A Novel Video Recommendation System for Algebra: An Effectiveness Evaluation Study

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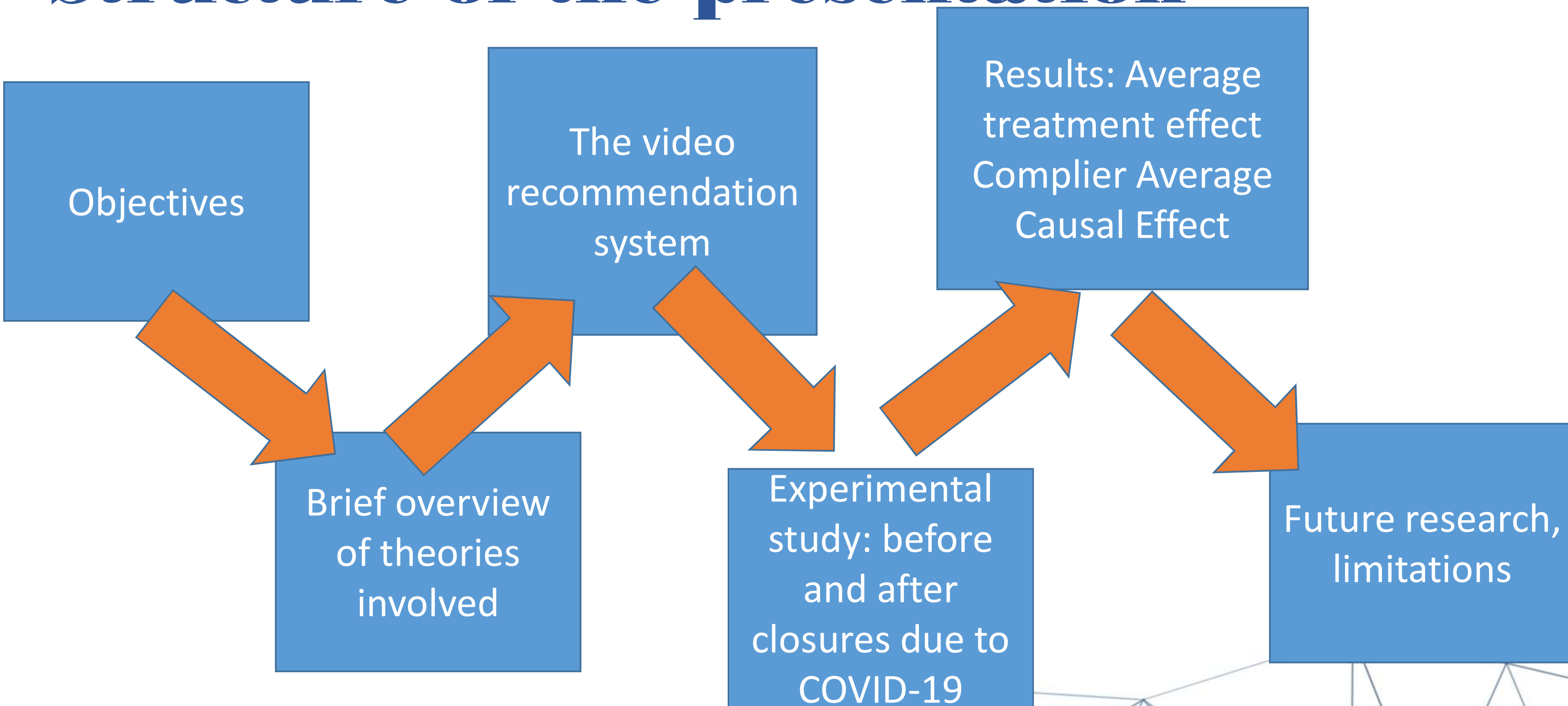
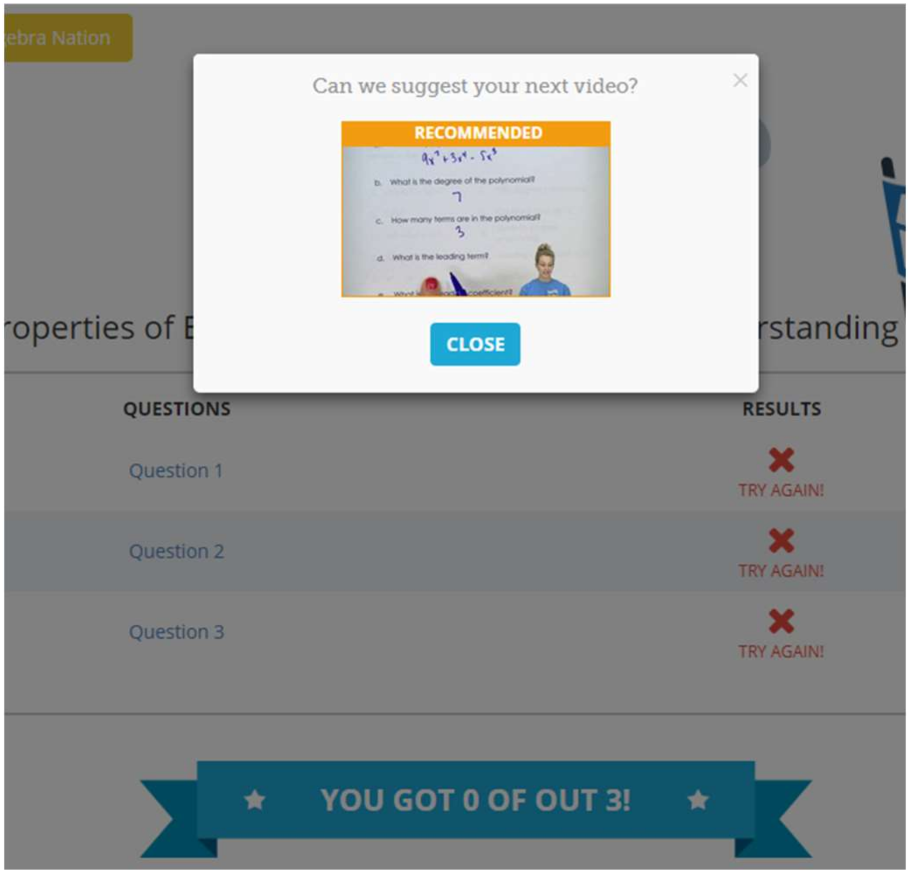
Structure of the presentation



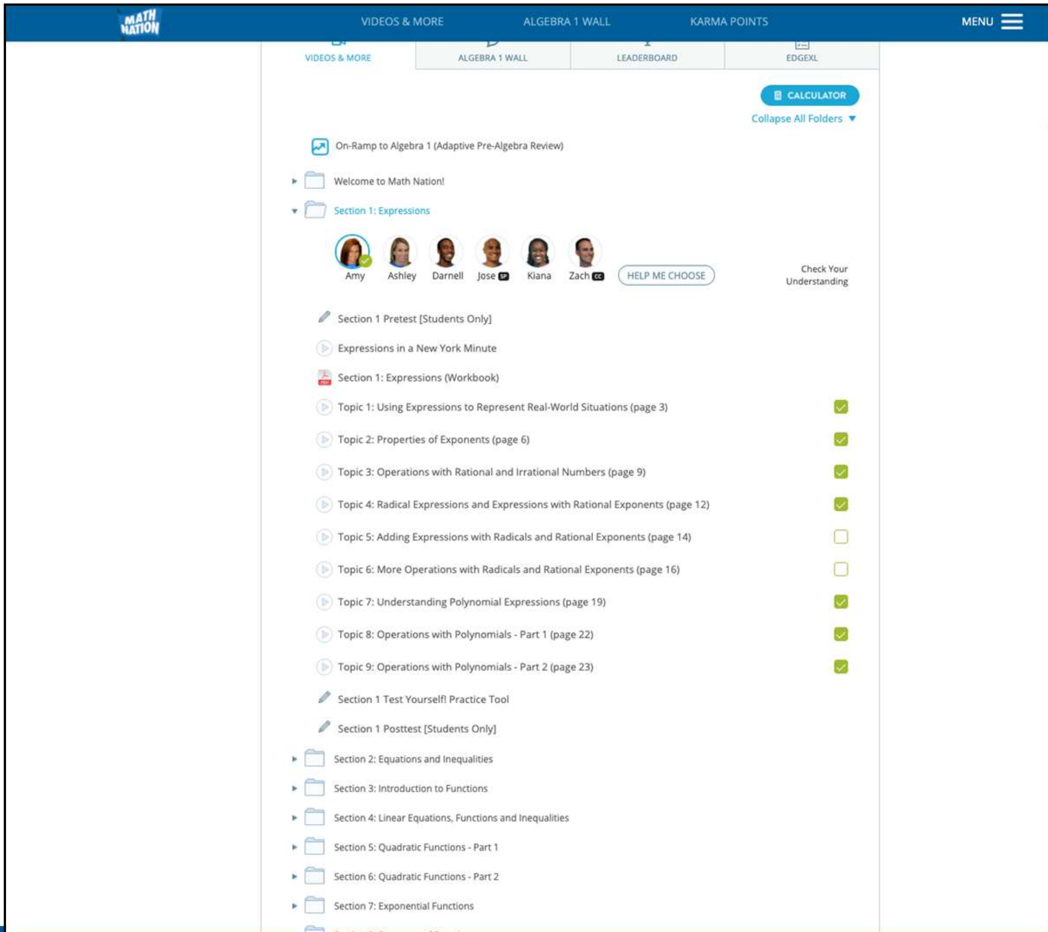
Objective of the Video Recommendation System

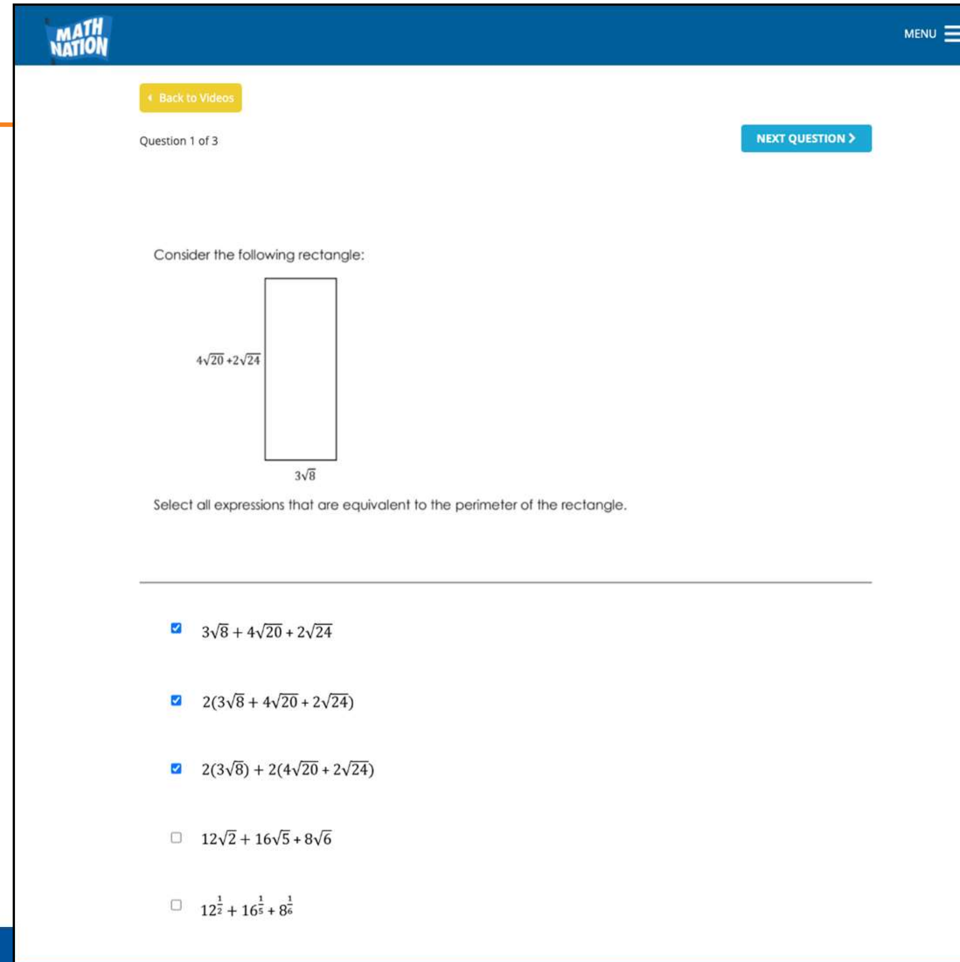
Provide students with a personalized video recommendation that takes into account their current **knowledge** as well as their **engagement** with the system.

Video Recommendation Screen in Math Nation



Context: Math Nation

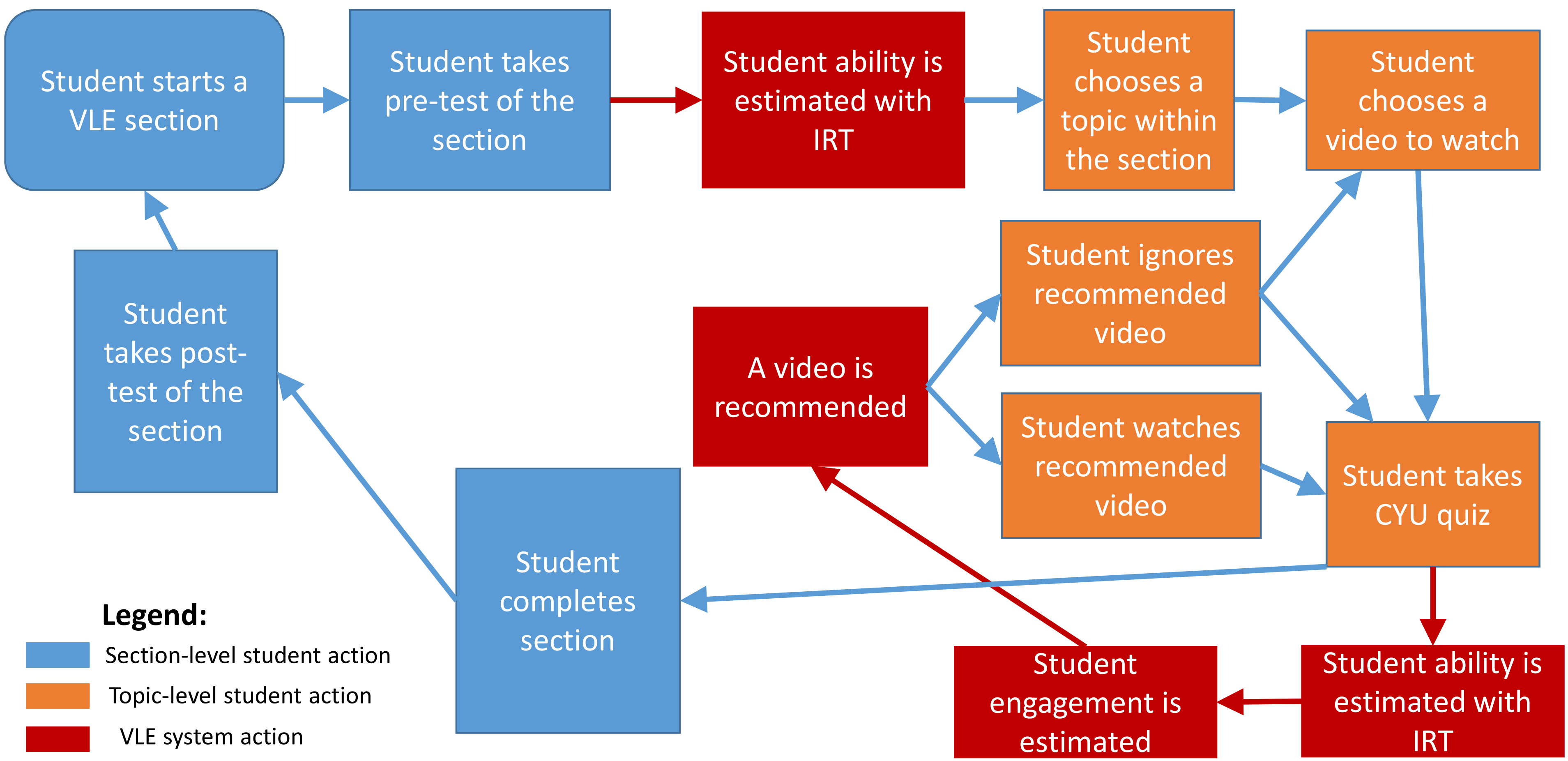




Theoretical Background

- Vygotsky's theory of Zone of Proximal Development
- D'Mello, Dieterle and Duckworth's advanced, analytic, automated (AAA) approach to measure engagement for interactions with digital learning technologies
- Item Response Theory

The video recommendation flowchart



The algorithm for new videos

ALGORITHM 1. New Video Recommendation Policy for Student *i*

Inputs: *initial ability estimates* $\{a_{ij}(0)\}$, $1 \leq i \leq n, 1 \leq j \leq r$.

Output: *sequence of recommended videos* $\hat{\jmath}\,(t) \in \{1,\ldots,r\}, t \geq 0$

for $t = 0, 1, \ldots$ **do**

Compute peer ability-estimates

$$b_j(t) = n^{-1} \sum_{i=1}^{n} a_{ij}(t).$$

Compute the probability distribution $\{p_j(t)\}, j = 1,2,\ldots,r$,

$$p_j(t) = \frac{exp\left[-w_j\,(a_{ij}(t) - b_j(t))\right]}{\sum_{j=1}^{r} exp\left[-w_j\,(a_{ij}(t) - b_j(t))\right]}.$$

Sample $\hat{\jmath}\,(t)$ *from the distribution* $\{p_j(t)\}_{1 \leq j \leq r}$.

Read $\{a_{ij}(t+1)\}$, $1 \leq i \leq n$, $1 \leq j \leq r$ *from the database.*

end for

The video recommendation system

Five categories of video recommendation:

1) View new video;
2) 2) Review current topic video with a new tutor;
3) 3) Review segment of current video with current tutor;
4) 4) Review segment of current video with a new tutor;
5) 5) View next video in curriculum sequence.

CYU score	Engagement Threshold	Probability of Recommendation of Category C
0	< 3.5	p(C=1) = 0.7 p(C=2) = 0.3
0	>= 3.5	p(C=1) = 0.3 p(C=2) = 0.7
1	< 3.5	p(C=1) = 0.3 p(C=4) = 0.7
1	>= 3.5	p(C=1) = 0.3 p(C=3) = 0.7
2	Any	p(C=3) = 1
3	Any	p(C=5) = 1

Research Questions

- Did the students, who were offered video recommendations perform better on the post-test assessments than the students who were not offered such recommendations?
- What is the causal effect of video recommendations on the achievement of those students who watched the recommended videos when offered?

Field Experiment

- Three large school districts in Florida:
  - ◇18,925 students from 152 teachers in 149 schools
- The study lasted for 17 weeks during the Spring 2020 semester (i.e., February 3rd to May 31st)
- Transition on March 17th when all schools were closed due to the COVID-19 pandemic and instruction resumed online.

Average Treatment Effects (Intention to Treat)

	Before school closure			After school closure		
	Coefficient	SE	p-value	Coefficient	SE	p-value
(Intercept)	-0.752	0.176	0.000	-0.339	0.602	0.573
ITT	**0.054**	0.027	0.043	-0.009	0.030	0.775
Pretest	-0.012	0.040	0.764	0.025	0.112	0.825
Engagement	-0.021	0.022	0.349	-0.007	0.028	0.805

Complier Average Causal Effect

- Before schools closed, the proportion of compliers among the students who were assigned to the treatment group was = 0.15921, SE = 0.0188, CI = [0.122, 0.196].
- Before-closure period, the final CACE standardized estimate is 0.34 (SE = 0.17, $p = 0.043$)
- After schools closed, the proportion of compliers was = 0.1123, SE = 0.0112, CI = [0.090, 0.134].
- The CACE was not statistically significant for the period after schools closed (CACE = -0.076, SE = 0.266, $p = 0.775$).

Where do we go from here?

- Completed a longer replication of the experiment (November 24th 2020 to June 1st 2021) to be presented at L@S 2022

- Key questions:
  - Are the effects larger with a longer exposure?
  - Do students who use the system more extensively benefit more?
  - Are there certain groups of students who benefit more?
  - Are there certain teaching strategies that moderate the impact of the video recommendation system?
  - What are the fairness and equity implications of personalization?