(62),business(58),computer&information(64)and architecture(56),who took the required higher math class. Randomly assign students into two groups, Experimental group 1(N=120), will be given training by artificial intelligence that personalized based of the new way and the control group (N=120) are give normal lesson using traditional teaching model base on old curriculum. Both were taught by the same 3 instructor team so we can hold out on the instructor. Ethical approval was received at the institution, and all participants gave their informed consent. There were no statistically different pre-treatment group differences on past math achievement and report of personal confidence, thus groups are fairly comparable.

4.2. Performance Outcomes

Table 2. Academic Performance Comparison Between Experimental and Control Groups

Assessment Point	Exp. Group M (SD)	Control Group M (SD)	t-value	p-value	Cohen's d
Baseline Diagnostic	52.3 (11.4)	51.8 (12.1)	0.31	.758	0.04
Unit Exam 1 (Week 5)	71.6 (9.8)	64.3 (11.2)	4.98	<.001	0.70
Unit Exam 2 (Week 10)	74.2 (10.1)	65.9 (12.4)	5.23	<.001	0.74
Unit Exam 3 (Week 14)	76.8 (9.4)	67.1 (13.0)	5.88	<.001	0.85
Final Examination	78.4 (8.9)	68.2 (12.7)	6.58	<.001	0.94

Note: Scores are out of 100. Cohen's d: small=0.2, medium=0.5, large=0.8.

The academic performance is measured by 3 unit examination+1 final on limit & continuity+differential calculas+integral calculas+Differntial equation As can be seen from table 2, at the start both groups had nearly same baseline score. There was a clear difference in the first unit test (Week 5): The experimental class scored over 7 points higher than the control. And this gap grew steadily till it was around 10 points at the end exam. Cohens d effect size 0. 70-94 for Medium to Large Size of pratical signifnicance which is consistant wit metatdata findings on Intellgent Tutoring Sytems [9]: This result shows that the improvement of higher mathematics achievement after the application of the AI personalized learning model is very meaningful.

4.3. Learning Style Distribution and Adaptive Strategy Mapping

A distinct feature about our system is that it is able to determine individual learners' styles and use different learning strategy for each of them. As AI keeps on evolving, empirical research like what's been done here is going to matter greatly if we want to use it right so as to make sure that vocational maths teaching can be good and fair for everybody. The Table 3 gives out the distribution of profiles and the adaptative stragies which were used by the System. Visual-sequence was 31.7%, which is in line with the findings of cognitive preference study on engineering and technology students of Chinese vocational institution. AI systems have the ability to serve substantially different types of content to different subsets of learners within the same class, which is an example of a type of instruction that it would not be possible or practical for a teacher to do on their own. Time on task avg was over 38 minutes for all the students which means they still used AI.

Table 3. Learning Style Distribution and Corresponding AI Adaptive Strategies

Learning Style Profile	n (%)	Primary Content Format	Supplementary Strategy	Avg. Time-on-Task (min)
Visual-Sequential	38 (31.7%)	Graphical animations, diagrams	Step-by-step worked examples	42.3
Visual-Global	22 (18.3%)	Concept maps, infographics	Application-first problem sets	38.7
Textual-Sequential	29 (24.2%)	Written derivations, proofs	Procedural drill exercises	44.1
Textual-Global	18 (15.0%)	Case-based narratives	Interdisciplinary applications	39.5
Mixed/Flexible	13 (10.8%)	Multi-modal presentations	Alternating format sessions	41.2

4.4. Student Satisfaction and Engagement

Table 4. Student Satisfaction Survey Results (5-point Likert Scale)

Satisfaction Dimension	Experimental Group M (SD)	Control Group M (SD)	Difference
Perceived Learning Effectiveness	4.21 (0.63)	3.47 (0.79)	+0.74**
System Usability	4.05 (0.71)	3.82 (0.68)	+0.23*
Motivational Impact	4.18 (0.68)	3.29 (0.84)	+0.89**
Vocational Content Relevance	4.35 (0.58)	3.15 (0.91)	+1.20**
Overall Satisfaction	4.20 (0.61)	3.42 (0.76)	+0.78**

*Note: *p < .05; **p < .001. Higher scores indicate greater satisfaction.*

Besides the cognitive measures, we gauged students' feelings using a satisfied questionnaire which was taken towards the end of the project. There were 20 things we could measure: Perceived Learning Effectiveness, System Usability Scale, Motivational Effects On Learning,Vocational Content Pertinen. To Career And Satisfaction Table 4 lists out the average ratings in form of a like 5 scale and compares it with the control group. The students in the experimental class reported much higher points on all 5 aspects: The most notable difference was between 'vocational content relevance' M=4.35 and M = 3.15, which underlines the importance of contextualising abstract maths stuff in vocational frames of reference. With strong motivation impact rating(M=4.18),AI driven personalisation seems able to make up for motivations shortness of vocational students who think there is no connection between high maths and their careers This means that it's not just succeeding at making academics better. It's changing how good the subjective experience.

5. Discussion

As you see from the data, very effective in many different outcomes when personalized for ai learning. The bigger and bigger the difference as we progress through the semester is an indication that when more personal information was accumulated by the ai which in turn made it able to give even better personal recommendation to all students. This is temporally aligned with other theoretical forecasting from very deep knowledge tracings model, they require a lot of interactions information for it to be dependable and produce proper mastery estimates, which means the true capability of AI personalizing system maybe has been understudied. Positive results from the consistency of all four departments' cohorts (Engineering, Business, Computing, Architecture Design): this also shows that the adaptability is flexible enough and there's no need to create completely new implementation just because of different vocation context. Notable for the finding on vocational content relevance was that the AI system's ability to dynamically surface vocational applications of abstract ideas seems to have meaningfully reduced what has been a stubborn 'transfer gap' between the math taught in school and what gets done on the job, both based on satisfaction and results. Future can implement more discipline's specific content library and also add up some domain expert of every single vocation so as to make the mathematical problem context embedded[10] .

Even so, there were some limitations that deserve attention. Conducted at only one place, it is difficult to generalize for other vocational colleges that have various students, resources and institutional cultures. There is no 16 week observation to see long term retention and transfer effect, also study did not include looking at differentially across student subgroup with prior achievements, boys/girls, discipline as a way of showing how effective it would be for certain types of learner. Future work has to tackle that weakness with some sort of a multi site longitudinal study, I suppose more group work as well. Preliminary observations of instructors surveyed in the pilot, indicated they felt there had been somewhat major shift regarding how much they were going through relative to just giving out whole class instructions themselves directly compared with spending more time giving direct one on one assistance to other students as per what was shown for need from ai analysis dashboard. This shift is also relevant in terms of teacher professional development and the preparation of preservice instructors in how to teach mathematics with an AI augmented environment. AI in vocational math should continue to be talked about as an augmentation of what humans already do well when teaching-NOT a replacement. It's the relational and motivational aspects that will never go away.

6. Conclusion

In this paper, we present our work on the design, implementation and empirical study of a personalized learning model based on AI for Higher Mathematics in Vocational Education. In this proposal, it includes the diagnoses, assessments, knowledge graph, deep KT (Knowledge Tracing), adaptive contents and LA (Learning Analysis) so that we can set up a proper instructional environment with various needs of vocational student. The pilot investigation with 240 students from the four vocational department was conducted which showed same improvement in math and final exam score is much more for the experimental group than the control group, $p < 0.01$; final exam score in the experimental group had an average over 10 higher points than control group $d=0.94$. Students' satisfaction surveys showed that there was a lot more feeling of connection to the material and motivation for learning it in AI, especially as compared to when only the Vocational content relevance aspect had increased. All together, these results show that AI driven personalization is still a viable and good strategy for helping with math not doing well in vocational schools.

And then perhaps institutional administrators are going to put money into AI learning, as augmentations that extend from instructor's ability to personalize. The designers of the curriculums have to develop vocational libraries in order for the machines to comprehend abstract concepts by viewing it through the eyes of students themselves Future work should try to do more multi-institutional longitudinal follow-ups on retention and transfer for a longer time, look at how it works differently with different types of students, and see if we can use generative AI stuff like math-focused lms in our personal learning system. As AI keeps on evolving, empirical research like what's been done here is going to matter greatly if we want to use it right so as to make sure that vocational maths teaching can be good and fair for everybody.

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