Merging Human and Non-Human (System) Data to Describe Students' Adaptive Learning Experience in Postsecondary Gateway Math Courses

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Abstract. Due to the historically high DFW (D-F-Withdraw) rates of College Algebra students at the University of Central Florida (UCF), adaptive instructional systems (AISs) have become an integral instructional component for the faculty who teach this course, with one strong impetus driving this shift: Prior to incorporating AISs into College Algebra, DFW rates averaged 31% (fall 2011 – summer 2015); however, since integrating AISs into the curriculum (c. 2015), this course has seen an approximately 58% percent decline in DFW rates from 31% to 13% (fall 2015 – summer 2022). One particular AIS, Realizeit, has been utilized consistently over the years to help close the learning gaps for students and support their academic success. To evaluate the extent to which Realizeit has impacted student achievement in College Algebra, results from a student-facing survey—aligned with a set of Realizeit data reports—were collected to tell both human and non-human (system) sides of the student journey, exposing how a combination of qualitative and quantitative data can be used to improve teaching and learning outcomes in future iterations of this course.

Keywords: Adaptive Instructional Systems, Educational Technology, Personalized Learning, College Algebra, Student Experience.

1 Introduction

Adaptive Instructional Systems (AISs) have been leveraged for educational purposes for many years [1]; however, the results have varied in terms of the impact AISs have had on student achievement, engagement, and overall experience [2]. Within higher education, AISs have been strategically deployed to help improve learning outcomes in the most persistently dropped/failed (DFW) courses [3]. College Algebra, in particular, has been an object of attention, as this course has one of the highest postsecondary DFW rates [4] and possesses considerable upside for at-risk students—making it a prime candidate for teaching and learning interventions with AISs [5][6].

At the University of Central Florida (UCF), for instance, the personalized adaptive learning (PAL) team and teaching faculty associated with the PAL initiative aim to provide appropriate learning content to the ‘right students’ at the ‘right time’ to maximize their potential for success. AISs, such as Realizeit, are utilized to support this effort, as they are designed to offer students a heightened level of agency / choice via system recommendations—allowing students to engage in meaningful metacognition around their learning goals.

Realizeit is a content agnostic AIS that requires course developers and/or subject-matter-experts (SMEs) to create or use existing educational content, arrange (granularize) that content into a pre-requisite sequence (Fig. 1), and configure the course-level settings in a way that leverages the AIS algorithms to furnish content pathways that optimize the student experience and result in learning mastery.

For UCF’s adaptive version of College Algebra, the course instructor authored original content directly into Realizeit to provide opportunity for the most flexible, personalized student experience.

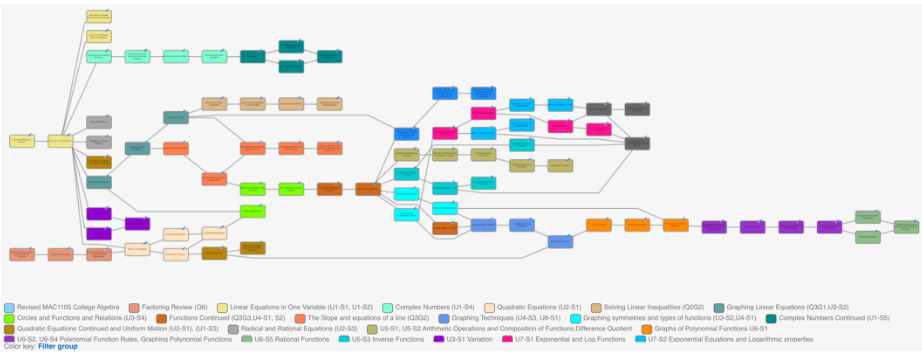

Fig. 1. Realizeit Prerequisite Map (course developer view): MAC1105 Revised, College Algebra (Weeks 1 – 14).

The content creation process in Realizeit generally begins at the ‘node’ (lesson) level, which represents a single learning concept. Multiple nodes are then collected into what is referred to as an ’objective.’ An objective is a collection of nodes which are time-based, interconnected (or related) subsets of the course content. Lastly, a collection of the objectives constitutes the academic course. Each node in the College Algebra curriculum has multiple sections including an Introduction, Learning, Worked Examples, Examples, Summary, Try It, and Check of Understanding. Five of the seven section types adapt to the learner (Table 1).

Table 1. *Individual section names, characteristics, and adaptive/personalized features*

Section Name	Section Characteristics	Section Adaptivity and Personalization

Introduction	the motivation for the node and applicable learning objective(s).	None
Learning	algorithmic learning content presented in multiple formats including passive reading, video, pencast, interactive reading, or mixed format.	Learning sections are formatted based on learning performance and learning characteristics. Learners are also given the option to request additional learning content from a menu.
Worked Examples	algorithmic examples with each step explained in detail. No mathematical steps are assumed; hence, all calculations are included and explained. Interactive examples are included to check the learners' understanding of the worked examples.	Preset conditions are used to deliver Worked Examples to the struggling learner. If the learner demonstrates poor understanding of the interactive examples, the AIS redirects the learner back to the Worked Examples section.
Examples	algorithmic examples with all the trivial steps removed leaving only the key steps and associated explanations. Interactive examples are included to check the learners' understanding of these streamlined examples.	Preset conditions are used to deliver streamlined Examples to high-performing learners. If the learner demonstrates poor understanding of the interactive examples, the AIS redirects the learner to the Worked Examples section.
Summary	the key concepts from the learning material.	None
Try It	a question bank (store) of algorithmic practice exercises. Some of the exercises include locations, events, and programs specific to UCF and the name banks used in examples and exercises are proportionally representative of UCF's student demographics and gender.	Application problems (word problems) included in practice exercises (Try It) and assessments (Check of Understanding) are personalized to the individual student's program of study to address concerns of course relevance.

Check of Understanding	a short formative assessment of knowledge.	This section determines the next step for the learner: to advance or complete additional work.

At the start of each assignment, Realizeit recommends that the learner complete a set of targeted questions (Determine Knowledge, DK) taken from the objective-based lessons (nodes) contained in the assignment.

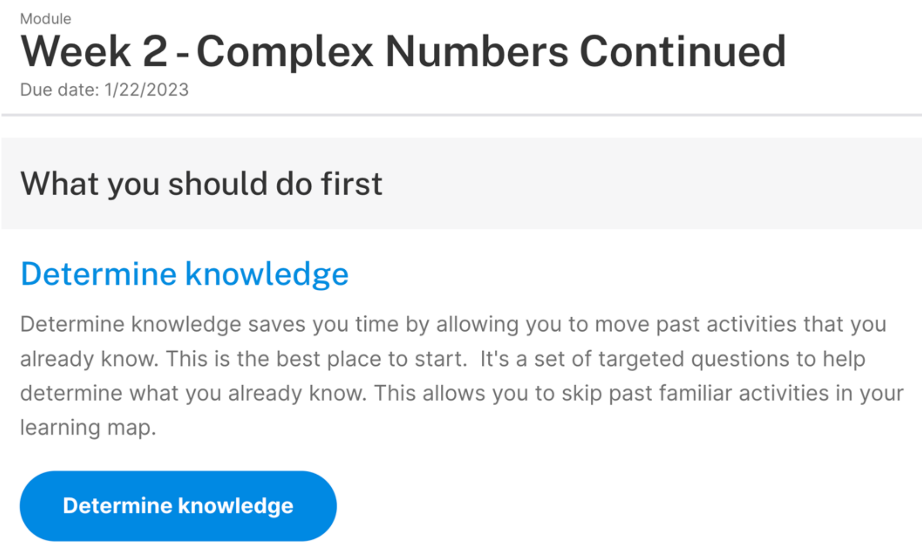

Fig. 2. Realizeit starting recommendation (i.e., no prior knowledge recorded): Week 2 – Complex Numbers Continued (MAC1105C-23Spring 0W60 – College Algebra).

Upon first entry (prior to completing DK), students encounter a collection of nodes that can be navigated in any number of ways—depending on their DK score.

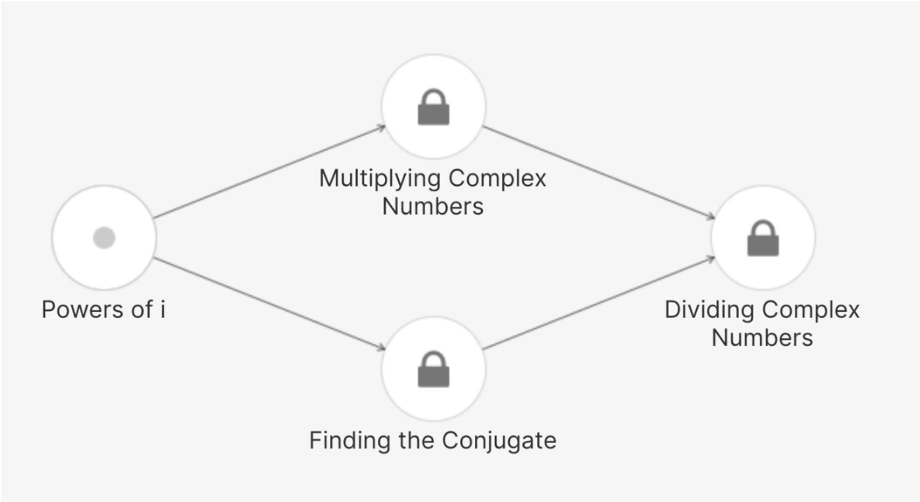

Fig. 3. Realizeit Learning Map prior to completing DK: Week 2 – Complex Numbers Continued (MAC1105C-23Spring 0W60 – College Algebra).

After students complete DK and show a basic level of content proficiency (e.g., 60% or above), the system unlocks one or more lesson nodes, and the AIS begins to recommend alternative pathways for students to improve their content knowledge.

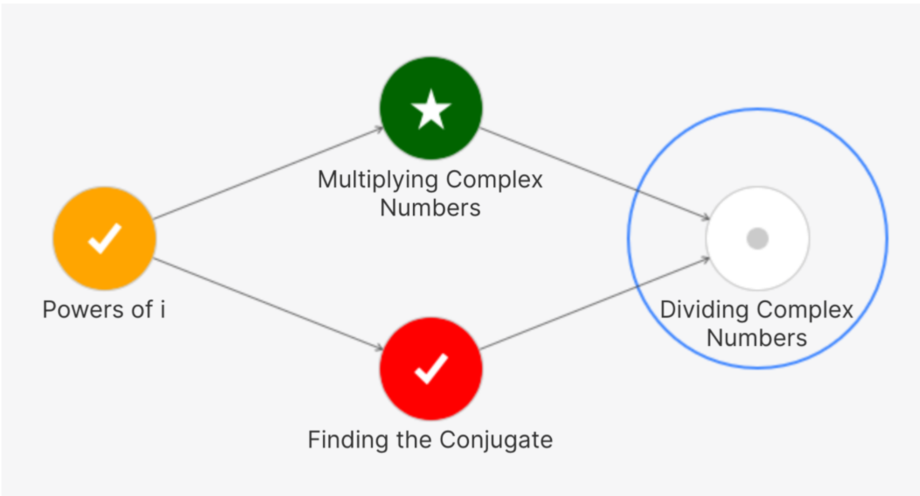

Fig. 4. Realizeit Learning Map after completing DK: Week 2 – Complex Numbers Continued (MAC1105C-23Spring 0W60 – College Algebra).

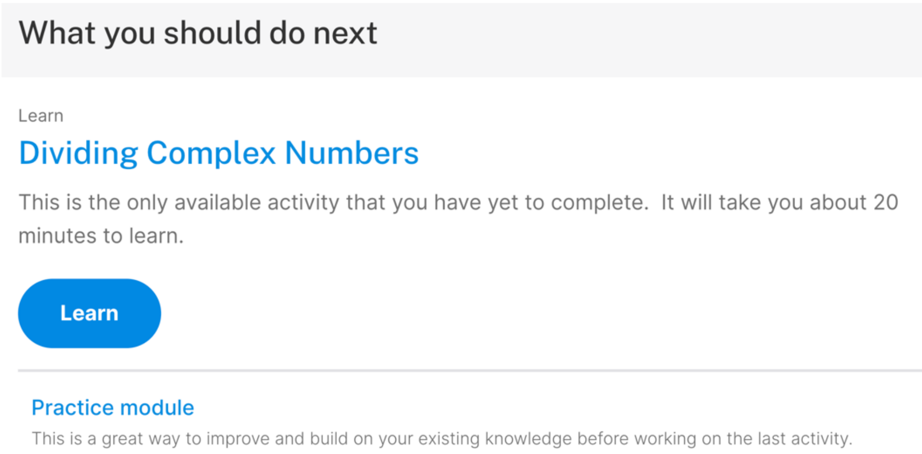

Fig. 5. Realizeit content recommendation(s) after completing DK: Week 2 – Complex Numbers Continued (MAC1105C-23Spring 0W60 – College Algebra).

This personalization is based on students predicted ability on each node and is adjusted continuously as students interact with interconnected material in the course (cf. Fig. 1). This information along with student perceptions of their learning experiences in the AIS have been combined to provide a dynamic look at the nuances that exist in the spaces between student perceptions and AIS data on student behavior, effort, and achievement.

2 Methods

In the current study, AIS survey data pertaining to 1) Realizeit's personalized recommendations, 2) the perceived accuracy of Realizeit's predictive features/metrics (i.e., predicted ability levels), and 3) the extent to which students' level of engagement within the course was impacted by Realizeit were collected from the most recent five semesters (fall 2020, spring 2021, fall 2021, spring 2022, and fall 2022) that College Algebra was delivered using Realizeit. A total of 254 students completed this fully online course over those five semesters—with 205 students (80.7%) completing the survey. The sample was 62.9% female, 48.8% White, and between the ages of 18 and 49 (M=20.72, SD=4.303). Thirty-eight percent (38.0%) of participants were college Freshmen, 30.2% were Sophomores, 15.1% were Juniors, 13.2% were Seniors, and 0.5% were Graduate students. This online survey was distributed to students at the end of each semester as a graded survey inside the learning management system (Canvas). Note: Respondents were able to skip any question during the survey; thus, the percentages reported in the study do not account for skipped questions.

Realizeit system data (aligned with the aforementioned survey responses) were then examined to 1) discover the frequency at which students make use of the personalized system recommendations along with their pass rate on the recommended lesson (if attempted), 2) determine students' "predicted ability" and "average ability" levels for each content objective, and 3) ascertain student engagement measures delineated as time working in the system and effort given toward lesson content and assessments.

3 Results

3.1 How does adaptive learning personalize the student experience?

Insofar as students maximizing (and embracing) the personalized learning experience offered by the AIS (Realizeit), survey analyses indicate that 52.9% of the respondents (n=108) always or often follow the recommended "What you should do next" path in Realizeit, and another 25.5% sometimes follow the recommendation (n=52) (Table 2).

Table 2. *How often did you follow the suggested "What you should do next" path in Realizeit?*

Rating	Frequency	Percent
Never	9	4.4%
Rarely	32	15.7%
Sometimes	52	25.5%
Quite Often	51	25.0%
Always	57	27.9%
I'm not sure	3	1.5%
Total	204	100%

Realizeit system data, on the other hand, revealed that 89% of students followed the AIS's primary "What you should do next" path and that 63% of the students who did so earned a passing score on their first attempt at the lesson. Ultimately, 42.4% of survey respondents (n=87) strongly agreed or agreed that the system became personalized to them over time (Table 3).

Table 3. *The Realizeit system became personalized to me over time.*

Rating	Frequency	Percent
Strongly Disagree	7	3.4%
Disagree	52	25.6%
Neither Agree nor Disagree	53	26.1%
Agree	71	35.0%

Strongly Agree	15	7.4%
I'm not sure	5	2.5%
Total	202	100%

3.2 How does adaptive learning affect student content mastery?

In terms of how students perceived their Realizeit determined 'ability levels' (which are based on a weighted mean of multiple accuracy and engagement measures), 52.9% of survey respondents (n=107) either strongly agreed or agreed that the ability levels reported by Realizeit were accurate (Table 4), and 51.5% of respondents (n=104) either strongly agreed or agreed that the Realizeit assessments were effective in measuring their learning (Table 5).

Table 4. *The ability levels reported by Realizeit were accurate.*

Rating	Frequency	Percent
Strongly Disagree	9	4.5%
Disagree	35	17.3%
Neither Agree nor Disagree	47	23.3%
Agree	94	46.5%
Strongly Agree	13	6.4%
I'm not sure	4	2.0%
Total	202	100%

Table 5. *Realizeit's assessment exercises were effective in measuring my learning.*

Rating	Frequency	Percent
Never	13	6.4%
Disagree	34	16.8%
Neither Agree nor Disagree	49	24.3%
Agree	89	44.1%
Strongly Agree	15	7.4%
I'm not sure	2	1.0%
Total	202	100%

In Realizeit, students' "predicted ability" (i.e., Knowledge State / Mastery) is the final value derived from their scoring "history" and represented in the form of "effect" change. The "effect" fluctuates each time a student attempts a question related to a designated learning "objective"—whether the question is being asked 1) in a lesson or 2) on an assessment that lives extraneous to the lesson.

While over 50% of student reported that Realizeit predicted ability levels were accurate, one noteworthy component to these results is that many of the final 'predicted ability' levels in the AIS were not factored into the final grade of an assignment, as only improved scores were sent back to the Canvas gradebook after the due date. In fact, system analytics show that many of the students' predicted ability levels actually lowered after the assignment due date. The lowered level is on account of questions from the lessons being repurposed on quizzes and tests and answered incorrectly by the students and/or students randomly entering erroneous answers on questions while searching for specific questions to study for an assessment.

3.3 How does adaptive learning impact student engagement?

Regarding student engagement, 66.8% of respondents (n=137) stated that they spent much more or more time learning content in their class using Realizeit than in a math class without Realizeit (Table 6), and 55.7% of them (n=112) strongly agreed or agreed that Realizeit increased their engagement with the content (Table 7).

Table 6. *How much time did you spend in Realizeit compared to a traditional math class without Realizeit?*

Rating	Frequency	Percent
Much Less	6	2.9%
Less	23	11.2%
The Same	30	14.6%
More	63	30.7%
Much More	74	36.1%
I'm not sure	9	4.4%
Total	205	100%

Table 7. *Realizeit increased my engagement with the course content.*

Rating	Frequency	Percent
Strongly Disagree	21	10.4%
Disagree	33	16.4%
Neither Agree nor Disagree	34	16.9%
Agree	87	43.3%

Strongly Agree	25	12.4%
I'm not sure	1	0.5%
Total	201	100%

The Realizeit system analytics also showed that students were highly engaged in the learning activities. The average learning hours (active time spent on task) per student ranged from 60 to 85 hours per semester—averaging 70 hours across the five targeted semesters. Fitting into a 14-week semester, that is about 5 hours per student per week excluding the first and last exam week of the semester. Students also completed (on average) 1,860 questions, ranging from 1,802 on the low side to 1,923 at the peak (cf. Table 8).

Table 8. *Realizeit learner engagement.*

Variable	2020 Fall	2021 Spring	2021 Fall	2022 Spring	2022 Fall
Class Size	39	36	36	47	96
Average Learning Hours Per Student	68.501	84.938	63.141	59.515	73.024
Average Questions Per Student Completed	1,857.69	1,883.11	1,883.17	1,802.11	1,923.20

4 Discussion

4.1 How does adaptive learning personalize the student experience?

While a large majority of students took advantage of Realizeit's recommendations when engaging with the learning materials, what was unable to be determined from the survey and system data was why students chose "What you should do next" over manually selecting an alternative pathway through the content.

Two motivations may be at work: 1) The visual (and cognitive) convenience of the recommendation and/or 2) the perceived trustworthiness of the recommendation based on the visual agreement between the learning map and recommendation (cf. Fig. 4 and Fig. 5)—making the recommended 'next' step hard (or seemingly foolish) to ignore. While 89% of students attempted the "What you should do next" lesson, only 63% of them passed that recommended lesson—bringing into question the validity of the recommendation(s). In Fig. 5, for example, the system may have done better to recommend additional practice on “Powers of i” and/or “Finding the Conjugate” rather than the final ‘unattempted’ lesson “Dividing Complex Numbers” since both of those nodes indicate moderate (orange) to low (red) level of understanding (cf. Fig. 6).

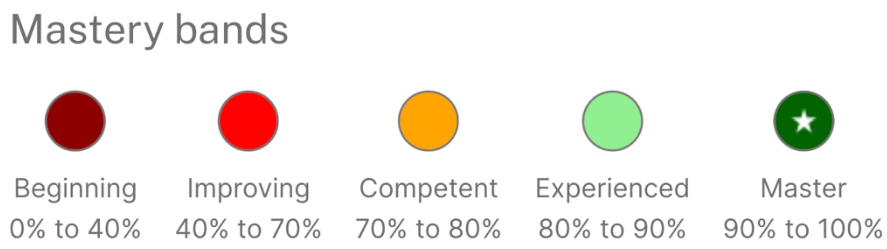

Fig. 6. Students’ predicted ability level designations in Realizeit (MAC1105C-23Spring 0W60 – College Algebra).

Untimely or ineffective recommendations may have also contributed to the nearly even spread between students who believed or did not believe the system became personalized to them over time with approximately 29.0% disagreeing or strongly disagreeing, 26.1% neither agreeing nor disagreeing, and 42.4% agreeing or strongly agreeing (cf. Table 3).

To be fair, the above assertion (regarding potentially unideal recommendations) is only one possibility for explaining the low pass rate of the recommended lessons. Other scenarios include students not passing due to having to exit a lesson abruptly or making an inadvertent data entry issue, such as leaving the “i” under the radical, which would later be designated as correct by the instructor (changing the student lesson outcome from failing to passing).

4.2 How does adaptive learning affect student content mastery?

Approximately 53% of the students stated the ability levels reported by Realizeit were accurate and 52% reported that the assessments were effective—leaving slightly less than 50% in both expressing a clear disagreement or neutral response (neither agreeing nor disagreeing with the above statements).These two survey questions (cf. Table 4 and Table 5) showed nearly identical statistics across the Likert-type scale, which may indicate the closeness in which students interpreted the meaning of both statements.

While students may rightly equate ability with their assessment scores, one is not directly proportionate to the other. For instance, getting 8 out of 10 correct on a question set represents an 80%, yet students’ ‘ability’ is an algorithmically derived number which takes many other factors (aside from raw score) into account, including effort and timing (e.g., more recent scores carry more weight). Therefore, the jump from 4% to 18% in ability (as shown in Fig. 7) is not an increase students will ever be able to determine from adding and dividing numbers they can see in Realizeit, as there are many calculations happening beyond the users' line of sight. (This may also help explain the 50/50 split in student perceptions.)

> My understanding of your ability has increased from 4% to 18%. My understanding of your knowledge state for this module (Week 1 - Linear Equations in One Variable) has increased from 36% to 43%.

Fig. 7. Realizeit on-screen message regarding student ability after completing a lesson. Week 1 – Linear Equations in One Variable (MAC1105C-23Spring 0W60 – College Algebra).

According to Realizeit, predicted 'ability' is generated by the AI of the system and considers the prerequisite network and a learner's performance, particularly on previous attempts. The average of each lesson ability is then accumulated and manifested as "knowledge state" at the objective level (which is combined with student completion of lessons to arrive at the final / composite score that gets sent to the learning management system gradebook).

4.3 How does adaptive learning impact student engagement?

Over two-thirds of students felt they spent more time engaged with Realizeit than in classes without it. This increased engagement partially occurred due to the AIS's dynamic approach to gathering student evidence toward content mastery, which rewards students for putting forth extra effort and prompts them via system recommendations to practice and revise their work.

Whether this increased engagement resulted in an improved final score in the course is not addressed in this paper; however, a correlation between student engagement and student achievement has been made by numerous studies in the past [7][8][9]. Therefore, further investigation is warranted to determine the relationship between engagement and learning, particularly when using an AIS.

5 Conclusion (and Future Work)

In an academic climate where educational technology is more heavily invested in than ever before, this study posits that looking precisely at the student experiences and technical affordances (e.g., recommender systems) of an AIS (Realizeit, in this case) could have considerable upside potential for historically challenging gateway math courses, such as College Algebra.

A deeper look into how matters of personalization, predicted abilities, and student engagement impact course outcomes (e.g., student grades) would provide an additional layer to the basic observations discussed in this paper and may be a logical next step for investigating how adaptive learning can improve academic outcomes for students.

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