

Using Virtual Environments to Motivate Students
to Pursue STEM Careers: An Expectancy-Value Model

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ABSTRACT

The purpose of this chapter is to bring a rigorous and well-studied theoretical framework of motivation to the study and design of virtual learning environments. We outline the key motivation constructs that compose Eccles and Wigfield's Expectancy-Value theory (e.g., Eccles et al., 1989; Wigfield & Eccles, 1992, 2000), and how it can be used in the creation of a virtual learning environment designed to promote students' interest in and motivation to pursue Science, Technology, Engineering, and Mathematics (STEM) careers. In addition, using Brophy's (1999) model of the motivated learner, we outline how this type of motivational virtual environment can be incorporated in classroom instruction to further bolster adolescents' motivation and competence in mathematics. Finally, we describe a NSF-funded project underway at Harvard's Graduate School of Education that seeks to develop a 4-day mathematics intervention merging innovative technologies with regular classroom instruction to spark students' interest in STEM careers.

There is no learning without engagement, a situation that happens all too often in our typically lecture-based classrooms. At the same time, engagement without learning, which frequently happens in today's digital worlds, is not a healthy alternative. Some claim that online gaming is the answer to engaging and motivating students in their academic work. Yet, students can frequently be engaged in these virtual worlds without actually learning anything or being more academically motivated. In this chapter, we argue that Eccles and Wigfield's Expectancy-Value theory (e.g., Eccles, 1983, 1987, 1993; Eccles et al., 1989; Wigfield, 1994; Wigfield & Eccles, 1992, 2000) offers researchers, educators, and designers useful and theoretically grounded motivation constructs that can be empirically studied in educational contexts. These constructs potentially provide a powerful way of linking engagement and learning.

In the first part of the chapter, we provide an overview of the theoretical frameworks in which prominent *expectancy* and *value* motivation constructs are based. In the second part of the chapter, we situate motivation within a larger picture—Brophy's (1999) model of the motivated learner, which extends Vygotsky's (1978) cognitive Zone of Proximal Development (ZPD) by incorporating a motivational ZPD. As a case study for the application of Brophy's model of the motivated learner, we describe a NSF-funded project underway at Harvard's Graduate School of Education called *Transforming the Engagement of Students in Learning Algebra* (TESLA). The chapter ends with a description of the design decisions in creating a motivating virtual environment for mathematics students in Grades 5-8, along with implications for educational practice.

Expectancy-Value Models of Motivation

Although there has been a wealth of research exploring motivation within technological environments, very few of these studies employ frameworks that are grounded in well-studied

theories of motivation (Moos & Marroquin, 2010). Eccles and Wigfield's Expectancy-Value theory of motivation (e.g., Eccles, 1983, 1987, 1993; Eccles et al., 1989; Wigfield, 1994; Wigfield & Eccles, 1992, 2000) provides a useful framework for understanding students' beliefs about how competent they are and what they value within the context of their academic studies. The motivation constructs we describe below are theoretically grounded and have been extensively studied in educational contexts.

Expectancy Beliefs

Students are motivated toward or away from particular activities by answering the question, "can I do this?" This question lies at the heart of the expectancy component of Eccles and Wigfield's model. In this section of the chapter we describe the following three expectancy constructs: causal attributions, implicit theories of ability, and self-efficacy. We first situate each construct within its theoretical home, and then describe its correlates and antecedents.

Causal attributions. Imagine you have just failed an important math test. What do you do when you discover this troubling news? According to contemporary attribution theorists, you are likely to search for a cause to your failure. Perhaps you failed because you were in a bad mood that day. It is also possible that you believed the test to be too difficult, or because you did not apply the appropriate study strategies when preparing for the test. You might also believe that you simply do not have the math "smarts" necessary to do well on math tests. According to Bernard Weiner (1979, 1984, 1985), students attempt to find the causes of their academic successes and failures. These *attributions* can be categorized using three dimensions: *locus*, which refers to whether a cause is located internal or external to the student; *stability*, which refers to whether the cause changes over time or is relatively persistent; and *controllability*,

which refers to whether the cause can be influenced by the student or not. Table 1 illustrates these dimensions and provides examples of each one.

Insert Table 1 about here

Research in academic settings on attributions typically show that the types of attributions students make have a significant impact on the effort they put forth and how long they will persist, especially in the face of failures. When students attribute failures or difficulties to internal and controllable causes (e.g., inappropriate strategies or insufficient effort), they tend to put forth more effort and persist in the face of difficulties more so than if they attribute these failures to external or uncontrollable causes (e.g., bad luck or lack of ability). Consider, for example, students who believe that they failed their math test because they did not study for the test the right way. If the cause of failure is an inappropriate strategy, these students have reason to believe that if, in the future, they do study using the appropriate strategies, their efforts will be rewarded. However, if students attribute their failures to the fact that the math tests their teacher gives are too difficult, these students have little reason to believe that anything they do will result in a better test score.

Attributions may also have an effect on students' emotional and affective states. Weiner (1986) has shown that students who believe that they succeeded on a math test due to internal causes such as long-term effort or "math smarts" are more likely to experience an elevated sense of self-esteem, whereas failure attributions based on these internal causes may result in feelings of shame or reduced self-esteem. In contrast, attributing successes or failures to external causes (e.g., teacher help or teacher favoritism) are less likely to affect self-esteem. Instead, students are more likely to experience feelings of gratitude (successes attributed to external causes) or anger (failures attributed to external causes).

Clearly, the attributions that students make when they succeed or fail have important motivational consequences. But how do they arise? Graham and Williams (2009) list a number of attributional antecedents: Students' previous experiences can bias how they view future endeavors. For example, if students have always done poorly in mathematics, this belief is likely to influence the types of attributions they make. Similarly, students' sensitivity to social comparisons can affect the attributions they make. For example, receiving a low grade when everyone else performed well can make certain attributions (e.g., "I just wasn't feeling very well that day) more likely than others (e.g., "the test was too hard").

Students also tend to see effort and ability as inversely related (Kun & Weiner, 1973; Nicholls, 1978). For example, if two students received high grades on the same test, the student who studied the least is typically seen as the more able student because this student exerted less effort with maximal gain.

One antecedent to attributions that is especially relevant to academic situations concerns teacher feedback, in the form of indirect cues (e.g., emotional responses). Graham (1984) showed that a student might use her teachers' emotional responses to infer why she failed. If teachers communicate sympathy after failure, a student is more likely to attribute her failure to low ability. But if teachers communicate anger or frustration, a student is likely to attribute her failure to insufficient effort (Graham, 1984). We will save a more in-depth discussion of teacher feedback in the form of praise for later, when we discuss implicit theories of ability.

Implicit theories of ability. According to Dweck and Leggett (1988), students tend toward one of two different personal theories about the nature of their intellectual ability. Those who adopt an *entity* view of ability are more inclined to believe that abilities are relatively static characteristics that cannot be changed. Those who espouse an *incremental* view of ability are

more likely to believe that abilities are changeable and thus within one's control. These implicit theories create a meaning system in which ability and effort are given disproportionate weighting—students with an incremental theory are apt to place more import on effort, whereas those with an entity theory tend to place more weight on ability. Individuals' implicit theories of ability can also be domain specific. For example, some students may believe that their math ability is a relatively stable entity but that their abilities in social studies are increasable (Stipek & Gralinsky, 1996).

Dweck and her colleagues have shown that the two theories of ability lead students down two different motivational paths. A fixed theory engenders within students a desire to either show off how smart they are (performance approach goal orientation) or to hide the fact that they are not smart enough (performance avoid goal orientation). In other words, holding a fixed view of ability encourages students to either flaunt what they have or hide what they do not have. For these students, their primary aim is to achieve the highest grade and to show others how smart they are, whereas learning for the sake of learning plays a less important role.

An incremental theory of ability, in contrast, engenders a mastery goal orientation. In other words, students who believe that their abilities are increasable are more apt to learn for the sake of learning. For these students, learning the material is of primary importance, whereas showing others how smart they are is less important.

As in attribution theory, Dweck and her colleagues contend that these two different self-theories color the ways in which students view the value of effort. Those who believe that their abilities are fixed tend to devalue the importance of effort and consider natural ability to be most important. Those who hold a fixed view of ability are likely to believe that, if they cannot figure out a math problem on the first couple of attempts, then additional effort will be of no value

because extra work will not change one's ability to solve the math problem. As a result, during times when these students are doing well, this fixed view of ability may not pose an impediment to their success; but, when they encounter setbacks, these beliefs become maladaptive.

In contrast, students who hold an incremental view of ability are likely to view effort in a positive light. If these students do not at first succeed, they are more likely to seek out alternative strategies or exert more effort to succeed. Instead of attributing their failures to lack of smarts or to an unfair teacher, these students are more likely than their fixed theory peers to say things like, "I didn't study enough," or "I didn't study the right way." In essence, students who hold an incremental theory believe that they are in control of their academic success.

Finally, Dweck and her colleagues contend that these two self-theories ultimately lead to two different achievement outcomes. Fixed theorists who hold performance goal orientations are likely to experience academic success *only if* they perceive themselves to be highly competent (Dweck & Leggett, 1988). If, however, they are not confident with their ability to do well, these students are likely to do poorly. Those who hold an incremental theory, in contrast, are likely to experience academic success regardless of their perceived competence.

The implications of research on implicit theories seem clear: Promote an incremental theory and avoid creating a fixed theory. But how are these beliefs engendered in academic settings? Dweck argues that the most salient factor that promotes these beliefs is the *praise* that significant others (e.g., parents and teachers) provide to students. Contrary to popular belief, not all praise is equal, according to Dweck and her colleagues. Some praise directs attention to students' "smarts" (or lack thereof), whereas other forms of praise directs attention the effort and strategies students used to achieve success. By praising students for their abilities, teachers may be inadvertently promoting the idea that abilities are an entity that students either do or do not

possess. In contrast, by praising students for the effort and care they put into doing their work and the strategies they employed, teachers communicate the idea that the ability to succeed is a skill that can be augmented.

Self-efficacy. The third and final expectancy construct that has received considerable attention is self-efficacy, which Albert Bandura (1997) defined as one's perceived capabilities to learn or accomplish tasks at designated levels of performance. The self-efficacy construct is situated within a larger framework—Bandura's (1986) social cognitive theory, which posits that human behavior is a product of people's own past actions, personal factors such as their thoughts and beliefs, and individuals' environmental conditions. A large body of research has shown that academic self-efficacy is related to key motivation constructs such as causal attributions, achievement goal orientations, academic help-seeking, anxiety, and value. Academic self-efficacy has also been shown to predict college students' choice of academic major and their career choices (Brown & Lent, 2006).

Self-efficacy has also been shown to ultimately be related to students' academic achievement (see Pajares & Urdan, 2006). The importance of these self-beliefs is emphasized by Bandura (1997) himself: "People's level of motivation, affective states, and actions are based more on what they believe than on what is objectively true" (p. 2). Teachers are all too familiar with the highly capable student who, beset by his own self-doubts, underperforms on academic tasks. Likewise, there are many accounts of students with very weak academic preparation who still manage to achieve at high levels.

Given the importance of self-efficacy beliefs, researchers have begun to turn their attention to the antecedents of self-efficacy. According to Bandura (1997), self-efficacy is formed by how people interpret information from four sources. The most powerful source is the

interpreted result of one's past performance, or *mastery experience*. As individuals engage in tasks and activities, they interpret the results from these experiences and form conceptions about how capable they are in engaging in subsequent related tasks and activities. Students who view their past accomplishments in a positive light are likely to experience a boost in their self-efficacy. Experiences viewed as unsuccessful are likely to have the opposite effect.

Self-efficacy is also influenced by the observation of others' activities. These *vicarious experiences* are thought to be most influential when individuals are uncertain of the standards by which proficiency in an activity are measured. Social models, particularly those individuals perceived as similar (such as classmates), often act as a point of comparison as students form conceptions of their own academic capability.

A third source of self-efficacy comes from the *verbal and social persuasions* that individuals receive from influential others such as teachers, parents, and peers. Encouraging feedback and judgments bolster students' self-efficacy to perform a task, whereas deflating messages undermine it. Bandura (1986) argued that these deflating messages may actually be more effective in lowering self-efficacy than encouraging messages are at raising it.

The fourth hypothesized source comes from individuals' *physiological and affective states* such as anxiety, stress, and fatigue. Interpretations of these states often serve as indicators of students' competence. Accordingly, students who view a heightened level of anxiety as threatening are generally less confident in their academic capabilities than are those who interpret these feelings as energizing.

Information conveyed through these four sources is not inherently informative. Rather, it must be selected, weighted, and incorporated into individuals' judgments of personal efficacy. For example, an elevated heart rate and shaky hands may be the main focus of one test taker's

attention, to the point that they are debilitating, but for another student such physiological states may serve as an invigorating motivator. Therefore, information from each of the four sources exerts its influence on self-efficacy only after being cognitively processed by the individual.

Value Beliefs

Now that we have reviewed various constructs about how expectancy influences learning, we turn our attention to a second important component of expectancy-value theory: value beliefs. To be motivated to do something, students must not only believe that they have the competence to do it, but they also need to see the *value* of doing it. Students can easily decide that they are highly capable at succeeding in math; but, if they do not see the point of becoming proficient, there is no reason for them to exert the necessary effort to succeed. This is a central premise of the expectancy-value framework of motivation.

Eccles and Wigfield (2002) suggest that there are four major components to this value component: *attainment value*, which is the importance of doing well on a given task; *intrinsic value*, which is the enjoyment one gains from doing a task; *utility value*, which is defined as how a task fits into an individual's future plans or personal agenda; and *cost*, which refers to what the individual has to give up in order to do a task and how much effort must be exerted. Research has shown that students' task values predict both their intention to pursue a task and whether they actually do pursue it (Battle & Wigfield, 2003; Durik, Vida, & Eccles, 2006; Simpkins, Davis-Kean, & Eccles, 2006).

One important note we make is that Brophy (2009) has argued the career choices people make are often more about value than they are about perceived competence or expectancies of success. When young people think of possible careers to pursue, many people close the door on an entire field of possibilities either because they know nothing about what is involved with

them, or because they perceive these careers or jobs as unappealing. Once students do select a group of careers to pursue (e.g., STEM careers), it may be true that they begin whittling down those possibilities due to self-efficacy or other expectancy beliefs. But there can still be a further focusing that involves a sense of wanting to belong or a seeking of rewarding experiences that drives individuals to their ultimate career.

There has been little empirical or theoretical work outlining the antecedents of value beliefs. However, some results suggest that parents' and teachers' feedback concerning the usefulness and importance of certain activities help form students' beliefs about value (Wigfield, Eccles, Schiefele, Roeser, & Davis-Kean, 2006). Eccles (2005) has also suggested that perceived cultural norms may have an influence on the value that students place on particular activities. For example, if students perceive computer science to be a field dominated by men and White and Asian ethnicities, then women and students of color may likely shun this field, seeing it as culturally unsuitable.

Motivation and Instruction: Brophy's Model of the Motivated Learner

One of the tenets of Vygotsky's (1978) Zone of Proximal Development (ZPD) is the notion that students should be continually challenged within a zone where the skills and knowledge required for successful completion of the task are slightly out of reach for where the student is presently functioning. However, through guidance, feedback, and sufficient instruction, students can overcome these challenges in ways that are not overly taxing. Brophy (1999) has suggested that such a concept should also be brought to the study of motivation. His concept of a motivational Zone of Proximal Development postulates that there should be a match between the learner's knowledge and experiences and the ways in which learning tasks are

presented. By connecting the learning task to students' personal lives, teachers can arouse students' interests in pursuing the activity.

In essence, a learning environment that helps students operate within their motivational Zone of Proximal Development includes teachers or other mentors who enable their students to appreciate the value of learning opportunities and to connect them to students' personal lives and agendas. These "teachers and other mentors" to whom Brophy referred can be students' classroom teachers or even well-designed technological activities, as we discuss below. Indeed, Brophy (2004) posited that game-like features help promote learning and motivation and are typically better at accomplishing these goals than are typical commercial games. That said, whereas many game-like activities can help enhance motivation and learning, some games, especially competitive ones or ones that activate students' anxieties, distract from learning and can frustrate learners. To better understand how this motivational theory should guide instructional design, we next present a case study,

Innovative Technology as a Motivational Tool: A Case Study of TESLA

How can motivation based on expectancy-value constructs and Brophy's (1999) model of the motivated learner be incorporated into innovative instructional technologies? This is a main question we are addressing in a new NSF-funded project at Harvard's Graduate School of Education, entitled *Transforming the Engagement of Students in Learning Algebra* (TESLA). For this project we are creating a 4-day mathematics intervention, two days of which will involve one of three technology-based motivational inductions for students in Grades 5-8. The first induction we describe is a Multi-User Virtual Environment (MUVE) that serves as a game-like activity introducing students to the concepts to be learned later in the 2-day classroom math lesson through their avatars' active involvement in an event. The second induction is also based

on the MUVE, but students participating in this activity are not interacting directly with the virtual world from a first-person perspective. Rather, students are vicariously watching computer agents in the MUVE think through and model different ways of solving various mathematical problems, with one of these agents being someone with whom the student can identify. The third induction provides a contrast to the MUVE interface, utilizing a non-immersive, passive video presentation typical of what a math teacher might use to foster student engagement. By comparing these three inductions, we can study how the effects of alternative types of motivation might work for various kinds of students.

Like most video games, our two MUVE activities immerse students in a 3-dimensional virtual environment where students are able to either take on the identity of a STEM professional and solve mathematical puzzles in an engaging manner (the first activity), or can vicariously observe others solving these puzzles (the second activity). Unlike commercial video games, however, our activities are designed to target specific mathematical learning goals and motivation variables. In designing a game-like environment that was both instructionally and motivationally sound, we removed elements of commercial games that either undermine or distract from the learning and motivational goals (e.g., competition, time-sensitive pressures, and overt performance goals). Below, we describe each of the two MUVE-based activities and sketch the third technology-based induction. We also describe the ways we used motivation theory to inform our design decisions.

Alternative Technology-based Motivational Inductions

What are the goals of our 4-day math intervention? First, the lessons are designed to teach students to identify mathematical patterns (e.g., the Fibonacci sequence) that arise while collecting complex data. We also wanted students to be able to generalize these mathematical

patterns in such a way that they could use them to solve novel but similar problems. Within the context of the two MUVE inductions, we created a number of cognitive scaffolds to facilitate students' understanding of the mathematical concepts to be taught, as well as motivational scaffolds to aid students in developing their mathematics motivation.

First Induction: Students as Active Protagonists in a MUVE

During the course of the first day of the intervention, students receiving the first induction solve a total of two puzzles in the MUVE that involve recognizing mathematical patterns in the context of a space rescue mission (see Figure 1 for a screenshot of the interface). The first puzzle allows students to

Insert Figure 1 about here

become accustomed to the virtual world and how to function and interact in it. As such, the mathematical puzzle is relatively easy so that students can familiarize themselves with the controls and so that they can experience an early success to build their self-efficacy. This first puzzle is similar to a combination-lock problem in that students must identify all possible ways that three numbers can be combined to produce a unique 3-digit number (see Figure 2 for a simple illustration).

Insert Figure 2 about here

When students finish this first puzzle, they proceed to a more complex and difficult second puzzle. This second puzzle is broken down into many smaller steps to scaffold students' learning and motivation. If students were given the entire puzzle all at once, many would be overwhelmed and could quickly become discouraged. This second puzzle serves as the entry point for the 2-day mathematics lesson on the second and third day of the intervention.

For this puzzle, students encounter a door that is locked. Next to the door is a box with some complex circuitry. Parts of this circuit board are complete, but the great majority of it is broken. Students must “fix” each section of the circuit board by building circuits with 1- and 2-unit length fuses. The circuits that must be constructed differ in size—at first, students build a 1-unit long circuit (only one possible combination if presented with only 1- and 2-unit long fuses). Then they build circuits that are 2-units long (2 possibilities: 1+1, and 2), 3-units long (3 possibilities: 1+1+1; 2+1; and 1+2), and so forth, until they reach a circuit that is 9-units in length (55 possible combinations) (see Figure 3 for a simple illustration).

Insert Figure 3 about here

What emerges from this activity is the fact that a Fibonacci series underlies the pattern (1, 2, 3, 5, 8, 13, 21, 34, 55). Because pupils are not explicitly taught the Fibonacci series in school, most students are likely to enter this activity unaware of this pattern. However, due to its simplicity, the activity is well within students’ cognitive zone of proximal development. We have designed this activity with many cognitive scaffolds in the beginning and progressively remove them as they progress. For example, students start out by building actual circuits that are 1-unit, 2-units, and 3-units in length using only 1-unit and 2-unit long fuses. By building each circuit, students are able to see for themselves how many circuits can be built at each height.

When students reach circuits that are 4- and 5-units long, the number of circuits that can be built at each height increases dramatically. Building each individual circuit becomes not only more difficult, but also more tedious. Therefore, students are shown all the different combinations that can be built at 3-units high (e.g., 1 + 1 + 1; 2 + 1; and 1+2 for a total of 3 circuits) and 4-units high. From this information, they must make an educated guess as to how many circuits can be made, using 1- and 2-unit length fuses, when the circuit is 5-units in length.

Students are no longer building this circuit from scratch (removing a scaffold). If they guess incorrectly, feedback is provided to students so that they can begin to build the individual circuits in a systematic and orderly fashion.

As students progress through this step to more complicated circuits (6-, 7-, 8-, and 9-units high), more scaffolds are removed so that students are progressively given more autonomy and responsibility for providing the correct response. Again, however, appropriate feedback is provided every time a student does not generate the correct response. At the end (for the 9-unit long circuit that requires 55 unique combinations), the environment is constructed so that students are not given the opportunity to build the circuits if their initial estimate is incorrect. Rather, students are given a visual cue showing the entire series of circuits that have been constructed and highlighting how many circuits were built at each length (1, 2, 3, 5, 8, etc.); students are then asked if they can identify a pattern from these numbers.

To heighten engagement, for every successful circuit students build, they receive a “key,” which is a square piece with a design on it. These keys are used to unlock the door in the end; when they are all interconnected, they form the golden spiral, which is a way to help students see the connection between the Fibonacci series and the golden spiral. This design decision was made in an effort to balance the importance of having minor extrinsic rewards with the need to provide intrinsic motivation in the form of an “ah ha” moment when students see the connection between the numerical series and the aesthetically interesting golden spiral, which can be found in nature as a Nautilus shell.

Recall that, in Brophy’s (1999) model of a motivated learner, he suggests providing educational activities that are within both the cognitive and motivational zones of proximal development. This MUVE was designed such that cognitive scaffolds provide the necessary

increasing levels of difficulty and the appropriate feedback for students to succeed. We also have designed the MUVE with motivational scaffolds that help students recognize that they have the competence to succeed in mathematics (i.e., building self-efficacy), and we have ensured that the content students are learning is interesting and connected to real life (i.e., connecting the Fibonacci series to nature, in the form of a Nautilus shell).

In addressing some other expectancy constructs in the expectancy-value theoretical framework, we took care that students attributed their successes and failures to factors that were internal and controllable. For example, we debated whether, in the second puzzle, students should be given a time limit within which they should finish the puzzles. However, this idea of including a time limit was discarded because students who fail the task (which could be a substantial proportion of the students) would make the unfortunate attribution about the cause of their failure as something that was external to themselves, but *uncontrollable*. If students failed because they believed they lacked sufficient time to be successful, they are likely to experience frustration at the activity or think of the activity as meaningless and unhelpful. In designing the activity such that time is not a factor, and that appropriate strategies are at the heart of the activity, we helped ensure that students would make adaptive rather than maladaptive attributions for their successes and failures.

Furthermore, to focus students on the fact that strategies are at the heart of successfully solving the mathematics problems, we designed the MUVE such that students receive the implicit message that their ability to successfully solve complex mathematical puzzles is dependent on strategies that are well within their own personal control. Successful completion is not dependent on some innate mathematical intelligence that is completely out of their personal

control. This design element serves to bolster students' incremental theory of ability and counteract the idea that ability is fixed.

These engagement scaffolds are designed to help students enter the motivational zone of proximal development. By equipping students with the beliefs that they are competent in solving mathematical puzzles, and that these puzzles are not isolated and completely unrelated to real-life, we are helping students enter the second and third days of the math intervention with the cognitive *and* motivational propensities that help ensure optimal learning.

Second Induction: Students as Vicarious Participants in a MUVE

The second technology-based induction was based on the game-like MUVE. However, this *vicarious* activity was created as a video where students watched a 5-minute video clip of a young, real-life, STEM professional who talked about the nature of the work they do (e.g., designing astronaut space suits), the difficulties they encountered in their K-12 math and science classes, and how they were able to overcome these difficulties. We are developing a number of these videos using a range of demographic attributes of the STEM professionals, so that most students can experience a video in which they individually identify with the person whom they are viewing.

After this clip finishes, students are able to watch a computer-generated agent that looks like the STEM professional they just watched solve the same series of puzzles that were described above in the first induction. This computer-generated agent leads a team of scientists in attempting to solve these puzzles. The student is a vicarious bystander who has the privilege of hearing the conversations of the team.

By listening to the conversations of the team members solving the puzzles, students are able to learn how to solve the puzzles through modeling. The agents convey ideas and

demonstrate strategies for learning about how to recognize mathematical patterns. But these computerized agents do not *only* model cognitive information. They also model *motivational* and *affective* information to help students understand the importance of learning the material and the importance of persisting and figuring out the correct strategies.

In addition, the 5-minute video interview of the STEM professional is meant to convey the message to students that, not only does persistence pay off affectively, but it also can result in a personally rewarding STEM career. Because the models in the interview are young, are in careers that students are apt to view as attractive (e.g., space suit designer for NASA), and are racially/ethnically diverse, we hope that students can readily identify with the role model to whom they are matched and can reap the motivational benefits more easily than if the models were perceived as completely dissimilar to the students.

This principle is congruent with Bandura's (1997) contention that self-efficacy beliefs are formed through vicarious experiences, but that these vicarious experiences are most powerful only when students see the models as similar to themselves. Although there is not much consistent empirical evidence informing us about the criteria that students use to identify similar models, we plan to initiate several pilots to investigate how students identify appropriate vicarious models. Our hope is that this information will help us refine our technological interventions to more finely target students' vicarious experiences.

Third Induction: Students Passively Assimilating Information

We are still developing the details of our third induction, which will use a video-based intervention to motivate students. The video segment will consist of a mixture of documentary material (e.g., the beauty of patterns in nature) and material from the entertainment industry (e.g., science fiction movie segments that involve pattern recognition, such as *Stargate*). This

induction is designed to provide a contrast to the MUVES typical of what a mathematics teacher might use to motivate students.

Inclusion of Other Theories about Instructional Design

Contrasting Our Approach to the ARCS model. Components of these theoretically rigorous motivational frameworks have been used before in Keller's (1987a, 1987b, 1999) ARCS model for instructional design. The ARCS model is based on applying the four factors of Attention, Relevance, Confidence, and Satisfaction to promote and sustain motivation. An instrument, the Instructional Materials Motivation Survey (IMMS), was developed by Keller to address each of these four factors. However, we believe that, by using constructs housed within sound psychological theory (e.g., self-efficacy or implicit theories of ability), educators, researchers, and designers can more effectively assess participants' motivation.

For example, the IMMS assessment, though attempting to assess things like "confidence," does not validly assess self-efficacy. Bandura (1997) argued that,

The construct of self-efficacy differs from the colloquial term "confidence." Confidence is a nonspecific term that refers to strength of belief but does not necessarily specify what the certainty is about. I can be supremely confident that I will fail at an endeavor. Perceived self-efficacy refers to belief in one's agentic capabilities, that one can produce given levels of attainment. A self-efficacy belief, therefore, includes both an affirmation of a capability level and the strength of that belief. Confidence is a catchword rather than a construct embedded in a theoretical system. (p. 383)

Nevertheless, the ARCS model was influential in the way we designed our technology activities that went beyond what expectancy-value constructs offered. For example, Attention

(from Keller's ARCS model) can be aroused using 1) *Perceptual arousal*, which uses uncertainty and environmental context; 2) *Inquiry arousal*, which stimulates motivation through the use of challenge and problems; and 3) *Variability*, which promotes motivation through change.

Grabbing and sustaining students' attention is not something that is inherently a part of the expectancy-value framework. Yet, this is highly important when designing technological activities for students.

Our 3-D immersive game-like environment implemented challenging puzzles to meet these attention needs. Active participation in solving the puzzles promotes engagement while providing enough motivational and content scaffolding to keep the player motivated to continue. Furthermore, we designed each puzzle to be more sophisticated and technologically advanced than the previous ones that students have encountered. By increasing how challenging the puzzles are and by varying the context in which students are immersed, we hope to promote students' ongoing motivation to engage with the environment and therefore to continue learning more sophisticated mathematical patterns.

Wlodkowski's time-continuum model. School-aged children living in today's technology-rich culture are accustomed to using technology to know and understand themselves and the world around them. For this reason, it seems clear that mathematics instruction that is both motivating and intellectually rigorous for today's 21st century learner will require both well-designed technological activities and classroom instruction that is seamlessly tied together. For this reason, we used Wlodkowski's (1985, 1989) Time-Continuum Model to help us inject motivationally relevant material at appropriate times. The Time-Continuum Model specifies three stages for learning that occur before, during, and after instruction to help bolster students'

motivation. In a sense, the model aids instructional designers in designing and implementing material that will situate students in their optimal motivational zone of proximal development.

The first stage occurs before instruction begins, and focuses on the attitudes and needs of the students. In TESLA, for example, we designed the 4-day intervention such that students would experience a technology-based motivational activity before classroom instruction began. By doing this, students are given the opportunity to explore the content in a fun and rewarding context before beginning formal mathematics instruction. In the first two inductions, the experience of interacting with the content in a 3-D immersive game-like environment that is relevant to learners provides a context of learning that is different from the classroom. Self-directed exploration of the content provides a safe and fun environment for the introduction of the two day lesson.

The second phase of Wlodkowski's model occurs during instruction. In this stage, attention is focused on increasing students' stimulation and affect. Wlodkowski provided several ways to address students' stimulation and affect during instruction. For example, teachers should make use of relevant questions, different presentation styles, and modes of instruction to keep students stimulated while learning. As an illustration, during the second and third days of our mathematics intervention, students are exposed to a problem-based and inquiry-oriented math lesson. Teachers ask students interesting questions and allow students to work in small groups to brainstorm strategies for solving mathematical problems that are similar to the ones they were introduced to in the technology activities. Furthermore, because the mathematical patterns are explored in the classroom using physical manipulatives instead of digital ones, students are given the opportunity to understand the mathematical concepts using a different context, thereby further bolstering their mathematical understanding.

The final phase of the model focuses on competence and reinforcement after instruction. Wlodkowski argues that the learning experience should end with a strong message that emphasizes student competence through reinforcement. This is best done using targeted and personalized feedback. With TESLA, for example, on Day 4, students are allowed to return to the 3-D immersive environment to explore and test their understanding of the content of the two day lesson. Students are able to see new puzzles that extend and reinforce what they have learned over the course of the past two days of classroom instruction. Feedback and progress in the immersive environment provide the student with necessary feedback of their understanding of the content. The staggered content and motivational scaffolds that are built into the immersive environment reinforce students' beliefs that they possess the knowledge and skills, as well as the competence necessary to succeed in learning mathematics.

Conclusion

Our purpose in the TESLA project is to bring a rigorous and well-studied theoretical framework of academic motivation to the study and design of virtual learning environments. We also hope that, by providing a case study of an NSF-funded project underway at the Harvard Graduate School of Education, we could illustrate heuristics for how motivation theory informed the design of our virtual environments, and how Keller's ARCS model and Wlodkowski's Time-Continuum model aided the design of our overall mathematics intervention. By incorporating innovative technologies into a 4-day mathematics lesson for middle school students, we intend to target a "sweet spot" that resides at the intersection of cognitive and motivational readiness. The technology activities bolster students' motivation; and the classroom lessons, framed in problem-based and inquiry-oriented pedagogical practices, support students' cognitive development in learning mathematics. In so doing, we hope to prepare both

competent and confident learners who are excited about pursuing the types of careers that are rapidly growing in a technology-based economy.

Table 1

Three Dimensions of Attribution Theory With Examples

	Internal		External	
	Controllable	Uncontrollable	Controllable	Uncontrollable
Stable	Long-term effort	Ability	Teacher Bias	Difficulty of Task
Unstable	Knowledge or Strategy use	Health or Mood	Peer or teacher help	Luck

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Key Terms and Definitions

1. **Attributions:** The perceived cause(s) of one's successes and failures.
2. **Implicit theories of ability:** The belief that one's abilities are either static or malleable.
3. **Self-efficacy:** How confident people are that they can successfully perform a task at a given level of attainment.
4. **Value:** Beliefs about how a task meets an individual's needs.
5. **Engagement:** The physical, affective, and/or cognitive aspects of an activity that holds a person's attention.
6. **Induction:** An engaging activity that introduces students to a concept.
7. **Zone of Proximal Development (ZPD):** The range of knowledge and skills that students are not yet ready to learn on their own but can learn with the help of their teachers.

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Figure 1
Screenshot of Interface for the Immersive Virtual World



Figure 2
Illustration of First Puzzle



Figure 3
Screenshot of one Section of Puzzle 2

