eLearning

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1 Why Do We Care About Engagement in eLearning?

It might be worth taking a moment to set the stage of why engagement is a worthwhile construct to study when looking at learning in general and eLearning in particular. It's important to remind ourselves that the reason so many researchers and educational designers are interested in engagement is not because they simply want to engage people, but it is because they want to change people's behavior. In eLearning contexts, behaviors such as clicking on video links more frequently, revisiting an online course more often, or even spending more time with learning materials are not the goals in and of themselves. Rather, instructional designers want to create learning environments to shape behavior that leads to enhanced learning outcomes; they wish to encourage learners to put forth time and effort toward thinking and experiencing learning content and activities that are deemed to be central to schema (i.e., mental concept) development and skill acquisition.

In order to understand what kinds of observed behaviors exhibited by an individual are indicative of engagement that leads to learning, educational researchers such as ourselves need to consider not only *what* is learned but also *why* we saw the outcomes we did. For example, if we looked at an engineering student taking an undergraduate course as part of their curriculum, we would want to be able to both understand the mechanisms at work that shape the student's learning outcomes in the course and also hopefully use the same general model to drill down and look at specific elements of the course while also being able to pull back and take a broader

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look at this student's educational arc of experience. One such model we could apply at all these levels is a *cascading goal hierarchy*, of which engagement is a central driving component.

To better understand this concept of a cascading goal hierarchy, let's take a closer look at our student. She is a sophomore mechanical engineering student who has set a goal of graduating near the top of her class and going to work for an aerospace firm. Right now, however, she has to do well in her classes this semester, including an introductory statics course for which she has a goal of getting an "A". The class has a number of learning components online, including the homework problem sets that are due each week. Since the homework sets are worth 30 % of the grade and form the basis of what is on the quizzes and tests, she has set a goal of completing every homework set, understanding the concepts being utilized, and solving most of the problems correctly. Coupled with each of the stated goals is a requisite mode of engagement. She wants a mechanical engineering degree; therefore she has engaged with this goal by enrolling in a set of classes. Successful completion of the statics course requires going to class, taking notes, reading the textbook, and completing the online homework—all of which leverage behavioral and cognitive engagement. The homework problems will require focused, cognitive engagement in reading, comprehension, and problem-solving. For each of these goals in which she has engaged in, there is a set of explicit and implicit outcomes against which she will measure herself. In both the long and short term, she will reflect on the outcomes against her engaged effort and how far these outcomes get her toward her goals. She will then formulate at varying levels of complexity her next set of goals and strategies for engagement.

As you see, engagement sits dead center in this model between goals and outcomes. It effectively represents where "the rubber hits the road" for learning. Learning happens because she has decided to engage in the instructional tasks. If learning is the goal of our engineering student, our instructor, and the instructional designer of the curriculum, then each one of them has some level of responsibility for creating positive engagement with learning. That is, the goal is to shape both psychological states and behaviors that result in productive engagement. As educational researchers informing both instructors and instructional designers, we want to create learning environments that shape behavior by encouraging learners to put forth time and effort toward thinking and experiencing learning content and activities that instructors have deemed central to conceptual or skill development.

In both the small- and the large-scale learning contexts, one of the most important goals instructional designers are interested in are schema development on the part of the student that links new information with existing knowledge, forming more robust cognitive structures. These cognitive and physical skills may also be rehearsed in a variety of settings to the point of expert use and application. In addition, metacognitive skills may be developed to help our engineering student decide when, where, and how knowledge should be applied. Understanding these goals will help designers and instructors decide what productive behaviors they want our engineering student to engage in and, just importantly, how to create a learning environment that motivates our student to put forth effortful engagement in her learning. Our instructional designers may have rightfully concluded that they will have little influence over a student's larger goals—for example, the desire to obtain an engineering degree and work for an aerospace firm. However, instructional designers understand that they have the potential to significantly influence these overarching goals through the design of engaging day-to-day interactions such as coursework and in-class skill development.

Historically, the design of learning materials and environments was commonly made on assumptions about a learner's engagement. Take, for instance, our engineering student example. One such common assumption was that our student was not only motivated to become an engineer but that she was willing and able to positively engage with instructional content day in and day out. For instructional designers and class instructors, the goal for curriculum development has typically been to create a linear sequence of content in an optimal order of increasingly complex content. As computer-based (eLearning) instructional environments became more prevalent, there arose more interest in the flexibility and the usability of instructional content and its delivery mechanisms. For example, instructional designers began questioning whether the delivery of key elements could be manipulated such that they could be perceived and processed with the least amount of cognitive effort (e.g., [65]). There was a similar, parallel movement that also explored alternative pedagogies in presenting and supporting learning activities [42, 59]. However, much of this effort worked under an implicit assumption that learners would motivate themselves to positively engage in the instructional materials.

Today, a growing line of research recognizes that both the affective and cognitive dimensions of learner engagement must be attended to. While it is necessary that instructional environments need to be designed so that they are usable and comprehensible, it is now known that this is not sufficient. Learners need to engage with instructional content as a necessary precondition to learning, and for this, they typically need to be motivated to do so. While instructional designers can leave it to chance that this motivated engagement will happen, it is better to create instructional environments conducive to both engagement and learning.

2 What Underlies Our Willingness to Engage?

Working from the assumption that learning can be a positive enjoyable experience, educational researchers and the designers of eLearning environments have tapped the literature of positive psychology (e.g., [15]) to better understand how computer-based environments can be designed that are fun, enjoyable, and productive to the end goals (learning or otherwise) [44, 54].

The rise of powerful, interactive computing interfaces has understandably led to interest into how these interfaces can be designed to result in both positive affective and cognitive outcomes [39]. Researchers have begun to look to activities outside of the traditional educational world—sports, games, theater, and movies—as inspiration for behaviors, activities, and environmental stimulations that both give rise to positive affect and motivate individuals to engage in these activities.

Appropriately, with both the emergent technologies and social phenomena of computer-based entertainment, parallel developments in the art and science of video game development have also provided impetus to look more deeply at the links between gameplay, learning, and engagement [57]. In fact, since the very first computer-based training programs emerged in the 1960s and 1970s, instructional designers have explored ways to make learning a more engaging experience by adding game-like elements in their learning material. It stood to reason that if a game could engage players, then why couldn't aspects of game design be integrated into training and used to engage learners? After all, through simple observation, it was clear that most people experienced high levels of engagement and delight while playing games. Through these observations, early instructional designers developed computer-based training materials with a heavy emphasis on fun, yet the designs lacked the deeper insights into what mechanisms within a game were appropriate to use in learning contexts. As researchers continued to explore game design in the context of learning, a common theme emerged from social psychology in the form of Csikszentmihalyi's Flow Theory [2, 15].

Instructional designers noticed that concepts described in Flow Theory were commonly observable in game players. For example, players in flow often report being in an optimal experience with feelings of exhilaration and deep enjoyment. They are almost always intrinsically motivated and commonly report states such as focused concentration, feelings of control, and a lack of awareness of time. These are also the types of appealing experiences that instructional designers seek to create in online learning environments. But just how can instructional designers leverage game design mechanics to create these types of captivating experiences? After all, it is not as simple as "making learning fun" as was once thought. Insights from Flow Theory led to the recognition that a critical strategy for designing learning environments was to include elements of both work and play [71]. Understanding that learners, like other humans, have both work and play as a goal provides a starting point for unpacking the motivations that drive engagement.

One way of framing the motivation that resides behind engagement is the willingness to undertake future learning as a goal. Applying this lens raises the importance of the temporal dimension in understanding engagement. That is, our engineering student's willingness to engage in a learning activity at some point in the future is heavily influenced by both her current psychological state and her prior experience in similar activities. By extension, her perception of a current task or challenge will be shaped by what she believes the outcome will be which, in turn, is shaped by her past experience in similar situations [5, 61]. As pointed out earlier, goal-setting is often very hierarchical in nature. It follows that what is motivating our student to engage with a statics homework set is likely to be a combination of immediate goals concerning this specific homework set and longer-term goals for the semester or her academic career. Similarly, shorter-term goals may be artificially linked to goals somewhat extraneous to the task at hand; for example, our student may link going out for an ice cream as a reward after completing her homework set.

By doing so, she has created a temporal contingency as part of a personal strategy to motivate herself through a possibly not-so-exciting homework set with another shorter-term goal that will provide immediate pleasure.

Finally, the social dimension is critical to understanding the mechanisms of engagement. The reward for engaging in a learning task may not only be ice cream at the other end but the opportunity to work with other students. Social interaction, either direct or mediated by technology, is a very powerful force in shaping the motivation to engage. The relationship between the learner and those they are interacting with can be quite varied in terms of both their social relationship, the resulting nature of their interaction, and the degree to which the student finds these interactions motivating and engaging. Our engineering student may choose to do the homework set as part of a group activity in a library meeting room where she and her peers are all (hopefully) equally engaged in working through the problem set. This social interaction both mediates the cognitive aspects of learning and the affective dimensions driving the motivation to engage in this learning task. Just as easily, our engineering student may be engaged in the homework set by setting up a Google Hangout with her fellow students and virtually connecting with them [17, 28]. Instead of her peers, the student may be engaged by her teacher in a classroom setting [27] or an online setting where one-on-one tutoring may be taking place. For younger students, other adults besides a teacher (including parents) may be the motivating force [10]. Clearly, the social dynamic and the resulting engagement may be very different between peers and parents.

In this section, we have provided a simple scenario of our undergraduate engineering student to contextualize how engagement relates to learning. We have situated engagement as a central pivot point as to the quality of learning that occurs. Instructors and instructional designers not only need to design quality instructional content and present it in an efficacious manner, but the overall learning environment needs to be designed in a way that motivates learners to engage in effortful learning. A successful learning environment will attend to both the cognitive and affective needs of learners. Such design strategies recognize that learning can also be a psychologically positive experience. Because of this, the designers of eLearning environments have borrowed from social psychology research on other positive contexts such as gameplay and social interaction to design effective, engaging learning environments. These environments also recognize that engagement is deeply rooted in the temporal dimension of learning, the ever-changing state of the learner over time. Finally, emerging technologies and advanced learning theories have helped unlock a range of innovations that maximize engagement for learning.

3 Models of Engagement

This section explores a number of well-established and interrelated psychological models that help form an understanding of engagement. As is the case with many important constructs in the psychological sciences, there is no one unified model of

Motivation > Engagement > Learning

Fig. 1 General model of engagement—Step 1

engagement that we can make use of. Instead, we will use multiple lenses to create an integrative understanding of engagement in different learning contexts, resulting in different behaviors and outcomes. All of these models will link to a high-level connected sequential model (Fig. 1).

Let's start by exploring this model's end goal of learning through the lens of information processing models of cognition as they provide very useful insights into this facet of engagement [79]. Such models provide a structured way of looking at cognition in a task-oriented environment, assessing cognitive aspects of task demand and resources required to meet cognitive processing needs. At the heart of information processing models is the notion of resource allocation. That is, the human cognitive system functions in a constant stream of information from both the natural and human-built world. From this fire hose of information, decisions are constantly being made with regard to which streams of information should be attended to and processed. While some of these streams are automatically processed to some degree, only a limited amount of this information can be processed at a conscious, cognitive level. To do so requires attention to, and engagement with, these information streams. Executive functions in the cognitive system make decisions as to what to attend to and, therefore, what (limited) cognitive resources should be directed to these information streams for further processing [78, 80].

A relevant framework built from this general model is Cognitive Load Theory [52, 75]. This theory is predicated on the basic information processing model of limited working memory and (effectively) unlimited long-term memory. This theory was developed specifically to better understand both how students learn and what learning environments are best suited for which kinds of learning tasks. Allied theories developed from the same general information processing model have come to similar conclusions concerning underlying cognitive mechanisms and outcomes [45]. These models work under the assumption that a primary goal is schema formation and the activation and modification of existing schemas for learning [73]. While entire books have been devoted to this concept, the relevant idea here is that Cognitive Load Theory posits that our limited short-term memory is central to the accessing, formation, and modification of schemas, which reside in long-term memory. Our metacognitive and attentional resources determine how short-term memory is going to be allocated. While the learner has made the higher-level decision to engage in a learning task, the design of the learning environment will heavily influence what specifically is attended to over the arc of a learning session.

Cognitive Load Theory posits three primary types of load that are applied to our limited short-term memory system. Intrinsic load is determined by the relationship of the characteristics of the learning task relative to the knowledge and abilities of the learner. This construct predicts that, generally, experts will experience lower cognitive load than novices with the same material. Extraneous load is dependent on the nature of the learning environment and the degree to which it creates cognitive load on the learner that is not directly related to the learning task at hand. Much research has gone into development of empirically derived design heuristics based on this construct [46, 53]. Perhaps the most relevant line of work, and also the one that has been of considerable research interest in recent years, has been on the third construct: germane cognitive load [47, 64]. This load is the voluntary cognitive effort the learner commits to schema formation above and beyond the other forms of load. At the risk of oversimplification, for a given learning task in a given learning environment, if intrinsic load is the given load and extraneous load is the bad load, then germane load is the good load necessary for maximizing the learning opportunities. The goal therefore is to have the learner maximize germane load within the capacity limits of short-term memory. Given the voluntary nature of germane load, how do we get learners to commit this effort? It is here that we now bridge from the purely cognitive domain to the affective domain.

For our engineering student, a novice at solving many of the kinds of problems she will eventually be asked to do as a professional engineer, the learning environment needs to be designed with a recognition of the intrinsic cognitive load on novices for such homework problem sets. In addition, this learning environment should be designed in a way that maximizes support for engaging in the cognitive task at hand and minimizes extraneous load. More of a challenge is figuring out how to maximize the germane load our student is willing to put into the learning task. In summary, information processing models help us better understand the learning component of our overarching sequence (Fig. 2).

Now it is time to move upstream and better understand what created the decision to engage in the learning task at a level appropriate for learning. Self-determination theory [61] takes us back to the beginning of the sequence and explores why, and under what conditions, individuals in learning contexts and elsewhere are willing to engage in effortful tasks. Based on a fundamental understanding of human need for self-fulfillment, this theory explores the conditions for self-motivation around specific goals and states. In this case, we're particularly interested in what makes individuals motivated to learn, both the existing traits and experiences an individual brings to a learning context, but also under what conditions within the learning task psychological states will be created that continue to motivate the learner. These motivations can come both from external (extrinsic or instrumental) influences and factors and internal (intrinsic) ones. Intrinsic motivation is a fundamental manifestation of the human tendency toward learning and creativity [15]. Here, we can see the interaction of an individual learner's traits with the current learning conditions to either motivate or de-motivate the individual to engage in learning. Extrinsic motivation recognizes that most individuals function a good part of their

Motivation > Engagement > [Cognitive effort towards schema formation in a learning context] > Learning

Fig. 2 General model of engagement—Step 2 lives in a social context that has requirements or pressures to engage in activities that we otherwise might not be intrinsically motivated to pursue. Though research has consistently shown that extrinsic or instrumental motivating factors do not have the power of intrinsic factors for long-term motivation, they are a recognizable influence, both positive and negative, for our current state of motivation [86].

Self-determination theory and cognitive evaluation theory (a related sub-theory) posit that self-motivation is our natural state and will flourish if provided with the right conditions [21]. However, individuals will only be intrinsically motivated to do things that hold intrinsic interest to them, activities that have the appeal of novelty, challenge, and aesthetic value. More distally, these activities need to be related to either longer- or shorter-term goals and help to reinforce one's autonomy and competence. Collectively, this broad framework provides many avenues for learning environments that either motivate or de-motivate an individual. It is important to realize that factors driving extrinsic motivation are not wholly separate from intrinsic ones. Quite often, immediate tasks may be driven extrinsically with the knowledge that, in the larger picture, the tasks that will provide fulfillment of goals are intrinsically motivating. It will be, in part, the degree to which an individual has the self-regulation to motivate through these otherwise extrinsically driven tasks by linking them to longer-term goals.

Linking intrinsic and extrinsic motivation can perhaps best be done by thinking how temporally framed goals are a primary driver of these motivations. Let's return to our engineering student. Her long-term goal of being an engineer is intrinsically motivating to her because she believes this career will help her demonstrate socially desirable competencies (for which she will be well compensated for) and express creativity through self-volition. However, first she has to get through this homework set. There may be a combination of both extrinsically driven motivations (her instructor has told her this homework set is due tomorrow or it will be assessed a late penalty) and other intrinsic motivations (she truly enjoys the ice cream she will reward herself with at the completion of the assignment) that she will use to move herself closer to that long-term goal.

Expectancy-value theory [24, 82] takes the fundamental notions of self-determination theory and sets it within a task-driven environment where learners are setting goals at varying temporal scales. In a sense, while this is a very robust theory that generalizes into many contexts, it also is extremely helpful in operationalizing the particulars of engagement. For example, by understanding what the learner believes to be the mechanism(s) and strategies for the desired goal or outcome, we are able to discover the critical elements used for goal-setting as a driver for motivation. Our student will need to assess what is the likely cognitive effort (load) based both on the material to be learned and the context in which the learning will take place. Similarly, she may weigh the risk-rewards of multiple possible pathways or strategies. Central to this decision-making are considerations of both general self-efficacy and specific self-efficacy around the task at hand [8]. That is, how capable does our student feel she is at learning and problem-solving in general, and how capable does she feel at solving this specific homework set? Similarly, control beliefs will drive decision-making by assessing how much the individual feels the outcome(s) is under their own control. Collectively, self-efficacy and control beliefs help form the degree of agency the learner feels they have in determining the outcomes for specific goals they have set.

We can see how these factors will drive the multitude of ways in which a learner may engage in the material. Generally, students are more likely to become engaged when academic work intellectually involves them in active processes they find meaningful. Such activity enhances one's perception of competence and autonomy, contributing to students' engagement, likely by increasing self-efficacy and perceptions of self-worth as suggested by these models of motivation [24, 55, 71]. For example, they may feel that they are good at problem-solving in general, but don't feel very confident in the kinds of problems presented in this homework set. They may also feel that they are capable of solving this homework set, but the learning management system has been acting up all day and they do not trust the system will stay up long enough to allow them to complete the homework set. More broadly, they may be weighing strategies of seeking help from the course teaching assistant versus trying to tackle the homework set on their own, based on the time and effort required and the likelihood of getting an acceptable grade on the assignment. Implicit in this decision-making with how and where to engage in learning is the student's self-regulatory ability to make good decisions [66]. Another central driver to this decision-making is going to be the value that the individual places on the various goals and alternative outcomes. These, of course, can be driven both by a positive desire for a particular outcome and the negative desire to avoid other ones. In addition, there almost inevitably will be conflicting goals—often short-term goals pitted against long-term ones—which need to be weighed based on their intrinsic and extrinsic value.

Theory has now fleshed out the sequence on both sides of engagement (Fig. 3). These broad cognitive and social psychological theories have been applied in many contexts and used to address many theoretical and practical questions. Here, we have brought these theories together to understand the antecedents and outcomes of engagement in a learning context. Now the task will be to see what are the specific strategies that are likely to lead to positive, productive engagement. In addition, we need to understand what engagement looks like, so that it can be recognized and facilitated.

[Goals, values and the expected outcomes]
[Extrinsic and Intrinsic] Motivation > Engagement > [Cognitive effort towards schema formation in a learning context] > Learning

Fig. 3 General model of engagement—Step 3

4 Elements of Engaging eLearning Environments

At the broadest level, engaging learning environments will need to both engender and support motivation to learn, limit barriers to engagement, provide feedback as to a student's progress toward their learning goals, and provide a robust environment that adapts and supports learning based on a student's current affective and cognitive state. Fundamental to this is an understanding that this process proceeds cyclically over time as a hierarchy of goal states unfold. Additionally, a student's perceptions based on how they have cognitively and affectively responded to the task will ultimately drive the engagement process.

A student will engage initially with an eLearning environment with a set of shorter- and longer-term goals in mind. The environment will hopefully provide a clear set of information that facilitates this goal formulation and strategies to meet these goals. Our engineering student, at the beginning of the semester, has signed up for the statics course based on information she has received from her advisor. More immediately, she is now on the learning management system formulating goals for successfully completing this homework set. The environment needs to help her quickly assess what needs to be done, what is the likely effort required, and what are the risks and rewards of different strategies to achieving these goal states. This information feeds into setting both extrinsic and intrinsic motivational factors. Incorrectly assessing these factors means surprise and possibly maladaptive responses to negative affective states such as disappointment and frustration [7]. These negative states can be de-motivators that feed disengagement. If this happens often enough, a student may question their agency in achieving their goals: do they have control over their ability to successfully complete this course and reach this important longer-term goal? This crisis of faith will put considerable downward pressure on engagement.

Once the decision is made to engage with the learning environment, the goal of the instructional designer is to make sure that the experience engenders those positive psychological states that lead to both continued (short term) and returning (long term) engagement. A number of positive factors can help propel engagement forward. The best learning environments will strike the appropriate level of both challenge and immediate enjoyment. The challenge needs to come in forms that allow learners to demonstrate the mastery, continue to build on it, and know that they are in a supportive environment that will help them achieve their goals. Immediate enjoyment can come from many forms; while it may be derived from achieving short-term goals ("I got that problem right!"), it may also derive from more universal positive experiences, such as an aesthetically pleasing learning context, positive social interactions with peers and instructors, or other elements that create a fundamentally positive physiological experience [77]. Perhaps this is worth expanding on. As noted earlier, humans naturally seek out positive psychological and physiological experiences—either simply for the sake of it or because it represents achieving some other goal [15, 71].

In learning environments, this often takes the form of seeking out achievable challenges tied to goals a student might have. The resulting state, flow, is both what is sought and the result of engaging in these activities. This state of flow is complex and researchers are still a long way from fully unraveling this construct. It is clear that it is related to the concept of immersion, or telepresence, which is characterized by many of the same psychological states as flow, including loss of awareness of time and place. Gameplay [12] and narrative-driven environments [22, 72], supported by perceptual experiences that dominate the senses (i.e., virtual reality), are designed to create these types of positive experiences. A compelling story can quickly sustain a person's engagement for hours on end. This can be so influential that it can induce a parasocial interaction where people intrinsically desire to interact with story characters [16]. This aspect of "computers as theater" induces a willing suspension of disbelief just as when a person becomes enthralled while watching a film [40]. When a person engages with a story, they typically report feelings of flow, enjoyment, persuasion, and telepresence [23]. A good narrative should facilitate the ease of which a person experiences learning over time. Hazari et al. [32] call this ease of cognitive access, and it is directly related to the more general goal of creating a highly usable eLearning interface. In sum, quite often the most engaging learning environments are those that manage to find a balance between (achievable) challenge and play and can be situated in immersive, narrative-driven contexts—too rarely seen in current learning environments [71].

Throughout history, people have created communities of practice that provide environments where collective learning can be achieved [70]. The introduction of electronic social media and user-contributed content on the Internet lends itself extremely well to these types of communities of practice. It should be no surprise that social media is considered highly engaging, and sometimes addicting, as it dominates many people's online activities. The lines between work and play are increasingly becoming blurred as students are commonly integrating their use of social media with their scholastic activities [16]. This provides an opportunity for researchers and educators to carefully examine which elements of social media are engaging and can be used to thoughtfully facilitate learning.

One such engaging aspect of social media is simply the act of interacting with others. This can profoundly influence what and how much people learn [70]. Collaborative wikis and shared blogs are common and simple approaches for providing these types of opportunities for learners to collaborate and share in the learning experience [32]. However, simply creating environments where collaboration may occur does not always ensure high levels of engagement and, more importantly, higher learning outcomes compared to traditional educational approaches. In order to design engaging collaborative environments where it is more likely for learning to take place, a thorough understanding of the mechanisms required to encourage engagement must be identified.

One aspect of social media that has been shown to impact learning by encouraging engagement and behavior change is simply the number of people in a social network, otherwise known as a network's social influence [56]. One reason behavior change may be affected by interacting in larger groups is due to the power of normative social influence where people often mirror what they see others do in order to fit in and be accepted. Furthermore, people generally collaborate in the context of learning when they feel that the people they are collaborating with can provide them with information more efficiently compared to learning solo [52].

It's also important to be aware of the potential obstacles that online learning environments may produce. For example, the group as a whole may be engaged in learning, while some individuals disengage yet still benefit from the outcomes produced by the group. This problem is known as the freerider problem [43] and must be monitored by any educator who leverages social collaborative learning tools. Additionally, it's important to make sure that students are not simply socially engaged, but rather that they are intellectually engaged, because simply collaborating and interacting in an online shared environment does not necessarily guarantee that a person will learn [43]. Interacting in an online learning environment does not mean a person is engaged in actively learning new and increasingly challenging content. Research has demonstrated that people may elect to engage in a task yet purposefully maintain a low level of challenge as long as the environment remains fun and continues to produce a degree of positive affect [67].

Central to the application of these engagement strategies is communication back to the learner. The art of good instructional design often hinges on how performance feedback is provided to the learner. When does our engineering student want feedback? After every problem or only at the end of the set? Do they only want positive feedback when they get a question right or also encouragement when they get one wrong? When do they feel pandered to with false praise, and when does the environment feel unfeeling and cold? Not surprisingly, feedback needs to be carefully tuned to factors that reinforce intrinsic motivation and the mastery goals associated with them [1]. Appropriate feedback sends the message to the learner that they properly assessed their ability and strategies for achieving the goals they set out to tackle. It supports them affectively and helps them cognitively calculate strategies for moving forward toward the next set of goals. A recent trend has been to provide this feedback in the form of "badges." However, it is important to consider whether the feedback is private and targeting intrinsic motivational factors or more public acknowledgement of one's successes. This latter form tends to support extrinsic, instrumental factors and may not be as successful for longer-term engagement [1, 3].

Not surprisingly, many of the factors that detract from engagement are foils for those that enhance it. Usability of the learning environment is a necessary but not sufficient factor for engagement. Poor usability creates unnecessary extraneous cognitive load, saps agency from the learner, and leaves a negative aesthetic impression. Poor instructional design can present educational challenges to learners that are either perceived as too hard to achieve or unrelated to their intrinsic goals. Finally, insufficient or the wrong kind of information can detract from a learners ability to assess their progress toward goals or present unwanted or inappropriate feedback. Usability can also be seen at the center of many information failures. While performance information may be available to the learner, usability issues may make it hard to access or interpret this information.

While there are both positive and negative factors that contribute to engagement, it is important to note that engagement followed by disengagement is not only expected but necessary. Embedded within the cascading goal structure is a natural hierarchy of engagement-disengagement cycles. In the short term, it is simply too cognitively demanding for an individual to stay at a high level of cognitive performance on any single task for any considerable length of time. While some level of cognition, affect, and its accompanying physiological arousal is necessary for productive engagement, optimal levels of arousal in the short run will result in fatigue, stress, and accompanying performance decline in the long run [79]. Natural physiological needs for sleep, food, etc., will also invariably interrupt many learning tasks, whether the student likes it or not. For that reason, well-designed learning environments are created to engage students, but only for lengths of time considered manageable. While an online synchronous class may run for 2 h, an attentive instructor knows to break this time up into cognitively and physiologically manageable chunks and to give students breaks to get up, change focus momentarily, stretch, and take care of other needs. Our engineering student working on her homework assignment is given more freedom to decide how to regulate her time. However, good instructional design will not only sustain engagement in the assignment but will create appropriate breakpoints or changes in activity. Again, the video game industry has developed highly evolved design heuristics that maximize the effort of players while also recognizing their cognitive and physiological limitations. These designs work to find ways to increase a level of psychological momentum that encourages the game player/learner to continue despite natural cyclic disengagement effects [69]. Finally, there is a sound cognitive basis for this engagement/disengagement cycle in that limited cognitive resources effectively demand disengagement from external stimuli to give the brain time to process, organize, and consolidate newly acquired information into new and existing schema. There needs to be "time for reflection" in all learning situations [63, 74].

5 Operationalizing the Study of Engagement in eLearning

Both the broader theory presented here and general strategies for creating engaging learning environments provide insight into how instructional designers and instructors might create environments that leverage engagement strategies. However, as with all design problems, they must be created, tested, and modified to serve specific learning contexts and learner audiences. For that reason, it is necessary to operationalize these more broad-brush concepts and heuristics into tools that can be used by designers and researchers trying to understand and measure engagement in learning environments. Returning to Shernoff and colleagues [71], a very useful heuristic is that high-quality learning environments should contain elements of both work and play, and one can design instruments that measure both of these aspects. Similarly, given the nature of how instructional tools are designed, utilized, and studied in educational settings, it is also useful to consider factors that load primarily on the interaction between an individual and the instructional content and those interactions primarily driven by social (multi-individual) contexts. Both of these educational contexts are, in many cases, mediated in some way by technology. While we need to acknowledge the impact of many demographic and other individual differences on engagement, we are going to focus on operationalized models that apply broadly to educational environments utilized across the age range. That said, many measures of engagement allow you to apply individual differences as a lens to understand why differences emerge.

5.1 Self-report Measures

In many ways, self-report measures provide the most proximal measure of engagement. That is, we simply ask how engaged a student is in their task. Since whole books have been written on the methodological strengths and weaknesses of self-report, suffice it to say that self-report of engagement parallels the challenges of most other psychological constructs. Perhaps most important to note is the challenges of near-real time, interstitial reporting versus retrospective, post hoc reporting. While there is a great desire to avoid the inevitable increase in error from having individuals reconstruct past states of engagement on a post hoc instrument, there is the real concern that regular interval reporting will interrupt and, therefore, disengage individuals during their task. In general, self-report measures of engagement measure state-like constructs that are expected to be impacted by a specific activity or task. That is, they ask a learner to report on some specified past period across one or more scales that, collectively, provide insight as to their level of engagement. For that reason, they are administered post hoc with specific reference to the task/activity that the individual is to report on. Also, it is not uncommon to be paired with other instruments measuring additional constructs of interest, such as cognitive load, self-efficacy, etc.

At the individual level, a number of researchers have developed and researched self-report scales that provide post hoc measures of engagement. The user engagement scale (UES) [49–51] provides a template as to how engagement can be measured across a set of subscales that represent both the work and play aspects of engagement. As analyzed by Wiebe et al. [81], the UES can be thought of as consisting of four different subscales:

- Focused Attention. This subscale is based on Flow Theory and measures the degree to which the learner felt during the time a state of focused concentration, to the point of total absorption in the task or temporally disassociating.
- Satisfaction. This subscale asks the learner to reflect on their experience and the degree to which it is fun, interesting, endurable, and novel—essentially, whether they were satisfied with their experience.
- Perceived Usability. This subscale, as the name implies, concerns the perceived ease of use of the learning environment.

- Aesthetics. This subscale encompasses the visual appearance of the learning environment including, implicitly, its functionality and layout.

These four subscales, in turn, can be grouped based on how they load on the hedonic, play-oriented goals of the learner and the utilitarian, work-oriented goals [31, 48]. As designed, thinking about their experience from a hedonic standpoint of how enjoyable and positive their experience was, the Focused Attention and Satisfaction subscales provide an opportunity to report on that side of their experience. Conversely, they can report on the utilitarian, work-oriented experience through the Usability and Aesthetics subscales. Collectively, these four scales can provide a self-report measure of the antecedent sources of engagement with a learning context.

5.2 Behavioral Measurement

An alternative to self-report measures is the measurement of behaviors by a third party. The challenge of such a measure, again, parallels the general methodological literature of such approaches. In this case, a researcher must make a strong connection between observable behaviors and the psychological state of engagement. Not surprisingly, the knowledge that the observer has of the student over a longer period of time (such that a teacher might have) can help with recognizing behaviors related to cognitive engagement [4]. Traditionally, behavioral measures are often used in conjunction with other measures to provide additional evidence rather than as a stand-alone source [18, 35]. Perhaps one of the most exciting avenues for the behavioral measurement is within online eLearning environments. Here, there is the potential to capture large quantities of real-time data across multiple dimensions (including learning outcome and self-report measures), where statistical power and cross validation of data sources can provide robust input into statistical modeling tools [11, 34, 62]. Along with being used by the researcher, this data can also be processed and visualized for use by the learner or instructor in the form of dashboards [13]. Here, data can be used to provide insight into learner engagement to instructors or used as a form of self-motivation on the part of the student. As with other forms of analysis, usability of this data for use by researchers or instructional designers will only be as strong as the psychological models that underlie the interpretation of the data.

As a special case of online learning environments, MOOCs (massive open online courses) provide a particularly interesting challenge for measuring user engagement through behavioral data [20]. The commonly voluntary nature of sign-ups to MOOCs would tend to point to the assumption that everyone in the MOOC is there because they are motivated to learn the material being presented in the course. However, the low penalty for engagement or disengagement at differing points of time means that users are allowed to formulate widely differing sets of goals for their engagement with the course. Unless the researcher has the ability to directly elicit what these goals are (and assuming students are able to articulate them), it can be a formidable challenge to attempt to model positive engagement outcomes based on their behavior and academic outcomes within the course. One element that many MOOCs have that provides a powerful mechanism both to engender engagement and to provide a method of measurement is online discussion forums. These forums provide rich communication streams between students and with instructors that can provide insight into the level and quality of engagement [3, 60].

5.3 Physiological Measurement

Another emergent area of measurement is the use of physiological measures. The rapid increase in the ratio of quality to price of biometric sensors that capture data plus the increased capacity for computational tools to process, visualize, and model this data has opened the door to inclusion of a wide range of measures by both researchers and developers [25]. One way of organizing physiological measurement methods is to distinguish between remote and direct measurement techniques. Those measures that can be collected remotely via cameras and image processing equipment include facial expression, body posture, and eye movement [29, 80]. More direct measures include sensors applied directly to the body to collect heart rate, brain activity (including EEG), and electrodermal (skin conductance) data [30, 76].

In general, remote collection is more scalable since it does not require “wiring up” individuals with sensors. Since so many computing devices now have built-in cameras, there is the potential of leveraging this data stream to help measure engagement. Even measures that require immediate proximity to the human body have become easier to leverage. The general movement toward self-measurement (i.e., the Quantified Self) means that many individuals are willing to wear multipurpose wireless sensors connected to cloud-based data analytics tools [41]. Physiological measurement, as is the case with almost all real-time trace data sources, embodies the paradox of having a wealth of data yet lacking the tools and techniques to meaningfully interpret it [6, 11]. Increased sophistication of computer modeling algorithms and power has meant a rapid increase in the utility to leverage these data streams. With physiological data streams, as with all data streams that can be collected without the individual’s knowledge, it is particularly important that the proper safeguards are in place to acquire meaningful, active consent before it is leveraged as part of eLearning research activities.

In summary, we have discussed how we can use expectancy-value theory [24, 82] to take the fundamental notions of self-determination theory and set it within a task-driven, goal-oriented learning environment. These goals work within the motivation engine that drives engagement with cognitively demanding, but personally meaningful, learning tasks. We went on to describe how the design of eLearning environments can engender and support motivation to learn and limit structural barriers to engagement while providing feedback on progress toward learning goals. More advanced systems can also provide a robust environment that adapts and supports learning based on a student's current affective and cognitive state. Finally, methodological approaches to the study of engagement in eLearning environments were discussed in order to better understand how this field of work and its theoretical underpinnings might be moved forward.

6 Case Studies

We now present two case studies that have built off this overarching framework. In the first case study, GridBlocker, we discuss an experimental game-based learning environment that was specifically designed to manipulate motivation based on Flow Theory's notion of achievable challenges in order to maximize both level of engagement and learning outcomes. In addition, it leveraged the temporal cycle of engagement/disengagement to provide an additional measure of intrinsic motivation. In the second case study, MOOC-Ed, an exploratory study to better understand engagement in a free-choice learning environment is described. Here trace data of behavioral engagement with the eLearning site over time is used in conjunction with data mining techniques to see how learners could be characterized and clustered. These cases are meant to provide a pair of examples, albeit limited, as to the breadth of study designs and entry points into the above-described theoretical, design, and methodological frameworks.

6.1 GridBlocker

As we have demonstrated, instructional designers often borrow insights from video game developers when seeking to develop engaging online learning environments. Such learning environments often make use of both challenge and narrative design elements from the video game genre. One of the more common challenge-based design patterns borrowed from video games is the balancing of player control for selecting new challenges as they progress throughout a game. If players are given too much freedom, they may select challenges that they are not skilled enough to overcome which could lead to disengagement. Alternatively, in narrative-driven games, selecting challenges that are too easy could also lead to disengagement due to boredom and stagnation in the storyline. In this case study, a video game called GridBlocker [68] was developed to test the feasibility of applying an adaptive algorithm to automatically control the level of difficulty a player experienced based on real-time measures of performance, cognitive load, and affect. The goal was to keep the player engaged while also promoting skill development in as little time as possible.

One of the challenges this project sought to overcome was a previous finding that players are often content with maintaining a low level of difficulty as long as the game levels they play are considered fun [67]. In those findings, players were found to be passively engaged, resulting in a state of positive affect yet low desire for challenge. When developing simple, repetitive-action video games, this may actually be desirable if the only outcome of interest is self-perception of enjoyment; however, in terms of learning, this type of noncognitive engagement rarely promotes learning and skill development. This type of passive engagement is commonly found in eLearning courses that have emphasized the fun elements of video games without taking into account the more serious aspects of leveraging video game mechanics for enhancing engagement and schema development.

In order to investigate the efficacy of an adaptive algorithm to promote learning while maintaining positive affect, GridBlocker was developed with over 100 levels of varying difficulty. These levels were carefully developed in separate studies based on performance data and self-report measures of difficulty, challenge, and frustration. Gameplay in GridBlocker is based on a rectangular block that a player must navigate around an isometric tile-based game board. The goal is to place the block vertically over a target using a combination of three main types of movements. These movements are used to change the block's physical orientation and thus the position and location of the block on the game board. During the easier initial levels, the combinations of these movements are fairly straightforward and do not require much planning or expertise. As the game progresses, more complex combinations are required as the layout of the game board configuration becomes more complex. Players gain experience by observing and recognizing that certain combinations of movements can be used to position the block in desired locations, much like in chess or in the process for solving a Rubik's cube [38].

Three design conditions were developed: linear, choice, and adaptive. The linear condition simply incremented the difficulty of each subsequent level that a player completed. This is the most straightforward approach to developing eLearning courses. Content increasingly becomes more difficult as learners progress throughout the course. Typically, the slope of the increase in difficulty is based on the ideal learner of median ability, thus not matching either slower or faster learners. In the choice condition, players chose an easier, more difficult, or similar level of difficulty to play next. Promoting user autonomy by providing these options has often been thought to produce engaging experiences for purely entertainment-based video games; however, engagement in the context of learning requires a person to not only engage with the game but also to learn new and more challenging content over time. Thus, it was unclear whether learners would choose appropriately challenging levels. The adaptive condition selected the difficulty of each level based on a player's past performance, cognitive load, and affect. Performance was measured as the length of time it took a player to complete a level compared to an ideal time based on data captured during the level-building design studies. Real-time affect was indirectly measured based on a novel game-clock that captured a player's desire to play the game when given the opportunity to stop in between game levels. Finally, cognitive load was measured as secondary task performance through an embedded monitoring task integrated within the game.

When comparing the players on all three conditions, it was found that players in the adaptive algorithm maintained high levels of positive affect while also solving more challenging levels compared to players in the linear and choice conditions. Those in the choice condition recorded equally high levels of affect, but they did not select increasingly difficult levels. The linear condition produced slightly less affect, and players in this condition required more time to reach levels of difficulty equal to those in the adaptive condition. These findings reinforced prior research that predicted level of challenge needs to be tuned to the ability of users, as seen in the linear condition. Similarly, the choice condition supported the assumption that users would seek out levels of challenge that fulfilled hedonic desires for enjoyment through challenge, but not necessarily an optimal level of challenge for learning outcomes. Finally, the adaptive condition has supported prior research that (near) real-time measures of cognitive load and affect can be paired with user profiles of prior experience to help shape an engaging experience. Further research needs to be conducted to test the reasoning that the more engaged a person is, the more likely they are to experience optimal learning conditions. These findings may have implications for the design of online programs, such as eLearning courses, which could benefit from adaptive content of varying difficulty that is automatically selected based on real-time measures of engagement. Online learning content lends itself well to this type of design because it is fairly easy to divide and chunk content based on difficulty. However, considerable more work needs to be done to translate these findings from a fairly simple game-based environment into a complex, large-scale learning environment.

6.2 MOOC-Ed Project

Massive online open courses (MOOCs) are a way for learners to engage with educational content through a relatively new paradigm for delivering large-scale open access to online instruction, resources, and social networks or communities [3, 20, 33]. Web 2.0 technologies, backend cloud-based processing and storage and emergent intelligent pedagogical agents, coupled with the increasing access to web-enabled devices by the global population have meant that both traditional and nontraditional forms of instruction can be delivered at scale to large numbers of individuals. This scalability situates MOOCs in an ideal position to address a number of educational issues and research questions about the nature of online learning using large-scale data mining techniques [33]. However, the distal nature of MOOC activity makes for considerable challenge when it comes to measuring engagement. While traditional classroom settings allow for direct observation/measurement of learning activities [26] and experimental studies provide a good venue for collecting self-report or direct-measure physiological data, the distant, free-choice nature of MOOCs means that studying user engagement in this eLearning environment will mean depending primarily on trace data generated by learners interacting with web-based educational resources.

MOOCs attract a diverse population of users with different motivations and goals for participation compared to a traditional course [19, 36, 83, 84]. While MOOCs are widely criticized for their low completion rates—only a fraction of participants who register for a MOOC actually complete the MOOC [58]—there is reason to believe that the motivations and goals of MOOC users are decidedly different than that of traditional students [14]. Research by Clow and others (e.g., [3]) points to the importance of better understanding how learner goals and expectations for success may be very different for MOOCs than for traditional courses (online or not). In addition, the interplay between goals, effort, and cues used to gauge outcomes may lead to dynamic patterns of engagement that look different than traditional educational settings. Revealingly, for a MOOC offered by Google, only half of the participants indicated that they intended to complete the whole course [83]. Low completion rates may represent a reasonable outcome for many participants and typifies the great diversity of MOOC user goals, making it necessary to reframe and possibly restructure typical analyses relating to student dropout, participation patterns, and learning outcomes.

The nature of MOOCs enables this new platform for online education to provide exceptionally low barriers to participation in high-quality educational opportunities and, thus, has the potential to radically alter the educational enterprise [33]. However, it poses the need to re-operationalize and broaden what participation and success means within a MOOC [20, 85]. Similarly, the large numbers of diverse students who have voluntarily signed up for a MOOC provide the ideal context for theory-based quantitative modeling of students' motivations [21, 24, 61, 82] and resulting behavioral patterns of engagement [5, 26]. Using these psychological models within this context also provides an opportunity to engage in person-centered analysis to better understand the characteristics of MOOC users based on their behavioral patterns [9]. Insight into user characteristics provides the opportunity to better design MOOCs to meet the needs of these nontraditional students. A study evaluating alternative data mining techniques to understand student engagement through interactions with course content was conducted using trace data from an 8-week course designed specifically for educators (MOOC-Ed). This course engaged students in an online curriculum designed to provide critical professional development to educators through self-directed, peer-supported, and projected-based learning [37]. Students were professionals from all levels of an institution, including district planning teams, teachers, and students of education. Of the 1322 individuals who registered for the course, 1086 engaged in curriculum activities for either lesson content or forum discussions. Of these students, 68 % had master's degrees, 18 % had bachelor's degrees, 10 % had doctoral degrees, and 4 % had high school, 2-year, or professional degrees.

Based on prior data mining work with MOOCs and statistical principles of cluster analysis, three clustering techniques that use alternative distance metrics were implemented to cluster individuals based on their participation for each week in the MOOC: hierarchical agglomerative cluster analysis, two-step cluster analysis, and latent class growth analysis.

Overall, the clusters from each of the models reveal distinct patterns of MOOC usage and interaction across the 8 weeks of the course. However, the hierarchical clusters tended to overlap with one another more than either the two-step or LCGA clusters for the lesson interaction data. The pairs of clusters (one and four and two and three) were not distinguishable from each other for most of the weeks. In contrast, both the two-step and LCGA techniques produced clusters that were readily distinguishable from each other in terms of lesson interaction over time. LCGA cluster values only crossed each other once over all the weeks of the course, while two-step only had one cluster with more than one crossover. Therefore, for this data, the hierarchical technique did not provide results that were as interpretable as the fairly separate clusters produced by the other two methods.

Cluster agreement between the hierarchical technique and other methods was generally poor for lesson interaction, meaning that the class assignment was not comparable between methods. In contrast, LCGA and two-step cluster assignment for lesson interaction was quite good. The fairly strong agreement between the hierarchical model and the LCGA model for the forum data could be due to the fact that the forum data was more sparse with more people not participating at all, and the hierarchical model was better able to partition this data compared to the lesson data where a greater number of people participated at various weeks. On the other hand, LCGA and two-step clustering for forum data were not as strong. In examining the class trajectories, the two-step clustering model seems to be more sensitive to picking up dropout after initial participation in week one or two in the lesson data. Though not as sensitive, LCGA picks up the same trend while offering the added benefit of being able to assign a probability that an individual is in a specific cluster. Because of this probabilistic approach, cluster results from LCGA could be better situated to be used in an adaptive learning system as this analysis can be modified to predict cluster transitions.

This study provided additional insight to the research team as to how they might use student interaction with MOOC online content as one measure of engagement. Rather than use single, summative outcome measure of completion or dropout, this clustering technique provides a richer view of engagement with the educational resources over time. This data and the resulting cluster classifications can be integrated with other self-report and outcome data to better understand how to design engaging online experiences for a diversity of learners. Initial cluster models based on patterns of participation can be enriched with further data to better understand learner goals and whether their interactions with the MOOC have met these goals. Expectations that have not been met are likely to lead to either lower levels of engagement or discontinuation of participation altogether. Modeling approaches such as these may provide the groundwork for real-time monitoring tools for instructors or adaptive tools that provide guidance or recommendations for MOOC participants that help them find useful resources that align with their goals. The massive data sets generated by such courses open new statistical approaches for applying and refining psychological models of engagement, where researchers

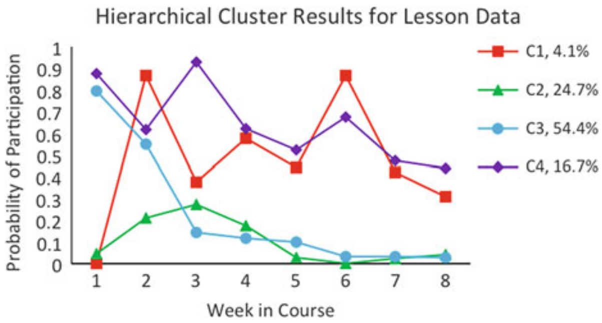

Fig. 4 Hierarchical (*top*) and latent class growth (*bottom*) models of learner cluster assignment

have typically relied on self-report data from smaller numbers of more homogenous groups of participants (Fig. 4).

7 Conclusion

The study of engagement in eLearning parallels the increased interest in developing models of learning that integrate both affective and cognitive elements of the human experience. This chapter began developing this model on a foundation of a cascading goal hierarchy. Exemplified by our model engineering student, there will be a set of interrelated goals that provide motivation to engage productively with an eLearning environment. Within this model, engagement sits at the center between the goals that trigger the motivation to engage in the eLearning environment and the outcomes that result from this engagement.

A model of engagement is developed by first exploring the underlying cognitive models of schema development that help both predict learning outcomes and also provide guidance for the design of eLearning environments that optimizes the application of cognitive effort toward learning. Moving to the antecedents of engagement, affective models that link goal-driven behavior to individual characteristics such as self-efficacy and agency are used to better understand what leads to behavioral and cognitive engagement in the first place. Central to this model is an understanding of the critical role of the temporal dimension. This model of engagement is heavily influenced by prior experience, and the outcomes, immediate and longer term, of engagement are constantly fed back into the model. Similarly, goal direction at the beginning of the cycle can be targeted to both long- and short-term goals that are varying degrees of relationship to the target engagement of interest to the researcher.

Finally, these basic, high-level models of engagement in eLearning are operationalized to some degree through a discussion of how instructional design elements such as game-based learning, narrative, and social can help productively engage learners. Conversely, these same heuristics, when inappropriately applied, have also been found to be detrimental to learning outcomes. Again, individual differences in learners need to be considered and accommodated within the application of these instructional design heuristics. The chapter closes with two case studies of how the authors team has applied these theoretical frameworks and design heuristics to the study of eLearning. In the first case study, experimental research driven by these theoretical frames is used to explore ways that game-based principles can be built into adaptive eLearning environments to maximize the cognitive effort and outcomes of learners while still providing an affectively positive experience. In the second case study, data mining techniques are used to investigate large-scale trace data from a MOOC to better understand how measures of engagement can be used to classify eLearning participants.

Both case studies point to the broad set of experimental and applied eLearning contexts in which these cognitive and affective models of engagement can be applied. Future work will continue to push along both of these fronts to continue to explore how eLearning contexts can be designed to dynamically respond to diverse learner populations and the evolving goal, motivation, and engagement states of learners.

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