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Technology-rich Activities: One Type Does Not Motivate All

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Abstract

We report on data collected at three time points during a four-day intervention designed to explore the value added of technology-rich activities within an inquiry mathematics curriculum. Two of the activities were computer-based, whereas the third involved a professionally created movie. Using latent profile analysis we explored (a) the profiles of experiences (indicated by self-reports of immersion, interest, usefulness, and relatedness of the technology activity) that students in Grades 5-8 (n=7,774) reported regarding their participation in one of three different activities; (b) the motivational and achievement outcomes in mathematics that were evident by being a member of one of these latent profiles; and (c) the factors that predicted students' membership into one of these profiles of technology experience. Results showed that: (1) three latent profiles emerged from the data; (2) the profiles predicted mathematics learning and motivation; and (3) grade level, prior mathematics achievement, prior mathematics interest, and students' feelings of how autonomy supportive their teachers are predicted membership into these profiles. Results support and refine the literature in educational psychology regarding models of motivation and engagement, as well as the literature in educational technology concerning the motivational affordances of technology.

Keywords: Motivation; Engagement; Science Education; Intervention; Technology

Technology-Rich Activities: One Type Does Not Motivate All

Researchers and practitioners often point to the use of technology-enabled instructional activities that employ constructivist pedagogical strategies as a key to engaging and motivating students in school (Blumenfeld, Kempler, & Krajcik, 2006). However, this assumption should not be taken as a given for a number of reasons, including factors such as how the activities are implemented by teachers (e.g., Wu & Huang, 2007) and whether the design and use of the technology-enabled activities might interfere with their willingness to engage with the content (Blumenfeld, Kempler, & Krajcik, 2006). The specific type of technology that teachers use in classrooms will not necessarily determine the level of motivation and engagement that students experience—teachers can use a low-tech, low-cost, movie just as successfully as they can use high-tech, high-cost, games and simulations (Authors, 2014). Thus, it becomes important to consider more nuanced questions about the specific *affective experiences* of students as they participate in activities rather than the medium (e.g., computer games versus movies). In fact, in our previous analyses of the same dataset using a variable-centered approach (Authors, 2014) and only investigating changes from pre-intervention to post-intervention, we found that there was little to no effect of the technology activity that students participated in on outcomes such as self-efficacy and implicit theory of ability. There were very modest pre- to post-intervention changes on mathematics learning and value beliefs. These findings led us to consider the possibility that perhaps it is not the technology activity that makes a difference. Rather, it may be how students *experience* the technology that matters.

Unfortunately, evidence related to these issues is limited and contradictory (Moos & Marroquin, 2010). Like any pedagogical tool, technology can be designed and used in ways that facilitate or thwart students' engagement and motivation. Also, motivation and

engagement are broad multi-dimensional constructs, such that technology-enabled activities may be successful in affecting some aspects of motivation and engagement but not others. These issues drive the present research, where we explore the variety of ways that technology-rich activities can engage and motivate students, and how students' experiences with the activity relate to their subject matter learning and motivation.

For the sake of clarity, we broadly define technology-enabled activities as those that involve some use of digital media. For our study in particular, we wanted to include digital media that spanned the spectrum from low interactivity and relatively low barriers for implementing (e.g., movies) to very high interactivity and relatively high barriers for implementing (e.g., immersive computer games). Also, because the terms engagement and motivation are often used interchangeably, we clarify how these constructs are defined and operationalized in the present study. Consistent with prior work on engagement (e.g., Furrer & Skinner, 2003; Skinner, Furrer, Marchand, & Kindermann, 2008), we broadly define engagement with technology as the degree to which students feel *immersed* in an activity and find the activity to be *interesting/enjoyable*. Drawing from the motivational literature (e.g., Eccles, 2009; Wigfield & Eccles, 2000), we define motivation as *beliefs about competence*, which answer questions like, "can I succeed?" and *beliefs about value*, which answer questions like, "why would I want to do this activity?"

The present research makes three unique contributions to the literature on engagement, motivation, and technology. First, as mentioned, scholars have noted the poor quality of empirical evidence investigating the affordances of technology-rich scholastic activities (Moos & Marroquin, 2010; Wouters, van Nimwegen, van Oosterndorp, & van der Spek, 2013). By using constructs drawn from rigorous theories of motivation and engagement, we investigated what

affordances (if any) are provided by three different technology-rich activities that were tightly integrated into teacher-led, inquiry-based, mathematics instruction. Therefore, any differences in students' observed outcomes could be attributable to how students experienced the technology activity because everything else that students experienced was constant. Second, we drew from diverse literature bases to conceptualize salient aspects of motivation and engagement *within technology-enabled environments*. Although scholars have conceptualized the construct of engagement fairly broadly to encompass the dynamics that take place within a typical classroom (for a review see Fredricks, Blumenfeld, & Paris, 2004), we sought to explore engagement in a manner that was consistent with the nature of technology-enabled activities. Third, our interest here is in individual differences regarding students' motivation and engagement with technology-enabled activities. Rather than documenting whether computer games versus movies are associated with larger or smaller gains in motivation and engagement on average (e.g., Authors, 2014; Annetta, Minogue, Holmes, & Cheng, 2009; Bai, Pan, Hirumi, & Kebritchi, 2012; Kebritchi, Hirumi, & Bai, 2010), we instead examined the patterns of motivation and engagement evinced by students, which represented their individual *affective experiences* with the technology activity, regardless of which one they participated in.

We asked three main questions. First, what patterns (i.e., profiles) of motivation and engagement emerge regarding students' experiences with technology? In particular, we focused on profiles regarding how *immersive*, *interesting,* and *useful* the technology activity was. We also focused on how *relatable* the characters were to students. Second, because the technology activities we used were integrated within a classroom-based mathematics lesson, we wondered what motivational and achievement outcomes in mathematics do students' technology engagement profiles predict, even as *all students* (regardless of technology activity) received the

same teacher-guided, inquiry-oriented, mathematics instruction? Exploring this question would allow us to provide evidence for predictive validity regarding the profiles of technology motivation and engagement. Finally, because technology is not a one-size-fits-all solution for all students, we wondered which factors predict students' motivation and engagement with technology-enabled activities?

Engagement, Motivation, and Technology

Framing this study requires that we explore two literatures that are conceptually related. First, educational technology researchers have a long history of building technology activities that are designed to motivate and engage students. Second, there is a rich literature from educational psychology on how to motivate and engage students in school generally. The theories and empirical studies from this literature make predictions about how to design and use technology in classrooms to motivate and engage students.

Immersion and interest. Educational psychologists distinguish between fleeting moments of interest (referred to as *situational interest*) and more robust *personal interests*, which can be defined as a long-term and relatively enduring enjoyment in an activity such that individuals are likely to re-engage with this activity on their own accord (Hidi & Renninger, 2006). Hidi and Renninger describe interest development as a four-phase model that begins with a "hook" or triggered situational interest. This "hook" can then proceed to a *maintained situational interest* in which students maintain their initial interests and stay engaged with the activity, which can then lead to the development of personal interests.

Immersion could be framed within the interest development literature (Hidi & Renninger, 2006). It may be that immersive environments use immersion as a "hook" to spark students' initial interest in academic content (i.e., emotionally engage students). Immersion alone,

however, cannot develop more robust personal interests, especially in a subject area. Rather, once students' interests are sparked, the content has to be interesting enough that students continually re-engage with it. This continual re-engagement with rich, high-quality, content, allowing for students to choose what they learn, and providing individualized feedback is one major affordance that technology-enabled activities can do easily.

When considering the educational technology literature, scholars in this field generally suggest that two features of technology-enabled activities play especially powerful roles in motivation and engagement. These features are immersion and interest (Goh, Ang, & Tan, 2008; Hainey, Connolly, Stansfield, & Boyle, 2011; Marsh, 2011; Squire, 2008). Immersion is defined within this literature as the subjective impression that one is participating in a comprehensive, realistic experience, such that individuals willingly suspend disbelief (see Hale & Stanney, 2015). Interest, on the other hand, is commonly conceptualized as enjoyment or fun.

Scholars in educational technology typically find that immersion facilitates positive academic outcomes (see Dede, 2009), and support the transfer of knowledge learned within a virtual context to a real-world context (Weinstein et al., 2009; Winn, Windschitl, Fruland, & Lee, 2002). The results linking immersion to learning outcomes notwithstanding, little research has been conducted concerning the *motivational* affordances regarding immersion despite the assumption that technology-enabled activities such as immersive virtual environments (IVEs) have motivational appeal due to their ability to create a physical and affective experience of "being there" (Dede, 2009). Some research has suggested that IVEs are effective when they incorporate a cohesive and compelling narrative, which facilitates learners' engagement (Barab, Sadler, Heiselt, Hickey, & Zuiker, 2007; Girard et al., 2013; Rowe, Shores, Mott, & Lester, 2010). Overall, the few studies investigating immersion (whether perceptual or narrative

immersion) and motivation or engagement suggest that IVEs engage students by "suspending their disbelief" and thereby compelling them to participate in instructional activities.

With respect to interest, the literature also suggests that educational technologies that are perceived to be interesting and fun also facilitate positive student outcomes such as completing academic tasks (Allen, Crossley, Snow, & McNamara, 2014; Habgood & Ainsworth, 2011). Taken as a whole, the focus on interest and immersion points to a larger picture that scholars in educational technology mostly see computers as a tool to engage students in academic work— the more "time on task" in a learning environment, the more educational benefits students can gain. But a more important question (for educators) that has been addressed to a lesser extent is whether engaging in technology-enabled activities leads to increased engagement and motivation for the *subject matter*. Authors (2016) showed that, students who experienced both a "spark" of interest at the beginning of the IVE *and* a gradual (rather than sharp) drop in interest for the IVE reported higher *science* interest, whereas their peers who only experienced a spark of interest but then lost interest more dramatically evinced lower science interest. On the other hand, other researchers have reported less impressive results regarding the motivational affordances of technology-enabled activities (e.g., Adams, Mayer, MacNamara, Koenig, & Wainess, 2012; Girard, Ecalle, & Magnan, 2013).

Utility. Another factor that may promote a more robust motivation to pursue an academic subject is allowing students to discover the usefulness of an activity to their own personal lives. We chose to focus on utility for our present study because the technology-enabled activities used were designed to be useful to students in different ways, from the practical applications of mathematics to the utility of believing that mathematical ability is augmentable. Empirical research regarding utility value has shown that when students perceive a

task to be valuable for their future development, they are more likely to engage in the activity (Greene, Miller, Crowson, Duke, & Akey, 2004; Johnson & Sinatra, 2013; Miller, DeBacker, & Greene, 1999), and achieve at higher levels (Cole, Bergin, & Whittaker, 2008; Greene et al., 2004). Technology-enabled activities can allow students the opportunity to discover on their own the utility of an activity or a subject area.

Beliefs about competence. The National Academy of Sciences (2011) agreed that there are particular beliefs that are necessary for those who want to pursue careers in mathematics and science. Primary among these is a firm sense of confidence in one's capabilities to succeed in mathematics, and a strong belief that one's own capabilities can be augmented. Educational psychologists refer to individuals' confidence to succeed as *self-efficacy*, and individuals' beliefs about the augmentable nature of one's intellectual capacity as *incremental views of ability*. Building and supporting students' competence beliefs is especially important in mathematics because success in subjects like algebra in the middle grades is recognized as an important gatekeeper that either constrains or augments students' post-secondary career and educational decisions (Adelman, 2006).

Educators are increasingly relying on computers to aid in building students' competence beliefs because computers are able to provide individualized and real-time feedback about students' progress through learning activities. As a result, students are able to build their knowledge and skills, and just as important, the *belief* that they can indeed succeed. In addition, a new way of using computers to target students' competence beliefs has been the use of motivational interventions that target this belief.

Relatedness. One question that scholars have been exploring is how instructional activities can be designed to foster a more robust and enduring level of interest for an academic

subject. A number of scholars have shown that one way to facilitate this interest development is to design instructional environments and activities that allow students to interact with others and develop a sense of connection to others. A sense of relatedness, which is defined as the need to feel connected with others, is "centrally important for internalization" (Ryan & Deci, 2000, p. 73). Drawing from self-determination theory (SDT), teachers' approachability and ability to make meaningful social connections to their students can support the development of students' interest in a subject, as theory would suggest (Bergin, 1999; Krapp, 2005; Ryan & Deci, 2000). Although research investigating relatedness usually concerns feelings of relatedness to teachers or researchers (e.g., Sheldon & Filak, 2008; Walker & Greene, 2009; Wentzel, 1997) or peers in a classroom or virtual group (Furrer & Skinner, 2003; Przybylski et al., 2010), little to no research has investigated this phenomenon with digital characters in a virtual world, which is becoming increasingly important in a technology-rich world.

Autonomy. Scholars have also shown that teachers who provide their students with meaningful choices create a classroom climate that positively affects students' sense of autonomy (Greene, Miller, Crowson, Duke, & Akey, 2004; Jang, 2008; Patall, Cooper, & Wynn, 2010; Reeve, Jang, Carrell, Jeon, & Barch, 2004; for a review see Katz & Assor, 2006). This literature, which also emanates from Ryan and Deci's (2000) work in SDT, is quite clear in showing that an adequate sense of autonomy is essential in supporting the intrinsic motivation of students (Ciani, Ferguson, Bergin, & Hilpert, 2010; Patall et al., 2010; Reeve et al., 2004; Tsai, Kunter, Lüdtke, Trautwein, & Ryan, 2008). Despite this literature base showing the importance of an autonomy supportive classroom climate, what remains less clear is whether students' perception of the classroom climate has an effect on their level of engagement and motivation in

a technology-rich setting that requires little teacher involvement, which is common among many technology-based curricular packages.

Demographic variables. Many scholars have argued that race/ethnicity, gender, and socioeconomic status (SES) are important predictors of how students experience technology-rich academic content because of how students are socialized based on these socio-cultural factors (e.g., Meelissen & Drent, 2008; Vekiri, 2010; Vekiri & Chronaki, 2008). Results from these and other studies show that girls tend to have lower competence beliefs and value beliefs concerning computer usage, with girls being less interested in and less confident using computers and developing more sophisticated computer skills such as programming. Also, although both parents and students from low SES families value computer skills, students from low SES families have fewer opportunities to develop their computer competencies and are less self-efficacious in their computer skills than their wealthier peers (Vekiri, 2010). Finally, grade level is especially salient in studies of motivation and engagement because there is a consistent and long-standing finding that students, on average, become more and more disengaged from academics as they progress through school (see Wigfield & Eccles, 2002). This downward trend in motivation is especially evident in the transition from elementary school to middle (or junior high) school, which in the United States is typically from Grade 5 to Grade 6.

Overview of the Present Study

What constitutes effective technology-enabled activities? In this study, we propose that there is a need to model how beliefs interact in patterns. This person-centered approach, rooted in rigorous theories of motivation and engagement, has the potential to refine how educational technologists and educational psychologists understand the complex dynamics involved when students participate in technology-enabled activities.

Although past research has investigated such questions as the relationship between immersion and learning outcomes, or how autonomy in a game relates to motivational and achievement outcomes in a subject area, more nuanced questions regarding how these various beliefs interact with each other are needed. We know little about whether there are patterns that reveal how students experience technology activities, and whether those patterns can be generalized across different types of technology-rich activities. If there are patterns, we also know little about whether these patterns are predictive of academic outcomes. If we assume that not all students are engaged and motivated by the same types of technological experiences, we need to understand what factors predict how engaged and motivated students might be and to what end. Perhaps one reason for this gap in the literature is because the variable-centered approaches to answering such questions (e.g., path analysis) cannot be used when using variables that are highly collinear. In our case, immersion, interest, utility, and relatedness are likely collinear, which prevents us from being able to explore the multiple interactions among these four important aspects of a rich technology experience. A person-centered approach can aid in this respect. It allows us to describe the overall quality of students' experiences with the technology without the problem of multicollinearity. We can then examine how different experiences with the technology (e.g., low immersion and low relatedness, but high interest and utility) serve as an intermediary between students' individual and classroom contexts on the one hand (e.g., feelings of how much autonomy their teachers give them), and learning and motivational outcomes on the other (e.g., interest in mathematics).

In this study we explored the different ways that students could be engaged and motivated in a technology-enabled activity that was set within a larger mathematics instructional unit. Although we did not hypothesize a specific number of profiles, as this was an exploratory

study, we expected that at least four technology profiles would emerge. This hypothesis is based on prior person-centered empirical studies (e.g., Chen, 2012; Conley, 2012) that show that individuals often self-report all-high, all-moderate, and all-low levels on motivation variables. In addition, there is often a profile evincing a mixture of high, moderate, and low levels. We hypothesized that three profiles pertaining to high, moderate, and low levels of immersion, interest, utility, and relatedness in the technology would emerge. Consistent with the aforementioned work, we also hypothesized that at least one profile displaying a mixture of these four variables would emerge. For example, there could be students who report high levels of interest and utility, but low levels of immersion and relatedness.

Based on previous research and models of motivation and engagement (e.g., Skinner et al., 2008; Wigfield & Eccles, 2000), and because the technology activities were set within a larger four-day mathematics instructional unit, we hypothesized that a number of factors external to the technology activities would predict students' motivation and engagement with the technology. These factors included grade level of students because the technology activities were likely more appropriate for some grade levels than for others (see Authors, 2014). Another factor was the gender of the student, as girls are typically less drawn toward computer games, but do not show differences in their interests for movies. We also tested whether demographic variables such as race/ethnicity, social class, and previous achievement were significant predictors of students' membership into the technology profiles. We investigated these demographic and background variables because previous evidence suggested that these factors might be related to students' engagement and motivation with instructional activities (Marks, 2000). The last predictor variable we tested was autonomy-supportive classroom climate

because Skinner et al. (2008) has shown that autonomy support should predict academic engagement.

Finally, if engagement is a proximal process, as Skinner et al. (2008) argued, then it is important to specify the ways that the activities in our study facilitated motivation and engagement *for the technology*, and the extent to which the different ways of experiencing the technology related to differential outcomes for motivation and achievement *in mathematics*. Thus, before we outline the specific procedures of our study, we describe each of the technology activities that students experienced.

An Immersive Virtual Environment

The first technology activity that we used was a game-like Immersive Virtual Environment (IVE), which was designed to introduce students to the mathematical concepts that were to follow in Days 2 and 3. It was professionally produced to have the look and feel of the video games that many students play. The purpose of the IVE was to develop students' self-efficacy in mathematics by attuning to Bandura's (1997) hypothesized sources of self-efficacy. First, by presenting students with incrementally more difficult challenges and providing scaffolds that broke down complex concepts into smaller and easily achievable steps, we were targeting students' *mastery experiences*—giving students opportunities to succeed at increasingly more difficult problems. Bandura hypothesized that mastery experiences are the most powerful source of self-efficacy. Second, students watched a 5-minute video of real STEM professionals describe their job and the types of obstacles they faced regarding their struggles with mathematics in school, and how they overcame them. These *vicarious experiences* gave students a chance to see themselves in another person who was able to overcome difficulties to achieve a career using mathematics. Bandura argued that these vicarious experiences, especially ones in

which observers are able to witness fallible models make mistakes but learn from them, are especially instrumental when students have had very few mastery experiences. Finally, we attuned to students' *physiological/affective states* to target their self-efficacy by making sure that the game was fun and enjoyable and reduced anxiety, which is a common experience in mathematics.

A "Growth Mindset" Learning Module

The second technology activity that we designed was an abridged version of the Brainology® program created by Dweck and her colleagues. Regarding motivation, Brainology® is a series of web-based modules explicitly designed to target students' implicit theories of ability. According to Dweck and her colleagues (Dweck & Leggett, 1988; Blackwell, Trzesniewski, & Dweck, 2007), students possess particular "mindsets" that can influence their motivational and developmental trajectories through school. The abridged version of Brainology® that our participants experienced was created by Dweck and her colleagues for this study, and taught students that the brain "grows" (gets smarter) with effort and when students learn new strategies to overcome difficulties. The modules are designed specifically for students in Grades 5-9 because of the documented declines in motivation and engagement that a great majority of students experience in these grades—especially in the transition from elementary school to middle school. Although the modules do not focus specifically on mathematics (like the other two technology activities do), they are designed to affect students' conceptions about their capacity to succeed, regardless of the subject. By convincing students that the secret to success is in finding appropriate strategies and not in towering intellectual capacity (a common belief in mathematics), students learn to focus on effective strategies rather than prematurely giving up because of the faulty belief that they are "not smart enough" to do well in mathematics.

An Educational Movie

Movies have a long history of use in educational settings to motivate and engage students in academic content (see Orgeron, Orgeron, & Streible, 2011; Snelson & Perkins, 2009). For this reason, we chose an educational movie produced by Public Broadcasting Service's (PBS's) NOVA program, which was entitled *Fractals: Hunting the Hidden Dimension* (2009). This 1-hour movie showed students the discovery of a naturally-occurring mathematical pattern (fractals), presenting visually appealing animations and personal interviews with people who use fractals in their everyday lives (e.g., fractals in Computer Generated Imagery for movies). Although this movie was not designed with a particular framework of motivation or engagement in mind, we selected this particular movie because we believed that the visually appealing animations and storytelling made for an *interesting and enjoyable* film, and the personal interviews of how fractals can be used in everyday life showed the relevance and *utility* of mathematical patterns. The visually appealing nature of the movie along with the interesting storyline seemed to be designed to facilitate *immersion* in the movie. Finally, the characters in the movie appeared to be cast in such a way as to be *relatable*, fallible, individuals whose curiosity allowed them to find some interesting applications to life (e.g., making movies, building mobile phone antennae, and creating tie-dye shirts).

Methods

Participants and Context

Data were collected from all students in Grades 5-8, along with their teachers, in a large school district in Virginia. A total of 18,628 students and 476 teachers participated in the study. Students and teachers came from 38 elementary schools and 12 middle schools. We removed 137 teachers and their associated students from our analyses because these teachers were

teaching assistants, ELL teachers, or special education teachers who did not have their own

classroom. We also removed from analyses all students who did not provide consent to have

their data used. Ultimately, 7,774 students provided complete data for Day 0, Day1, and Day 4

surveys. Girls comprised 49.7% of the sample. The breakdown of completed surveys by

Induction was as follows: Computer game (Induction #1; 35.5%), Brainology modules

(Induction #2; 27.6%), and PBS movie (Induction #3; 36.9%). Grade level distribution of the

sample was as follows: Grade 5 (23.4%), Grade 6 (23.9%), Grade 7 (26.8%), and Grade 8

(25.9%). Race and ethnicity of the sample were as follows: White (53.9%), African American

(24.9%), Hispanic (7.7%), Asian (3.8%), and 9.7% reported another racial/ethnic background.

English language learners (ELL) constituted 6.4% of the sample, and 10.9% were identified as

special education students. Finally, 34% of students were eligible for free or reduced lunch (a

measure of socioeconomic level). At the school level, schools ranged from 2% to 85% of their

school population being eligible for free or reduced lunch.

Design of the Study

Table 1 shows the day-to-day activities involved in the study and the data that were

collected on each day. Before the intervention, teachers were randomly assigned to one of the

three technology conditions, and students were administered a pre-survey. The actual

intervention took place over the course of four consecutive days. On Day 1 of the intervention,

students participated in their respective technology-enabled activity, where Activity 1 was the

computer game, Activity 2 was the abridged Brainology® web module, and Activity 3 was the

PBS movie on fractals. Table 2 provides more information about these technology-enabled

activities, including the conceptual framework on which each was based and the content of each.

On Days 2-3 of the intervention teachers taught a two-day mathematics lesson, which we

designed, about identifying and using mathematical patterns. We ensured that *all* students (regardless of technology condition) received the same teacher-led mathematics instruction, with small differences based on grade level so that the material was appropriately challenging for the age of the students.

We designed the lessons around a combinatorics task often referred to as a "trains" problem, because it involves the creation of integer-length "trains" using different numbers and lengths of integer-length "cars." For example, students would determine the number of possible trains of length 4 that can be created. In this case, there are eight ways to do this (1-1-1-1; 1-1-2; 1-2-1; 2-1-1; 1-3; 3-1; 2-2; and 4). Many interesting variations and extensions of this trains problem can be made such as asking how many trains of length n can be made using only cars of length 1 and 2. Grade 5 students focus on questions involving the powers of 2, whereas Grades 6-8 focus on patterns such as the Fibonacci sequence and Pascal's triangle. All students in all grade levels represent and generalize their data, but in different ways. For example, Grade 5 students are asked to create a graph to describe the relationship between train length and total number of trains of that length that can be made. Grades 6-8 students, though, are asked to create a table to represent the total number of trains that can be made for different train lengths and numbers of cars used. Students in Grades 6-8 are then asked to extrapolate these findings to larger train lengths (lengths that would be far too unwieldy to solve simply by physically constructing the trains). Finally, beyond just grade-level differences, from self-reported fidelity responses from all teachers, we found that 75% of teachers either "exactly followed" or "very closely followed" the list of activities that we had suggested, but only 24% to 34% of teachers (depending on which sub-component of the lesson) followed the recommended timing/ordering of activities. From audio/video data collected from a small sample of teachers, we found that

these teachers did include most of the recommended elements of the curriculum. However, the timing and ordering by which the lesson unfolded varied widely.

Students finished the intervention on the fourth day by returning back to the technology-enabled activity. Our goal was to generate empirical evidence about the motivational affordances of using three different technology-enabled activities that are *integrated within teacher-led, inquiry-oriented, mathematics instruction. All teachers* taught the same content using the same pedagogical approach that we developed. Furthermore, we have a large sample size, which is representative of an entire school district because we were able to draw from all students from Grades 5-8 in an entire district. For these reasons, although we do not explicitly model Days 2-3 in our statistical analyses, we can assume that any observed differences in outcome variables can be attributable to differences in how students experienced each of the technology-enabled activities because everything else was kept constant, including all aspects of Days 2-3.

Activity 1 was designed to be difficult enough that students would not be able to finish the entire game on Day 1. Therefore, after having learned the necessary mathematical knowledge on the second and third days of the intervention, students would be able to apply their knowledge to the game and finish it on the fourth day. For Activity 2, students completed a module about how to manage anxiety when approaching stressful testing situations. Then, on Day 4, students finished with the module teaching students about the incremental view of ability, and that the brain can grow and become more capable with effort. For Activity 3, students watched the first half-hour of the video on Day 1 and then finished the movie on Day 4.

Because we wanted to create an authentic context in which teachers typically use technology activities, the overall intervention also incorporated a two-day mathematics

instructional component in which all teachers taught the same concepts, and used the same curricular materials. Although three different grade levels were involved, we did allow for grade-level variations so that the learning outcomes were developmentally appropriate. The authenticity of this study allowed us to explore whether a two-day experience with technology-rich content had an effect on student outcomes even if it was embedded within a classroom-based mathematics unit taught by the teacher. All teachers (including ESL teachers and teachers' aids) were provided with one full day (6.5 hours) of professional development. This professional development workshop was administered one week before the actual intervention and was designed and implemented by our project staff. Coordination of the logistics of the professional development workshops was done in close collaboration with district administrators and school principals.

Four hours of professional development centered on implementing the actual classroom mathematics lessons. We provided teachers with detailed lesson plans, visual aids, handouts, and manipulatives. The workshops were designed to provide teachers the opportunity to do the activities that their students would do, and to reason through the mathematical principles being addressed in the lessons. One hour of the workshop was dedicated to providing teachers with an overview of the project's goals, procedures, and logistics. Finally, the last 1.5 hours were dedicated to giving teachers an opportunity to interact with the technology-enabled activities that their students would experience. Because teachers were assigned to one type of technology, this part of the workshop was specific to the technology activity that the teacher was assigned to. Activity 1 teachers played the computer game, Activity 2 teachers interacted with the abridged version of Brainology®, and Activity 3 teachers watched the PBS movie. Overall, our goal was

to ensure that teachers were prepared well enough to teach the curriculum with a high amount of fidelity.

Instruments

Surveys were administered using an online survey (Qualtrics). See Table 1 for timing of the surveys. Students took the surveys on computers in school during their mathematics class. The pre-survey comprised of 79 questions, and was designed to assess students' knowledge of the specific pre-algebra skills that our intervention targeted (i.e., mathematical patterns), beliefs about competence (e.g., self-efficacy) and value (e.g., interest value) related to mathematics class. Other variables not pertinent to this particular study were also included on this survey, which included sources of self-efficacy, grit, science identity, and achievement goal orientations. Finally, we included demographic information on the survey also (e.g., gender and race/ethnicity). The post-survey included the same items, but also included students' beliefs about the level of autonomy their teachers provided them in class in general.

The post-technology survey was designed to assess students' experiences with the technology activity in which they participated. It comprised of 30 questions that targeted students' beliefs regarding their interest/enjoyment, utility, and immersion while participating in the technology activity. We also included items that assessed their feelings of relatedness to the characters involved in the technology activity. Other items that were included on the survey but were not pertinent to this particular study included feelings of autonomy in the technology activity, beliefs regarding how well they performed in the technology activity, and how much effort they were willing to dedicate toward participating in the activity (we did not include these in our study because these questions were only pertinent to the game and the growth mindset module).

Immersion, enjoyment, usefulness, and relatedness. This instrument was worded specifically for the technology activity that the student participated in. Therefore, students participating in the computer game answered questions that were worded as such. Students' feelings of being present or immersed in the technology activity (e.g., "when moving through the TESLA game I felt like I was actually there"), their enjoyment in participating in the technology activity (e.g., "I enjoyed participating in the Brainology activity"), their perceptions about the usefulness of participating in the technology activity (e.g., "I believe that watching the math movie could be valuable to me"), and their feelings of relatedness to the characters in the technology activity (e.g., "I felt like I could relate to the people in the math movie") were assessed immediately after their participation in the technology activity. Immersion was assessed with three items (α=.91); enjoyment was assessed with four items (α=.94); usefulness was assessed with three items (α=.89); and relatedness was assessed with three items (α=.85). The items for interest, usefulness, and relatedness came directly from Ryan and Deci's Intrinsic Motivation Inventory (IMI; Deci, Eghrari, Patrick, & Leone, 1994; Ryan, 1982; Ryan, Mims, & Koestner, 1983), which has been demonstrated to be psychometrically sound (Koka & Hein, 2003; McAuley, Duncan, & Tammen, 1989). The items for immersion came directly from the Player Experience of Need Satisfaction (PENS) scale, which has been used in other studies of video and computer game use and has been shown to have good psychometric properties (Przybylski, Ryan, & Rigby, 2009; Przybylski, Weinstein, Murayama, Lynch, & Ryan, 2012; Ryan, Rigby, & Przybylski, 2006).

Mathematics self-efficacy. Students' confidence in being able to manipulate the mathematical patterns involved in the intervention were assessed pre- and post-intervention using a four-item instrument [α=.88(pre), .89(post)]. The tasks centered on identifying

mathematical patterns and then using that pattern to predict subsequent numbers in that sequence. We chose these tasks because they were a central focus of the intervention curriculum.

Mathematics value beliefs. Students' interest value in the subject of mathematics (e.g., "How much do you like math?") and beliefs about the utility value of mathematics in their lives (e.g., "In general, how useful is what you learn in math?") were assessed at pre- and post-intervention. Interest value was assessed using three items [α=.73(pre), .78(post)]. Utility value was assessed using two items[α=.81(pre), .75(post)]. Both scales were drawn from the Michigan Study of Adolescent and Adult Life Transitions (n.d.).

Mathematics learning. This was a short, five-question, assessment on mathematics learning and dealt with the kind of algebraic reasoning that was related to the two-day mathematics lesson. All participants received the same questions. The questions covered data organization, pattern identification, and the ability to make generalizations (e.g., "identify the next number in the following number pattern: 3, 7, 11, 15"). Items on the pre- and post-tests were non-identical but isomorphic—they had the same problem structure, but involved different contexts and numbers. The reliability of the assessment was low (α=.30[pre], .40[post)]). However, this measure was used as an *outcome* variable rather than a predictor variable. Reduced reliability in an outcome variable is equivalent to increased residual variance, which downwardly biases detected effect sizes and reduces statistical power, which results in a lower probability of correctly detecting a statistically significant relationship between mathematics learning and our predictor variable, which in our case is latent profile membership (Cohen, 1992; Kanyongo, Brooks, Kyei-Blankson, & Gocmen, 2007).

Analysis

Description of Person-Centered Approach

A person-centered analysis (Magnusson & Stattin, 2006) was used for this study because the theoretical framework we employed assumes that a group of beliefs operates together within an individual while participating in technology-enabled activities. Our assumption in this study is that because the technology activities were designed around different frameworks of engagement and motivation, and because students have individual preferences for technology, students would experience these activities in very different ways. Our current analytical framework was latent profile analysis (LPA), which is a statistical technique in which researchers can uncover latent groups of individuals (i.e., typologies) based on patterns of observed responses (Masyn, 2013). LPA was conducted using Mplus 7 (Muthén & Muthén, 1998-2013). LPA models are typically fitted using a series of steps starting with a one-class model and increasing the number of classes until there is no apparent improvement in the model. After analyzing the design effects of clustering of students by teacher and school, we used robust clustered standard errors, clustering at the school level, to account for the hierarchical nature of the data. We used full information maximum likelihood estimation in accounting for missing data.

For our first research question, we wanted to examine how many profiles would surface regarding students' experience of *immersion, interest, utility,* and *relatedness* with the technology activity that they participated in. These data came from student surveys, which were completed immediately following their participation in the technology activity on Day 1. To uncover the number of latent profiles that emerged from the data, we started by testing a model with one latent class ($k = 1$), and then increased the number of profiles until there were no further improvements to the model. These analyses were done separately for each technology condition.

We compared the fit of each model using standard indices of fit, including the Bayesian information criterion (BIC), for which lower values indicate better fit. We also used the Lo-Mendell-Rubin (LMR; Lo, Mendell, & Rubin, 2001) likelihood ratio test, which produces a statistic comparing the fit of a model with k classes to a model with one fewer class (k-1). A p-value less than .05 indicates that the k-1 model should be rejected in favor of the model with k classes.

For our second research question, we explored whether students' membership in one of these technology profiles, which were formed based on surveys administered on Day 1 of the intervention, predicted post-intervention (i.e., Day 4) *mathematics* motivation and achievement. We included the following four outcomes: mathematics self-efficacy, interest in mathematics, utility of mathematics, and mathematics achievement. To do this, we employed the BCH approach, as outlined in detail by Asparouhov and Muthén (2014), which is a way to independently evaluate the relationship between the latent profiles formed and the distal outcome variables.

Finally, for our third research question, we explored the extent to which students' background factors, factors related to the design of the technology, and classroom-level factors predict membership into the technology profiles generated in the first research question. To do this, we regressed the latent classes surfaced in the BCH method outlined above on our vector of student background factors, which were self-reported from students' Day 1 surveys.

Determining the Number of Profiles

Tables 3-5 show the fit statistics for tests of models for each of the three technology activities. As is evident in Tables 3-5, the BIC values for all three technology conditions declined going from a two-class model to a seven-class model, and LMR p-values remained

statistically significant (*p*<.0001) until the four-class solution, suggesting that a three-class model was the best fit. To test the reproducibility of these results, for each technology condition, we split the sample into two random halves and performed two identical analyses on each sample. This split-halves procedure yielded the same results, suggesting that these three profiles are reproducible (see Figures 1-3).

Results

Research Question 1: Description of the Student Technology Profiles

For the first research question, we wanted to uncover the variety of ways that students could experience the technology activities in terms of how immersive, interesting, and useful the experience was, as well as how relatable the characters in the technology experience were. A three-class model was the best fit for all three technology conditions.

The computer game. The largest profile for the computer game condition was the "All High" group, which comprised 52.6% of the student sample in this condition (see Figure 1). The "All High" students reported the highest levels of *Immersion* (M=4.86), *Interest* in the activity (M=5.39), perceived *Utility* of the activity (M=4.94), and *Relatedness* with the characters in the activity (M=4.64).

Over a quarter (25.5%) of the computer game students could be classified in the "Low Immersion" group. Students in this profile reported low levels of *Immersion* (M=2.11), but relatively high levels of *Interest* (M=4.71), moderate levels of *Utility* (M=3.91), and moderate levels of *Relatedness* (M=3.65). Finally, the smallest profile, called the "All Low" profile, comprised 21.9% of the computer game students. These students reported that the game was not *Immersive* (M=1.71), was not very *Interesting* (M=2.15) or Useful (M=2.08), and felt minimal *Relatedness* to the characters (M=2.59).

The growth mindset modules. The largest of the three profiles that emerged from the growth mindset condition was the "All High" profile, which comprised 42.6% of students in this condition (see Figure 2). These "All High" students reported feeling somewhat *Immersed* in the technology (M=4.56). They found the growth mindset modules to be mostly *Interesting* (M=4.99) and *Useful* to their lives (M=4.87), and the characters to be somewhat *Relatable* (M=4.35).

The next largest group of students in the growth mindset condition was the "Interesting/Useful" profile, comprising 29.7% of students in this condition. These students did not find the growth mindset modules to be *Immersive* (M=1.99) and did not consider the characters to be especially *Relatable* (M=2.77). However, these students did find the growth mindset modules to be somwhat *Interesting* (M=4.33) and *Useful* to their lives (M=4.05). Finally, the smallest group in this condition was the "All Low" profile, comprising 27.6% of students. Students in this profile did not find the growth mindset modules to be *Immersive* (M=1.59), *Interesting* (M=2.04), *Useful* (M=2.32), or *Relatable* (M=1.93).

The PBS movie. Whereas in the other technology conditions where the "All Low" profile was the smallest profile, for the PBS movie, this "All Low" profile was the largest of all three profiles, comprising 39.7% of the students in the PBS movie condition (see Figure 3). These "All Low" students found the movie not to be *Immersive* (M=1.85), minimally *Interesting* (M=2.12) and *Useful* (M=2.66), and the characters to be minimally *Relatable* (M=2.04).

Similar to the other two technology conditions, the "All High" profile emerged. Although not the largest group, which was the case in the other technology conditions, in the PBS movie condition this profile was still quite large, comprising 38.7% of the students. These students found the PBS movie to be somewhat immersive (M=4.28). They also found it to be

mostly *Interesting* (M=5.06) and *Useful* (M=4.84). They also found the characters in the movie to be somewhat *Relatable* (M=4.30).

Research Question 2: Predicting Mathematics Outcomes From Profile Membership

Engaging students in the technology activity is one thing but directing students' motivational resources toward *mathematics* is an entirely different feat altogether. Because we wanted to provide empirical evidence for the predictive validity of the latent profiles regarding mathematics motivation and learning, even within the context of a teacher-led, inquiry-oriented, mathematics lesson, we explored the post-intervention mathematics achievement and motivation outcomes that were evident from being a member of one technology *profile* versus another. Overall, students' appraisal of the technology activities on Day 1 (i.e., immersion, interest, utility, and relatedness) was related to students' post-intervention beliefs about *mathematics* and their achievement in mathematics, which were assessed on Day 4 or Day 5 of the 4-day intervention.

Figures 4-6 show the results of our analysis exploring differences in outcomes between students in the different profiles, split into the three technology activities. Across all technology activities, students in the *All High* profile reported the highest levels of mathematics utility value, interest value, and self-efficacy, even while controlling for previous year's standardized mathematics test scores, demographic variables, and pre-intervention mathematics motivation. On the other hand, students in the *All Low* profile reported the lowest ratings of mathematics utility, interest, and self-efficacy across all technology conditions. Noteworthy in our findings is the fact that students in the *Low Immersion* profile for the computer game condition, and students in the *Interesting/Useful* profile for the growth mindset condition and the PBS movie condition, evinced the highest scores for their mathematics test.

Research Question 3: Which Factors Predicted Membership in the Technology Profiles?

In the previous research question we found that there were differential outcomes for being in the various technology profiles. If there are different outcomes for being in a profile, we wanted to explore which student background factors, and which classroom-level factors might predict membership into the technology profiles. To answer this, we tested demographic variables such as gender, race/ethnicity, grade level, English Language Learner status, Free and Reduced Lunch status (a measure of socioeconomic level), Special Education status, and previous mathematics achievement (using standardized mathematics scores from the previous year). We also included other student-level factors such as pre-intervention mathematics self-efficacy, and pre-intervention mathematics interest, which we assessed before students participated in the intervention. Second, we included as a classroom-level factor students' perceptions of their teachers' level of autonomy support (i.e., classroom climate). Results showed that race/ethnicity, English Language Learner (ELL) status, special education status, and free or reduced price lunch status did not predict membership into a latent class.

Grade level predicted profile membership. Figure 7 shows the results of our analyses regarding the extent to which grade level predicted profile membership. Grade 5 students across all technology conditions were between 1.7 to 2.0 times more likely to be in the *All High* profile compared to their Grade 8 peers. For example, the probability that Grade 5 students who participated in computer games were in the *All High* profile was 0.64, whereas the probability for their Grade 8 peers was only 0.37. In contrast, Grade 8 students were more than twice as likely to be in the *All Low* profile compared to their Grade 5 peers. For example, the probability that Grade 5 students in the PBS movie condition were in the *All Low* profile was 0.22, whereas the probability for their Grade 8 peers was 0.54. Although the overall pattern of these results was

consistent across all three inductions, there were subtle differences. For example, for students participating in the computer game, there were still relatively few Grade 8 students in the *All Low* profile. However, for those who participated in the PBS movie, Grade 8 students were highly represented in the *All Low* profile.

Previous mathematics achievement predicted membership. Figure 8 shows the results of our analyses regarding the extent to which previous mathematics achievement (scores on the prior year's standardized state test in mathematics) predicted students' profile membership. These results show that, for students with lower previous mathematics achievement who participated in the computer game and in the growth mindset module, they were more likely to be in the *All High* profile compared to their peers with higher previous achievement. This pattern was especially noticeable with students in the growth mindset module, where students with the lowest previous achievement were 2.6 times as likely to be in the *All High* profile (probability=0.74) compared to their peers with the highest previous achievement (probability=0.29). On the other hand, students in Induction 3 (PBS movie) evinced a pattern in which lower achieving students were more likely to be in the *All Low* profile compared to their higher achieving peers.

Initial mathematics interest predicted membership. Figure 9 shows the estimated probabilities that students were members of a particular technology profile as a function of how interested they were in mathematics before participating in our intervention. As predicted, students with higher pre-intervention mathematics interest had a greater probability of being in the more adaptive profiles than did those who entered the intervention with low mathematics interest.

Classroom climate predicted membership. Figure 10 shows the estimated probabilities that students were members of a particular technology profile as a function of how much they felt their teacher supported or thwarted their autonomy in class in general. Across all three inductions, students who reported a classroom that was very supportive of their autonomy were much more likely to be members of the *All High* technology profile compared to their peers who reported a classroom that thwarted their autonomy. Students who reported that their classrooms thwarted their autonomy were much more likely to be members of the *All Low* technology profile compared to their peers who reported a more autonomy-supportive classroom environment. This was especially apparent in the Growth Mindset modules, in which those who self-reported the lowest levels of autonomy support were close to five times more likely to be in the *All Low* profile (probability=0.62) compared to their peers who self-reported the highest levels of autonomy support (probability=0.13). Recall that in the classroom climate self-reports we asked students about how autonomy-supportive their teachers were *in general* rather than how autonomy-supportive teachers were with regard to the technology-enabled activity.

Discussion

We started with the premise that the mere presence of technology in classroom learning is not enough to motivate and engage students. Instead, more nuanced questions are needed in exploring the variety of ways students experience technologies, and how these *experiences* rather than the actual technologies themselves are related to differential outcomes. The reason we conceptualized this study in terms of the variety of ways in which students experience motivation and engagement in technology-rich activities is because we cannot assume that, for example, newer, more interactive, technologies like computer games are better at motivating and engaging students compared to older, less interactive, technologies such as movies. Rather, we need to

understand the experiences that students have with various technologies, and explore how different experiences relate to outcomes. This assumption is further reinforced specifically for our present study because in prior work we found that when student motivation and achievement outcomes were compared across the three different conditions results were inconclusive and mixed (Authors, 2014). This prior work suggests that the type of technology itself does not necessarily relate to the motivational or achievement outcomes of students. Rather, it might be the way in which students experienced the technology that mattered.

Types Rather Than Levels of Technology Engagement and Motivation

Engaging students in technology-enabled activities is one matter, but it is an entirely different matter to direct students' motivation for the technology *toward* motivation for *mathematics*. As noted earlier, the educational technology and educational psychology literatures both tend to emphasize immersion, interest, utility, and relatedness as important features to include in the design of learning environments. One may be tempted to assume that making learning environments "all high" for all of these factors should lead to better outcomes for everyone. However, we assumed that there may well be subpopulations (i.e., profiles) of individuals who share similar patterns of engagement in the technology activity, and that there may be more than one subpopulation that evinces positive outcomes. Our analyses provide interesting insights regarding the experience patterns that students evince while participating in the technology activities and how these patterns relate to achievement and motivation in mathematics.

This person-centered approach showed that, contrary to much of the educational technology literature, immersion did not seem to be an essential ingredient for motivation and engagement within a technology activity, nor did it seem to be a necessary component for

motivation and achievement outcomes in the mathematical learning addressed in our study. This complements and extends the work of Mayer and colleagues (e.g., Moreno & Mayer, 2002). Moreno and Mayer (2002) concluded that students in a highly immersive environment do not learn better or more deeply compared to their peers in low-immersion conditions. They hypothesized that immersion may be important for learning only if the immersion actually helps students understand the topic better. In a similar vein, immersion in our study may not have been a necessary component for engagement and motivation or for high achievement because the immersion was not necessary for students to become engaged and motivated or to do well. If usefulness is a motivational "gold mine," as evidenced by its presence in the most adaptive profiles, then it stands to reason that for immersion to be motivating and engaging, there needs to be a specific purpose for using immersion that must be aligned to the motivational goals of the activity. Instructional designers would do well to leverage immersion not as a kneejerk response to engage students, but rather to think specifically about the motivational and instructional goals that would be met in leveraging immersion.

Optimizing the Experience Rather Than Upgrading the Technology

In essence, the first part of the study suggests that, contrary to prevailing thought, the malleable factor to concentrate on may not necessarily be the type of technology activity used (i.e., a computer game instead of a movie), but rather the type of experience that students get while participating in the activity. For teachers and instructional designers, this complicates the design task because instead of thinking about whether to use a movie or a computer game, a different set of questions needs to be asked. Our study sheds light on this issue by pointing to four variables that educators can focus on when designing and choosing technology-enabled learning environments—grade level, prior mathematics achievement, previous interest in

mathematics, and an autonomy-supportive classroom climate. For example, the growth mindset

and the computer game were especially effective for people with lower previous achievement.

Why might that be? Perhaps with the growth mindset modules, the message of learning to

control anxiety and the malleability of one's intelligence had a higher utility value for lower-

achieving students compared to their higher-achieving peers.

Teachers matter: The role of autonomy support. It may be tempting to think that, in a

context in which students are engaging in technology-rich activities during school hours,

teachers play a diminishing role in engaging their students. Our results clearly show that this is

not the case. For our study, the results show that the degree to which teachers provide

meaningful choices in their classrooms *in general* can have an effect on the quality of students'

motivation and engagement with specific technology-rich activities—even activities that require

little to no teacher involvement. This suggests that there might be a residual effect of students'

general classroom autonomy-support beliefs on their more task-specific autonomy-support

beliefs. These results imply that the appeal and motivational effect of technology-rich activities

could certainly be limited or enhanced depending on teachers' ability to and willingness to

provide their students with meaningful choices in all classroom activities.

Background and demographic factors. We tested numerous background and

demographic factors as predictors of profile membership, including sex, race/ethnicity, free and

reduced price lunch status, English Language Learner status, special education status, grade

level, previous mathematics interest, and previous mathematics achievement (last year's state

standardized test score in mathematics). Of these variables, only grade level, previous

mathematics interest, and previous mathematics achievement predicted membership in profile.

First, developmental level of students was important—students in Grade 8 were less likely to be in highly adaptive profiles such as the *All High* group and more likely to be in the *All Low* group (see Figure 7). This was the case across all three technology conditions. This finding mirrors the trend that older students tend to become less motivated and engaged in academic work in general (Archambault, Eccles, & Vida, 2010; Durik, Vida, & Eccles, 2006; Jacobs, Lanza, Osgood, & Eccles, 2002).

To test whether this developmental trend was a function of older students being more academically capable to tackle algebraic concepts, we explored the degree to which previous achievement on mathematics standardized tests predicted membership into profile. We were surprised to find that lower scoring students who participated in the growth mindset modules were more likely to be members of the *All High* profile, whereas higher scoring students were more likely to be in the *All Low* profile. This suggests that, although it is important to design activities that are developmentally appropriate for students, even for students who came into the intervention with lower mathematical proficiency, the growth mindset modules were especially effective in providing an engaging and motivating experience. Given that the growth mindset modules were designed to address students' implicit theories of ability and their strategies for dealing with anxiety and stress in the face of tough academic challenges, this message may have resonated with those who had a history of lower achievement. We infer that, for students who have struggled in the past with mathematics, one possible way to effectively engage students in mathematics is by making salient their beliefs that with appropriate strategies students can become more capable in learning mathematics.

We saw a similar pattern in relating previous achievement to profile membership for students in the computer game, although the pattern was not as pronounced as the growth

mindset modules. Although the probability of being in the *All High* profile decreased for

students as prior achievement increased, the *All High* profile was still the most common even at

the highest level of prior achievement. This suggests that for students at all levels of prior

mathematical achievement the computer game provided a compelling context for them to engage

with the mathematical concepts. This is especially encouraging given that the computer game

was designed specifically to fit in exactly with the types of activities that the teachers were

addressing during Days 2 and 3 of the intervention.

We saw an opposite pattern for students participating in the PBS movie—as previous

achievement rose, students were more likely to be in the *All High* profile but less likely to be in

the *All Low* profile. This suggests that the movie was more compelling for students who had

higher prior achievement. Perhaps because the mathematical concepts (e.g., fractals) were fairly

complex, students who struggled in the past with mathematics may not have had the

mathematical fluency to engage effectively with the content of the movie.

Finally, regarding previous mathematics interest, we were not surprised to find that

students who entered the intervention with high previous interests in mathematics were more

likely to be in the more adaptive profiles compared to their peers who were less interested in

mathematics from the outset. This supports the four-phase model of interest development (Hidi

& Renninger, 2006), which argues that long-term individual interest in a subject can predict

triggered and maintained situational interest in a task.

Limitations

We acknowledge that there were limitations to our study. First, although we were able to

capture students' mathematics achievement using a short knowledge instrument designed to

assess the mathematical concepts mastered in our four-day intervention, this instrument had low

reliability making it difficult to generalize our findings. However, we modeled mathematics achievement as an *outcome* variable rather than as a predictor variable. Measurement errors in the outcome variable do not increase our chances of introducing Type I errors, as noted earlier in the methods section. Rather, reduced reliability in the outcome is equivalent to increased residual variance, which reduces effect size and power, thereby increasing our chances of getting Type II errors (Cohen, 1992; Kanyongo, Brook, Kyei—Blankson, & Gocmen, 2007). In our case, this means that we are increasing our chances of incorrectly concluding that mathematics achievement is not related to membership in a latent profile. But because our analyses show that achievement does in fact vary as a function of latent profile membership, this is a favorable finding given that even with an increased chance of Type II errors, we were still able to find statistically significant differences. One caveat to note, though, is that our certainty regarding the effect size is relatively small, so although we have some preliminary evidence for the predictive validity of profile membership to mathematics achievement, more research is needed to more reliably estimate the magnitude of this relationship.

One obvious source for the low reliability of our measure is the fact that our measure was short—containing only five items. To explore other possible reasons for why the reliability of this instrument was low, we found that none of the items was highly correlated—ranging from 0.024 to 0.221. However, one item in particular was the least correlated to all the other questions in the set, producing correlations between 0.024 to 0.104. We also observed that this item had a low loading on the hypothesized underlying factor—the measure is not tau-equivalent, thereby making reliability more difficult to interpret. Correcting for non tau-equivalence resulted in a slightly higher reliability estimate (omega=0.42), but was still relatively low. This one item asked students to predict the value of the next number in a sequence. However, unlike the types

of patterns we focused on with our lessons, this particular question required students to recognize that the two previous numbers in the sequence had to be multiplied together to derive the next number in the sequence—a pattern that was not discussed in our lessons. Furthermore, the lessons were taught with manipulatives (i.e., "trains") such that students could physically interact with tools that would help them solve problems. However, the mathematics learning measure presented students with tables and strings of numbers, presented without much context to solve the problems. Therefore, making the leap from manipulatives involving "trains" to context-less strings and tables of numbers may have been a difficult transition for students to make. It is quite possible, therefore, that students simply guessed on many of the items that required significant cognitive effort. Researchers who want to replicate and further this research would do well to ensure that the activities that students engage in are aligned more closely with the mathematics assessment.

The low reliability of the post-test mathematics test also negatively affects the validity of inferences that can be made from the test. The relationship between a given instrument and the criterion score it is measuring (i.e., its validity) is bounded by (must be less than or equal to) the square root of the reliability (Revelle & Condon, 2018). In our case, the square root of the post-test reliability (omega = 0.42) is approximately 0.65. Given the scale of 0 to 1, we can state that there is only moderate evidence that the assessment we used actually measures a *unidimensional* construct of mathematics ability.

That is not to say that inferences from the post-intervention mathematics test used here lack any validity. As Cronbach and Gleser (1959) observed, even tests with low reliability and therefore diminished psychometric evidence of validity can be used to make valid decisions about the people who took them. We note, for example, that the post-intervention mathematics

test is statistically significantly related to students' prior mathematics achievement ($r_{disattenuated}$=0.59, p<.001). On average, students who scored higher on a comprehensive end-of-year mathematics assessment the previous year tended to have higher total scores on the post-intervention mathematics test. This lends support to the use of the test as a general measure of mathematics achievement. However, as is often the case when assessments meant to clinically sort or spot-check are used to determine individual differences, the post-intervention mathematics assessment lacks the rigorous psychometric properties required for ideal use in correlational analyses such as those employed in this study (Hedge, Powell, & Sumner, 2017). We therefore interpret our findings regarding latent class membership and post-intervention mathematics as preliminary evidence of a relationship, and strongly suggest further research into this connection using instruments that demonstrate the necessary psychometric properties.

A second limitation that we note is the fact that our intervention was relatively short with respect to the professional development (6.5 hours), the technology-enabled activities (two out of four days), and the mathematics instructional component (two out of four days). For this reason, the effects of this intervention were modest. In future work, researchers could investigate the effects of technology-enabled activities that were more robustly integrated into the curriculum and for longer durations. Nevertheless, given our short intervention, it is still quite remarkable that we were able to capture differential effects of the intervention—not based on the specific technology that students used per se, but rather on the *affective experience* that students had while participating.

Third, although we did administer a delayed post-survey (three months after the end of the intervention), results were not interpretable, and the amount of missing data was high. For

this reason we cannot report on the intervention's long-term effects on students. In future work, researchers should explore the long-term impacts of technology-rich curricula on students.

Finally, we started out with 18,628 total students, but were only able to analyze complete data from 7,774 students. This is 41.7% of the original sample. The loss of cases had to do with the fact that we had to: (1) exclude a number of teachers from the study (as detailed earlier in the methods section); and (2) exclude students who did not have complete data for Days, 0, 1, and 4. There was also a miscommunication between the research team and the district regarding how students should enter in their ID numbers for the pre-intervention survey, which likely resulted in some missingness.

Conclusion

Despite these limitations, we were able to show using a large sample of students from Grades 5-8 the value that technology can add to a short mathematics intervention that involved high quality mathematics instruction. Our results point to the value of exploring these patterns *not* by creating *a priori* manifest categories such as the type of technology activity that students participated in, but rather by exploring *latent* categories describing the ways in which students experienced the technology activity to be immersive, interesting, useful, and the degree to which the characters were relatable. Our findings highlight the need for instructional designers, researchers, and educators to go beyond asking the question, "which technology activity would be most motivating and engaging?" to instead, start asking questions such as, "how do I provide the most optimally motivating and engaging technology experience for my students regardless of the type of technology activity I use?" Further research is needed to understand the elements of technological learning environments that can effectively trigger utility beliefs, enjoyment, and relatedness in both the technology *and* in the subject matter.

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