Examining Interaction Modality Effects toward Engagement in an Interactive Learning Environment

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Abstract. The primary goals of interactive learning environments (ILEs) are to improve student engagement and learning outcomes. In this paper, we examine different tablet-based user interaction strategies within the domain of analytical geometry (i.e., the intersection of algebra and geometry) that supports active learning for math problem solving. From a learning technology view, we ground our work using cognitive engagement theory and apply usability to evaluate and further infer user engagement by using different interaction metaphors. We propose two ILE features: 1) self-constructed graphing, which provides a Cartesian coordinate interface so that students can graph toward a solution and 2) system-generated graphing, where the ILE automatically translates written algebraic equations into their geometric equivalents. We recruited 24 college students and conducted a 2 x 2 mixed factorial experimental design by varying two levels (with & without) for each condition (self-constructed & system-generated graphing). We found that these two features combined optimally increased student engagement and solving performance. More importantly, letting students control multi-modal user interactions (given the self-constructed graphing feature) should be provided before introducing automated user interactions (given the system-generated graphing feature).

Keywords: Interactive Learning Environments; Multiple Representations; Student Engagement; Technology-enhanced learning

1 INTRODUCTION

Research has shown that interactive learning environments (ILEs) can improve students math concept comprehension and problem solving skills [1]. However, designing such systems is a nontrivial and iterative process. ILE developers must model domain knowledge, analyze cognitive processes [2], and implement appropriate instructional methodologies [3, 4] within the design of ILE systems. Further, designing for educational user experiences is difficult because there are a number of different goals and concerns that need to be balanced, as well as trade-offs that must be made [5]. In addition, learning engagement is a key factor that should be considered when designing such ILE user interfaces [6]. To improve students learning engagement, numerous techniques have been illustrated and integrated into intelligent tutoring systems, digital games or other learning systems [7–10]. For instance, Oviatt et al.

adfa, p. 1, 2011.

showed the tablet pen-input effectiveness to support students reasoning and further engage into math problem solving [11]. Marrikis et al. integrated automatic speech recognition into an interactive learning environment to support children's exploration and reflection [12].

In terms of concept understanding and knowledge acquisition, researchers have shown the power of using *multiple representations* to understand certain concepts [13], such as arithmetic fractions [14] and chemical bonds [15]. ILE designers consider multi-modal inputs toward representations to let students interact with each one. Some existing tools automate the connection between representations to demonstrate certain concepts. For example, Desmos automatically translates algebraic expressions into the corresponding geometric graph [16]. However, it does not allow students to enter or edit geometric shapes.

In this paper, with the aim of understanding how user interaction affects students' engagement, we demonstrate a case study to design and evaluate the *multiple representation* learning technique from one interactive learning environment. The sketch-based ILE helps students to learn analytical geometry concepts by connecting algebraic and geometric representations. To quantify the property of multiple representations, we ground our experimental design from educational psychology research, mapped as two ILE features: 1) *self-constructed graphing* – A feature that allows students to graph geometric shapes on their own, and 2) *system-generated graphing* – A feature that automatically translates the equations students write on an algebraic canvas to their geometric equivalents on a geometry canvas. We conduct an empirical study with 24 college students to evaluate the different combinations of these two features (with or without) across four experimental conditions, as well as comparing to a baseline condition of using pen and paper.

To our knowledge, there has been no prior study to apply multiple learning representations to evaluate student engagement. Our work presents a grounded approach to extract and differentiate features. We show evidence that a dependency between self-controlled and system-generated exists. It is recommended that before introducing automatic system-generated features, ILEs should maximally support user self-controlled features.

2 RELATED WORK

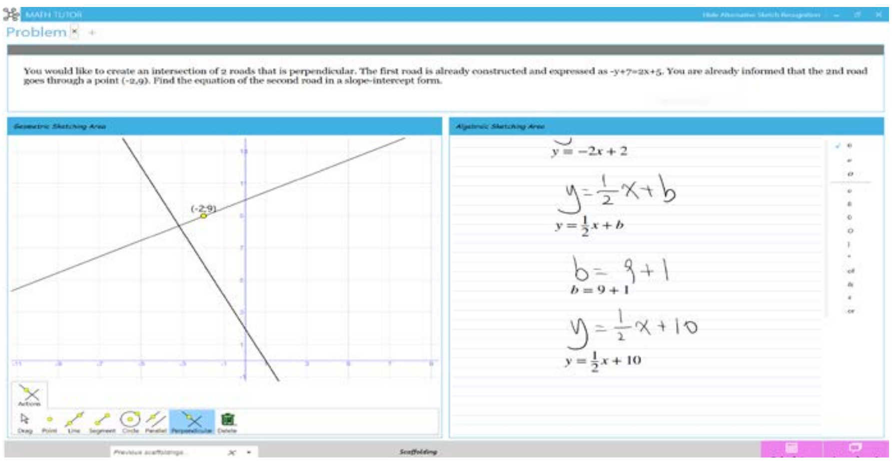
2.1 Math ILEs with Multiple Representations

Since our proposed math-based ILE is bi-modal (allowing students to engage in both algebraic equation solving and graphing geometry concepts), we reviewed the literature related to math-learning strategies using multiple representations, in general, and within the context of math ILEs. *Multiple representations* allow the same object or entity to be described or displayed in multiple formats. This instructional technique has been used widely across different learning domains, such as within chemistry [17], and specifically for math learning, such as understanding arithmetic fractions [14] and algebraic equation solving [18]. For algebraic equation solving, previous work has shown the importance of using *multiple representations* to understand math functions, which treat both algebra and geometry as two representations [14, 17]. Our ILE integrates tablet pen-input for writing and recognizes handwritten algebraic equations as knowledge patterns [19].

2.2 Engagement and ICAP Framework

We draw from the educational psychology literature related to how different user interaction features can incrementally escalate engagement in the user experience. Chi et al. [20] conceptualized and validated the ICAP framework, which links cognitive engagement to active learning outcomes. The ICAP framework postulates that student engagement increases across four modes as students' progress through learning activities: *passive*, *active*, *constructive*, and *interactive* engagement. Passive engagement represents receiving instruction without any action, such as listening to a lecture or reading a textbook. Active engagement means students' self-manipulative actions, such as repeating or rehearsing material during note-taking. Constructive engagement produces additional externalized outputs by synthesizing and applying concepts that have been learned, such as reflecting out-loud and self-explaining. Finally, interactive engagement requires defending and negotiating one's conceptual understanding in relation to others, such as through debating problem-solutions with a partner or group [20]. The ICAP framework presents this taxonomy of engagement modes hierarchically, where passive engagement impacts learning the least, and interactive discourse enhances learning outcomes the most optimally. Further, the hierarchy exists such that higher modes subsume lower modes. This framework has been empirically validated

Figure 1: Math ILE with self-constructed and system-generated graphing features



in the domain of material science [20]. We apply this framework in the analytical geometry math problem solving domain.

3 Methods

3.1 Self-constructed graphing and System-generated graphing

Albert needs to set up a light perpendicular to a stage. He knows the equation for the stage is 2x-3y=9. Also, he knows the stage goes through a point (-4, -1). Give the equation of line in the slope-intercept form if it is perpendicular to the stage.

Given the analytical geometry math problem above, students are required to understand and manipulate algebraic expressions to quantitatively reason about the problem [21]. Further they can use geometric forms as a qualitative view to facilitate their quantitative reasoning using algebra. Then, students should link these expressions as geometric forms on the Cartesian coordinate system. To help students consolidate this cognitive problem-solving process, the basic ILE design should allow students to enter algebraic expressions to support quantitative reasoning (**Figure 1** right canvas).

Further, *self-constructed graphing* lets students externally construct and directly manipulate geometric shapes and relations on a geometry canvas (**Figure 1** left canvas). This modality provides additional qualitative assistance that allows students to conduct quantitative reasoning using visual representations of the algebraic equations. For example, graphing a line to determine its slope. Relating this feature to the ICAP framework, the bi-modal interface facilitates students in reflective activities on both the algebra and geometry canvases, enhancing cognitive engagement from an *active* to a *constructive* mode of learning.

Last, *system-generated graphing* supports multiple representations by automatically translating written equations on the algebraic canvas to their visual equivalents on the geometry canvas. When students enter an algebraic expression that matches a knowledge pattern (e.g., a point, a line or a circle), the ILE translates and graphs that shape automatically. However, this feature does not allow students to interact directly with the geometry canvas, only through writing interpretable equations on the algebraic canvas that are then translated for them. Therefore, *system-generated graphing* supports a *passive* to *active* mode of learning related to the geometry representation, and a *constructive* learning mode only as it relates to algebraic conceptual learning. Systems, such as Desmos, support this type of *system-generated graphing* without *self-constructed graphing*.

Combining Two Graphing Features. We argue that the combination of *self-constructed* and *system-generated* graphing within our bi-modal ILE (**Figure 1**) will optimally support learning via multiple representations and by bringing learning activities to an *interactive* mode of engagement. In our proposed ILE [22], students have the flexibility of using either algebra or geometry canvases to work toward solving a given problem. This would allow them to engage in constructive learning activities for both algebra and geometry learning outcomes. Yet, when students write an equation on the algebra canvas, it will automatically graph the equation for them on the geometry canvas. Then, students can directly manipulate the *system-generated* geometric shapes as to negotiate with the ILE how to best solve the problem. As such, the ILE acts as a simulated conversation partner in co-constructing the solution to a given problem with the student. In our ILE, it is important to note that we intentionally chose to implement multiple representations unidirectional from algebraic to geometry representations and not the reverse. Our rationale for this decision is that algebraic knowledge is mandatory for solving analytical geometry problems, while geometry conceptual knowledge is helpful but not required. As such, allowing students to graph towards a solution, further letting the system generate the algebraic output based on graphical input would potentially allow them to arrive at the correct answer without demonstrating mastery of the underlying concepts.

3.2 Study Design

The aim of our experimental design is to evaluate two graphing features (*self-constructed* and *system-generated* graphing) and their relations based on ICAP cognitive engagement theory. Our study utilized a 2 x 2 mixed factorial design with a baseline control (i.e., pen and paper). We assumed that *self-constructed* graphing is the pre-requisite feature to further add the *system-generated* graphing feature. Thus, the *self-constructed* graphing feature was modeled as a between-subject factor, and the *system-generated* graphing feature was implemented as a within-subject factor. **Table 1** varies the inclusion of the two features in various implementations of an ILE and maps each version of the system to theory based on: 1) whether the ILE includes *multiple representations* (MR) via a bi-modal algebra and geometry interface, and 2) the stage of learning engagement as specified by the ICAP framework. For instance, in condition 2 (Non-MR), the ILE supports unimodal interaction without containing both features, which only shows one algebraic canvas without the geometric coordinate canvas. In the study, each participant solved math problems using three conditions separately: 1) Pen and Paper, 2) an ILE without *system-generated* graphing, and 3) an ILE with *system-generated* graphing.

Table 1: Summary of Experimental Conditions

#	MR*	ICAP	ILE Systems/Features
1	N/A	N/A	Pen & Paper (Baseline)
2	No	Algebra Constructive	Algebra ILE only
3	Yes	Algebra Constructive	Bi-modal ILE with *system-generated* graphing only
4	Yes	Algebra & Geometry Constructive	Bi-modal ILE with *self-constructed* graphing only
5	Yes	Algebra & Geometry Interactive	Bi-modal ILE with *self-constructed & system-generated graphing*

3.3 System Implementation

We developed four different ILE systems by varying the inclusion or exclusion of the two graphing features. All ILEs had some common features, which included the problem description area on the top and a sketched-based canvas to draw algebraic expressions. Students could sketch any notes or math expressions. Written expressions can be recognized using a math expression parser [19]. Students could touch to manipulate the algebraic canvas to manage their writing space and erase their writings by performing a scribble pen-gesture. Three versions of the ILEs provided bi-modal interfaces with both algebra (positioned to the right) and geometry (positioned to the left) canvases. In the version without either graphing feature, the geometry canvas was rendered useless, thus removed. For *system-generated* graphing when the system detected pattern matches between a written algebraic expression and a known knowledge pattern (such as point, line slope intercept form, line general form, circle standard form), it automatically graphed its corresponding geometric shape on the geometric canvas. The system could perform real-time geometric shape drawing from student input, including when they modified or deleted an algebraic expression. For *self-constructed* graphing, students could zoom and translate the visualized coordinate interface through single or double contact touch interactions. Students could enter geometric shapes upon the geometric canvas using a structured visual widget toolbar on the bottom of the canvas. The visual widget toolbar contained icons for creating a point, line, circle, two parallel lines, and two perpendicular lines [23]. Dragging and deleting visual widgets were also provided. Students could execute a command by first selecting a visual widget, and then pointing onto the geometric canvas to finish the input task.

3.4 Stimuli Design

We chose analytical geometry math word problems as the stimuli for our experiment, since solving word problems is considered both challenging and interesting to students [21]. Students might pay more attention to the problems, which allows us to capture students' implicit perception toward study conditions and user interface. We modeled problem-solving tasks to cover two main analytical geometry concepts: 1) Solving for a perpendicular line given the equation of an existing line, and 2) Solving for two points on a circle given an intersecting line. Both concepts required students to construct the relationship between two geometric entities. Since participants need to solve a word problem per concept and per condition, we found six math story-based problems from a high school geometry textbook [24]. We modeled the problems so that they were constructed using hybrid language that included both algebra- and geometry-oriented cues. Problems were randomly assigned across the experimental conditions.

3.5 Participants

Prior to recruiting participants, we conducted a priori power analysis to determine our target sample size. Using G*Power [25], to detect a medium effect size with a power of 0.80, we needed a total of 24 participants. Twenty-four adults, 14 females and 10 males, aged 19 to 21-years-old, participated in our experiment. All participants were college freshmen at our university. Participants had taken Algebra 1 and Geometry 1 in high school. 20 out of 24 participants previously used graphical calculators, such as the TI-84 and TI-89.

3.6 Procedure and Apparatus

Participants were invited to the user experience lab in our university to perform the experiment. After participants agreed with our IRB consent form, they began the study by first taking a pre-survey. Participants were then asked to solve the first two problems using Pen and Paper. Next, they were randomly assigned to the *self-constructed* graphing between-subjects condition or not. All participants engaged with the within-subjects factor of *system-generated* graphing (with and without) in a randomized order. The study design was counter-balanced to avoid order effects for both factors. Thus 12 participants experienced two ILEs with *self-constructed* graphing. Problems were also assigned randomly. During problem solving, participants were asked to talk aloud and try their best to solve each problem. After solving one problem, participants click the "Done" button, which directed them to the next problem. After finishing problem solving for one condition, participants took a web-based survey to evaluate the current condition of ILE in which they just used. After using all conditions to solve problems, a post-survey was administered to ask debriefing questions. The entire experimental session was video/audio recorded. The apparatus used was a Microsoft Surface Pro 3 with a digitizer. The experiment window was set in full-screen mode. Participants used the stylus to work on the system and could hold the tablet any way that they felt more comfortable.

4 Dependent Variables and Hypotheses

Based on the engagement literature, we accessed engagement through evaluating students problem-solving behavior under the cognitive category [6]. Though many forms of measurement coexist, we believed that most of them were too generalized which cannot fit for our own need. Thus, derived from human computer interaction, we accessed student engagement in three aspects: usability, cognitive load and perceived learning. Since usability testing plays a critical role to evaluate any system in HCI, we used perceived usability to partially infer engagement. Usability was measured by self-reported rankings on a pre-validated questionnaire that assessed four dimensions of usability: usefulness, ease of use, ease of learning, and satisfaction [26]. Each dimension contained four items. In term of cognitive evaluation, previous HCI research has been using cognitive load theory to measure user interface affordance [27–29], we evaluated self-reported cognitive load to infer engagement in a different aspect. We measured cognitive load using a pre-validated seven item survey scale for mental effort [30]. A high score on this scale equated to lower levels of cognitive load. Though evaluating perceived usability and cognitive load can deduce engagement, we also wanted to know our ILE's perceived learning effect, which might influence student engagement. Thus, we created a new construct to operationalize perceived learning at the intersection of algebra and geometry concepts. This construct was developed as a six-item measure on 7-point Likert scale. To specifically test the user interface's effect to help students link two representations, we devised the perceived learning construct with 6-items, which is shown below:

- *The interface helped me relate algebra + geometric concepts.*
- *The interface gave me a better understanding of how equations are represented.*
- *The interface could link my understanding of geometry algebra concepts.*
- *The interface encouraged me to utilize geometry as well as algebra to solve the problem.*
- *The system encouraged me to figure out how I was going to solve problems.*
- *The system motivated me to apply my knowledge to solve problems efficiently.*

Other than evaluating engagement, we also examined learning performance across different experimental conditions. which was scored based on correctness of the problem solution using a pre-validated grading rubric. The rubric contains: 1) translating the word problem correctly to either canvas, 2) recalling the appropriate knowledge (i.e., equations) needed to solve the problem, 3) meaningful progress toward problem completion, and 4) arriving at the correct answer [31]. To ensure reliability in grading for solving performance, we recruited two math tutors to grade participants' solutions. The inter-rater agreement between two graders was good (Cohen's Kappa = 0.87). We averaged the two graders' scores as learning performance. To infer student engagement into the ILE, we hypothesize:

Hypothesis 1 (Perceived Usability): An ILE with s*elf-constructed* and *system-generated graphing* will be perceived as significantly more usable than ILEs without either or both features.
Hypothesis 2 (Cognitive Load): An ILE with s*elf-constructed graphing* and *system-generated graphing* will require significantly less mental effort than an ILE without either or both features.
Hypothesis 3 (Perceived Learning): An ILE with s*elf-constructed graphing* and *system-generated graphing* will significantly improve perceived learning over an ILE without either or both features.
Hypothesis 4 (Learning Performance): An ILE with s*elf-constructed graphing* and *system-generated graphing* will significantly improve learning performance over an ILE without either or both features.

Table 2: Descriptive Statistics

Dependent Measure	With self-constructed graphing				Without self-constructed graphing			
	With system-generated		Without system-generated		With system-generated		Without system-generated	
	M	SD	M	SD	M	SD	M	SD
Usefulness	6.33	0.66	5.73	0.93	5.54	0.79	4.87	1.29
Ease of Use	5.88	0.75	5.50	0.90	5.06	0.91	5.33	0.92
Ease of Learning	6.29	0.72	6.04	0.77	5.40	0.95	5.90	0.83
Satisfaction	6.02	0.82	5.35	0.88	5.29	0.82	4.52	1.01
Cognitive Load	5.78	0.82	5.37	1.08	4.93	1.04	4.52	1.12
Perceived Learning	6.35	0.73	5.56	1.13	5.58	0.77	4.25	1.27
Solving Performance	77.08	30.16	59.37	26.16	63.95	35.12	52.50	36.57

5 RESULTS

We present our results by describing the validity and reliability of our dependent measures. We report MANOVA results for our perceived measures and a mixed factorial ANOVA for solving performance. We also analyze data from self-reported surveys, recorded video and supplemented quantitative findings with qualitative insights from participants' feedback. **Table 2** presents the descriptive statistics for dependent measures. Normality checking showed that all dependent measures are normally distributed. All scale reliabilities calculated as Cronbach's alpha are above the 0.70 threshold of acceptability. The results of hypotheses testing are presented in **Table 3**. To evaluate our hypotheses (which posit that both features will out-perform the other four conditions), we interpret both the main effects of each feature, as well as the interaction effects between the two features. Compared to the baseline condition of Pen and Paper the ILE with both features are perceived to be significantly more useful (t(11)=2.68, p<0.05), easier to use (t(11)=2.31, p<0.05), easier to learn (t(11)=2.85, p<0.05), more satisfying (t(11)=3.74, p<0.01), required less mental effort (t(11)=2.34, p<0.05), and improved perceived learning (t(11)=3.68, p<0.01). Actual solving performance is also significantly enhanced by our ILE system (t(11) =4.14, p<0.01).

Table 3: Hypothesis Testing Results

Measures		Statistical Results
Self-constructed	**Usefulness**	**F(1,22)=6.84, p<0.02, η_p^2=0.24**
	Ease of Use	F(1,22)=2.24, p=0.15, η_p^2=0.09
	Ease of Learning	F(1,22)=2.89, p=0.10, η_p^2=0.12
	Satisfaction	**F(1,22)=5.84, p<0.02, η_p^2=0.21**
	Cognitive Load	**F(1,22)=5.05, p<0.04, η_p^2=0.19**
	Perceived Learning	**F(1,22)=9.70, p<0.01, η_p^2=0.31**
	Solving Performance	F(1,22)=0.70, p=0.41, η_p^2=0.03
System-generated	**Usefulness**	**F(1,22)=8.13, p<0.01, η_p^2=0.27**
	Ease of Use	F (1,22)=0.13, p=0.72, η_p^2=0.01
	Ease of Learning	F (1,22)=0.84, p=0.37, η_p^2=0.04
	Satisfaction	**F(1,22)=19.35, p<0.01, η_p^2=0.47**
	Cognitive Load	**F(1,22)=5.02, p<0.04, η_p^2=0.19**
	Perceived Learning	**F(1,22)=19.57, p<0.01, η_p^2=0.47**
	Solving Performance	**F(1,22)=13.14, p<0.01, η_p^2=0.37**
Interaction Effect	Usefulness	F(1,22)=0.02, p=0.89, η_p^2=0.001
	Ease of Use	**F(1,22)=4.90, p=0.04, η_p^2=0.18**
	Ease of Learning	**F(1,22)=7.52, p=0.01, η_p^2=0.26**
	Satisfaction	F(1,22)=0.10, p=0.75, η_p^2=0.01
	Cognitive Load	F(1,22)=0.00, p=1.0, η_p^2=0.00
	Perceived Learning	F(1,22)=1.27, p=0.27, η_p^2=0.06
	Solving Performance	F(1,22)=0.60, p=0.45, η_p^2=0.027

Note: Significant p-values (<0.05) are shown in bold

5.1 Main Effects of Self-Constructed Graphing

As shown in **Table 3**, we found a significant (p<0.05) main effect of *self-constructed* graphing on all but two of our perceived usability measures (ease of use and ease of learning). Overall, participants found the versions of the ILE that included this feature to be significantly more usable (useful and satisfying). They also experienced less cognitive load and felt that the ILE helped them relate and understand algebra and geometry concepts more effectively. However, we did not find a significant main effect of self-constructed graphing on actual solving performance.

5.2 Main Effects of System-Generated Graphing

We also found a significant (p<0.05) main effect of *system-generated* graphing (**Table 3**) on all but two of our perceived usability measures (ease of use and ease of learning). Overall, the perceived effects of system-generated graphing were all in the same direction as self-constructed graphing. We also found a significant main effect of system-generated graphing on solving performance. When participants had this within-subjects feature, they performed significantly better than when the feature was not available to them. Based on these results, we can say that we found partial support for **H1** (perceived usability) and that our data fully supported **H2** (cognitive load), and **H3** (perceived learning). We consider our results as providing partial support for **H4** (solving performance) and discuss the implications of our findings in more detail in our discussion.

5.3 Interactions Effects

We detected significant interaction effects between the two features for ease of use and ease of learning (medium to large effect size), which were the two dimensions of perceived usability that we previously did not detect significant main effects. **Figure 2** illustrates the interaction effect for ease of use, which was similar to that of ease of learning. While our ILE with two features was still perceived as significantly easier to use and easier to learn than the other conditions, we found an unanticipated result, which suggests that *system-generated* graphing without *self-constructed* graphing was considered significantly harder to use and harder to learn than the other four conditions. Participants preferred the ILE that only provided an algebraic canvas without the geometry canvas or two features over this option.

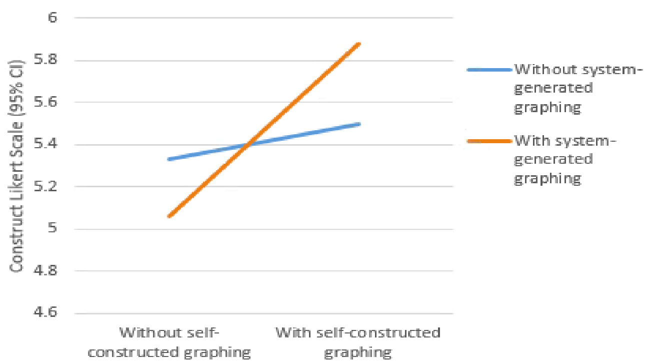


Figure 2: Interaction Effect for Ease of Use

6 DISCUSSION

For the *system-generated* graphing, students felt that the ILE helped them to relate and better understand algebra and geometry concepts. For example, one student said:

"I was able to see the geometric representation of my algebra which greatly helped in solving/checking work especially if I was solving the equation right."

This finding was consistent with the intelligent novice cognitive model that suggests that students can improve their conceptual understanding through self-checking capabilities [32]. However, the fact that we only found a significant main effect of *system-generated* graphing on actual solving performance is an area of potential concern. This finding suggests that the *system-generated* feature may be giving students too much help by partially solving the problem for them. Therefore, future research should further examine the potential learning benefits versus the potential negative "enabling" effects of this feature. Adaptive graphing features should be investigated based on students prior learning experience. In the current experiment, besides the system-generated graphing effect for certain conditions, all conditions do not have a cognitive tutor that provide procedural scaffolds or hints to guide students' problem solving. Another experiment to incorporate a cognitive tutor to verify this finding might be essential.

The results provided additional empirical validation for the ICAP framework as it applies to the context of ILEs for analytical geometry math work problem-solving. We confirmed that two-feature ILE system increased usability, reduced cognitive load and increased their perceive learning, which indirectly improve students engagement. The system with such features also improve learning outcomes. This finding coincided with the previous research that the combined set of multimodal features is most predictive, indicating an additive effect [33]. One student explained:

"I enjoyed editing geometric shapes by myself. I also enjoyed the effect of the automation as it encouraged me and engaged me in solving such problems. The automation helps me check and keep on going with my problem solving, which was greatly helpful."

The most unique finding from this experiment was the interaction effect for ease of use and ease of learning between the two features. From a theoretical view, it confirmed the hierarchical nature of ICAP's learning modes. *System-generated* graphing proved to be a less engaged learning mode without allowing students to reach a *constructive* level of engagement on the geometry canvas. Only with the combination of *both* features was an *interactive* level of engagement reached as students began to co-construct the problem solution with the ILE. Indeed, both features achieve the same goal to construct the geometric shapes linking to algebraic expressions. However, the result implied that students wanted to manipulate and interact with geometric shapes before introducing the automated graphing feature. This finding reveals that ILE designers should consider all modality input and features in the first place. Automated mechanisms should be considered after supporting all modality interaction features to give students more smooth user interaction and engaged user experience. Though we did find certain significant effects through the current sample size (N=24), future work can widen it to verify the findings in a large scale.

7 CONCLUSION

In this paper, we illustrated a human computer interaction approach to extract two user interface features and ground them in the ICAP cognitive engagement framework to access student engagement. We further conducted a mixed-factorial experiment to evaluate the system with or without each feature. We found the same result as previous research that the combination of graphing features accumulates student engagement level. More surprisingly, we found that two features do depend on each other, which meets the ICAP hierarchical view. This finding suggests that ILE designers should let students maximally manipulate and interact with each input modality before adding automated features.

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