Chapter

Intelligent Tutoring Systems That Adapt to Learner Motivation

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Abstract

This chapter provides an introduction to the topic of motivation from the point of view of those interested in the design or use of intelligent tutoring systems. To that end it introduces some of the complexities of motivational states and processes together with a range of motivational theories and their application in intelligent tutoring systems. The theories include learner beliefs about learning, including their goal orientation, their self-efficacy and their attributions of causality, as well as their academic emotions. It also introduces Keller's work on the design of tutoring systems that puts motivation at the heart of that design process. The chapter describes six tutoring systems that have been designed to deal with the learner's motivation, either as a one-off adaptation or dynamically. These six were chosen to cover a reasonably broad range of motivational theories and to cover the history of the field of motivationally adaptive intelligent tutoring systems from its start to the present day.

Keywords: intelligent tutoring systems, adaptation, motivation, learner

Introduction

The learner's motivation is a crucial element in determining the outcome of a lesson or a course. One of the strengths of human tutors is that they attempt to adapt to the

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individual progress of their learners in a dynamic way, moment by moment, including their motivation (Lepper & Woolverton, 2002). This dynamic adaption to the motivation of learners is also now an increasing focus of intelligent tutoring systems (Aleven, McLaughlin, Glenn, & Koedinger, 2017; du Boulay, 2016).

This chapter provides an introduction to the topic of motivation from the point of view of those interested in the design or use of intelligent tutoring systems. To that end it introduces some of the complexities of motivational states and processes, and a range of motivational theories and their application in intelligent tutoring systems. The chapter does *not* intend to be a detailed review of the field, but more a general introductory guide with sufficient references for the interested reader to study the topic further.

The next section provides a sense of how complex the phenomenon of motivation is. The section following it provides a brief description of three areas of motivational theory that have been applied in intelligent tutoring systems. In this chapter we use the term "intelligent tutoring system" to cover all kinds of adaptive instructional system (Aleven et al., 2017) as encompassed in the field of artificial intelligence in education. The section following that then describes six intelligent tutoring systems that span the development of the field in this area from the 1990s to the present day. Finally, some general conclusions are drawn with pointers to future work.

Motivational States and Processes Are Complex

In order to exemplify some of the complexity of motivation, we contrast two imaginary learners who exhibit opposite and extreme characteristics on various facets of motivation. Of course, real learners are unlikely to be so wholly positive or so wholly negative as these two caricatures but exhibit a range of positive and negative values on the facets.

At one extreme we can imagine a learner who really wants to understand the content of a lesson, who expects the work to be fun, interesting and even exciting, who is well prepared, who expects to be successful in the endeavour, who believes that both the process and the outcome are personally valuable, whose peer-group and culture are supportive, and whose likely positive experience as a result sets him or her up for future learning successes. At the other extreme we can imagine a learner who is indifferent about understanding the content, has little expectation of fun, who is not well prepared, who has little or no expectation of enjoyment or success, who does not believe that either the process or the outcome is worth the effort, whose peer-group and culture are unsupportive or even hostile, and whose likely negative experience will further undermine the possibility of successful future learning too.

While these two learners are at the extremes, most learners at some point fall into the middle ground where their motivation is initially, or later becomes compromised by some aspect of their negative expectations, their learning experience (including their affective experience) or their failure to see personal value in the lesson or course. This leaves the tutor with remedial, motivational work to do. This work may involve appeals to both intrinsic and extrinsic factors (Ryan & Deci, 2000) that might help motivate or re-motivate a particular learner, such as the higher salary they might hope to earn if they pass the exam, or the sense of satisfaction they well feel when they have mastered the material at hand.

Discounting issues around what they believe to be valuable to learn, another way of distinguishing learners' motivation at the two extremes is in terms of their understanding of themselves as learners: that is their meta-cognitive, meta-affective and meta-behavioural knowledge and self-regulation. In other words, their ability to monitor what they are learning and doing, and how they are feeling, as well as their effectiveness in managing the situation especially when they detect that things are not going well. The learner at the positive end of the spectrum will understand that new learning is assisted by certain ways of behaving, may well involve some uncertainty and anxiety, that difficulties and confusion may be encountered, that poor results may result in temporary despondency or even shame, but that these setbacks are to be expected as part and parcel of learning and can be dealt with effectively. Such a learner knows how learning works, both in general and personally, and is also likely to have acquired insight into their motivational processes and the ability to regulate these too: their meta-motivation (du Boulay et al., 2010). At the other end of the spectrum ineffective learning actions, task difficulties, confusion and negative outcomes, each with their negative affective responses can be motivationally disabling.

The typical intelligent tutoring system tends to operate towards the 'optimistic' end of the above spectrum of learners, with a certain degree of capability for dealing with short term and limited reductions in motivation but leaves it to human teachers to deal with any longer-term or deeper degrees of initial unmotivation or later demotivation. There are three reasons for this.

First, most intelligent tutoring systems are not designed to manage their own introduction into a lesson or course, as their designers assume that others will do that and that others will have undertaken the preliminary work required for the learner to be able to understand *why* they are learning the new material, what is in it for them and how it fits into the bigger framework of their learning. A large part of that introductory work will, of course, have been motivational in character.

Second, it is sometimes hard for human teachers, and even harder for intelligent tutoring systems, to gauge the state of a learner's motivation. There may be clues, of course, such as a slow-down in work rate, an increase in non-work activity, gaming the system (Baker et al., 2008), or signs of negative emotional arousal or disengagement, but these are just clues and not guaranteed to be linked in any direct way to particular states of motivation.

Third, it is not always clear what is best to be done to remedy a situation involving unmotivation or demotivation (du Boulay, 2011b). As indicated above in the contrast between the two learners at the extremes, there can be many different *kinds of reason* for demotivation, and different pedagogic moves by the teacher or tutoring system may be needed in each case. As Ryan and Deci (2000) have pointed out, it may be that the learner sees little intrinsic or, indeed, extrinsic value in either the process or the outcome of the work, so attention will need to be paid to trying to re-align the value of the learning to the learner or *vice versa*. As Elliott and Dweck (1988) and Ames (1992), among others, have shown, it may be that the learner's educational goals, e.g., just getting by or at least not failing, may not be the goals that their teacher might have wished for them, e.g., mastery learning. In this case the teacher/tutoring system has to decide whether to try to help the learner adjust their goals, or just work within the constraints of the learner's existing goals. As Keller (1987) has argued, it may be that the work has become boring, too easy or too difficult in which case it may need to be livened up or adjusted in difficulty. As Rosiek (2003) has explained, it may be that the topic of the work might arouse strong negative disabling emotions, in which case the way the topic is approached may need to be changed. As Dweck (2002a) has shown, it may be that the learner has a poor understanding of the nature of learning itself, e.g., in relation to effort, in which case some education and encouragement about learning itself is needed. As Bandura (1997) has demonstrated, it may be that the learner has little expectation of success on the content topic, in which case some immediate experience of success may be needed. As Ryan (2000) shows, it may be that the social context of the learner is interfering with their motivation, such as maintaining face amongst their peer group, in which case some social engineering may be needed. Sometimes the barrier to motivation is the way that the learning task itself is presented or organised; for example, as Arroyo, Beck, Woolf, Beal, and Schultz (2000) have pointed out, maybe the style of feedback on offer suits one learner better than another, and adjustments are needed to that. As Mayer (2014) has shown, it may be that the modalities of material have been chosen in such a way as to make learning hard, or involving too much cognitive load (Paas, Tuovinen, van Merriënboer, & Darabi, 2005).

Given the wide variety of reasons why a learner may be motivated, unmotivated or become demotivated, it is not surprising that there is as yet no detailed, overall motivational pedagogy to guide the design of intelligent tutoring systems. Two wide-ranging early attempts to explore how tutoring systems might be designed to be motivating were the "Taxonomy of intrinsic motivations for learning" (Malone & Lepper, 1987) and the "Attention, Relevance, Confidence, and Satisfaction" (ARCS) model of motivation (Keller, 1987), described below.

What we see at present is that individual intelligent tutoring systems track and attempt to remediate a limited subset of the issues that affect motivation (see for example, Arroyo et al., 2014). There are, of course, some generic pedagogic tactics to apply, such as adjusting the difficulty of the work to suit the learner, flagging up the purpose, progress and overall goals of the work, and offering encouragement and praise for effort. But even here care is needed in case they are misinterpreted (Dweck, 1999a). So perhaps the meta-rule of any motivational pedagogic strategy should at least be "try to do no harm."

THEORIES OF MOTIVATION

The literature on educational motivation in general is vast and cannot be easily summarised in this short chapter. Pintrich (2003) provides a good place to start and organises the motivation literature into the three areas of the learner's values, their expectancies (in other words, what they expect to happen) and their feelings. Eccles and Wigfield (2002) summarise the literature in a similar way but with less emphasis on issues around the affective aspects of motivation. For a longer introduction to issues of motivation in education, see Schunk, Pintrich, and Meece (2008). These researchers and the work they cite were not specifically concerned with the development of intelligent tutoring systems, but with how human teachers can manage and sustain the motivation of learners at all levels of formal education.

Given the coupling between motivation and affect and also between motivation and metacognition, the literatures on affect and learning (see for example, Calvo & D'Mello, 2011) and between metacognition and learning (see for example, Azevedo & Aleven, 2013) are highly relevant. Both these collections of papers explicitly address issues around theory as well as the design and evaluation of intelligent tutoring systems.

The following three subsections briefly introduce three areas of educational motivation research that have played a specific role in the development of the motivationally intelligent tutoring systems that are described later. These are (i) learner beliefs about learning including their goal orientation, their self-efficacy and their attributions of causality, and (ii) academic emotions. We then introduce (iii) Keller's work on the design of tutoring systems that puts motivation at the heart of that design process. His work inspired the early work on motivationally-adaptive intelligent tutoring systems.

Learners' Beliefs about Learning and Goal Orientation

Three ideas are explored in this subsection. The first concerns learner goal orientation, the second concerns learners' beliefs about what is possible to learn, and the third concerns how, and to what factors, the learner attributes success and failure.

Goal orientation is concerned with the learner's perception of their overall goal in a learning context. A contrast is drawn between those who see their goal in terms of mastering the ideas or skills to be learned and those who see their goal as not embarrassing themselves. In terms of beliefs about the nature of learning and what is possible to learn, again a binary distinction is draw between those who believe that they are incapable of learning some subjects (mathematics is a favourite example) and those who believe that with effort most subjects are learnable.

Dweck and various colleagues have illuminated many ideas that have fed into the design of motivationally intelligent tutoring systems. They identified a difference between learners who showed adaptive, mastery behaviour from those who showed maladaptive, helpless behaviour and argued that this difference could be explained, in part, in terms of their implicit beliefs about learning. The former believed that (their) intelligence was not a fixed entity and therefore that learning was possible, whereas the latter believed it was fixed. In other words, "conceiving of one's intelligence as a fixed entity was associated with adopting the *performance goal of documenting that entity*, whereas conceiving of intelligence as a malleable quality was associated with the [mastery] learning goal of *developing that quality* [my emphasis]." (Dweck & Leggett, 1988, page 256). So for one group failure to solve a problem was a spur to action, whereas for the other group failure was further unpleasant evidence of their incompetence.

The two kinds of implicit theory lead to striking differences in the way children who were solving a sequence of tasks viewed their difficulties.

> "In short, helpless children viewed their difficulties as failures, as indicative of low ability, and as insurmountable. They appeared to view further effort as futile and, perhaps, as their defensive maneuvers suggest, as further documentation of their inadequate ability.
>
> In striking contrast, the mastery-oriented children, when confronted with the difficult problems, did not begin to offer attributions for their failure. Indeed, they did not appear to think they were failing. Rather than viewing unsolved problems as failures that reflected on their ability, they appeared to view the unsolved problems as challenges to be mastered through effort. Toward that end, they engaged in extensive solution-oriented self-instruction and self-monitoring. Interestingly, their self-instructions and self-monitoring referred to both the cognitive and motivational aspects of the task at hand. That is, in addition to planning specific hypothesis-testing strategies and monitoring their outcomes, they also instructed themselves to exert effort or to concentrate and then monitored their level of effort or attention." (Dweck & Leggett, 1988, page 258)

The implicit beliefs about the nature of learning led to two contrasting kinds of learning goal: mastery learning where the goal was to "increase competence" and performance learning where the goal was to "gain positive judgements/avoid negative judgements of competence."

Importantly from the point of view of intelligent tutoring systems, the researchers found that the children could be persuaded to adopt either kind of goal, whichever their initial preference, by framing the task appropriately. Out of this understanding about learner's implicit (but malleable) beliefs about learning emerged the idea that teachers should support adaptive learning behaviours via the nature of their feedback (Dweck, 2002a, 2002b), and in particular by praising effort rather than by simply praising success:

> "When we focus students on their potential to learn and give them the message that effort is the key to learning, we give them responsibility for and control over their achievement—and over their self-esteem. We acknowledge that learning is not something that someone gives students; nor can they expect to feel good about themselves because teachers tell them they are smart. Both learning and self-esteem are things that students achieve as they tackle challenges and work to master new material." (Dweck, 1999a, page 5)

As we shall see below, Dweck's work had a strong influence on the design of the intelligent tutoring system Wayang Outpost (Arroyo et al., 2014).

Self-efficacy (Bandura, 1997) is a similar concept to the implicit self-beliefs discussed above, but is more concerned with the learner's beliefs about how successful specific episodes or types of learning may be: "I can't do maths," for example. It differs from Dweck's idea of implicit general beliefs about learning because it is rooted not so much in an implicit personal theory of learning, but derived from a variety of influences about specific learning experiences.

> "Learners obtain information to appraise their self-efficacy from their actual performances, their vicarious experiences, the persuasions they receive from others, and their physiological reactions. Self-efficacy beliefs influence task choice, effort, persistence, resilience, and achievement." (Schunk & Pajares, 2002, page 2)

Learner's beliefs about their capability are not always accurate, and are sometimes over-confident (Dunlosky & A.Rawson, 2012). The consequences for the design of intelligent tutoring systems are similar to those for Dweck's motivational theories, but also include the need to provide learners with the means to be successful (e.g., access to useful support materials) and also the means to monitor their own learning and its successes, see the description of Wayang Outpost, below:

> "As they engage in activities, students are affected by personal (e.g., goal setting, information processing) and situational influences (e.g., rewards, teacher feedback) that provide students with cues about how well they are learning. Self-efficacy is enhanced when students perceive they are performing well or becoming more skillful. Lack of success or slow progress will not necessarily lower self-efficacy if learners believe they

> can perform better by expending more effort or using more effective strategies." (Schunk & Pajares, 2002, page 13)

Attribution Theory concerns itself with how the learner accounts for success and failure in learning (Weiner, 1986) and this can have a strong influence on motivation. A learner who attributes her failure to the incompetence of her teacher will be in a different motivational state from one who attributes her failure to her own inability. The theory outlines three causal dimensions. First is "locus" which distinguishes causes as either internal or external to the learner. Second is "stability" which distinguishes causes as being either stable or unstable. Thus a learner having a general belief in her inability would have an attribution that is both internal and stable. Third is "controllability" which distinguishes causes which are under the control of the learner from those which are not. There are similarities here with Dweck's work discussed above in that "attributions" can function like "beliefs" and can be mistaken.

Academic Emotions

The affective dimension of learning is very important, not least that pleasant emotions during a learning activity and a hopeful outlook with respect to its outcome are both a consequence of, and a driver of motivation. Negative emotions during learning and anxiety about outcomes tend to diminish motivation. In the literature, academic emotions are those "achievement" emotions that occur in learners in academic settings (Pekrun, 2011).

> "When attempting to master difficult technical material, such as conceptual physics or mathematics, learners inevitably confront contradictions, anomalous events, obstacles, salient contrasts, and other stimuli or experiences that fail to match expectations. In response to these discrepant events, the autonomic nervous system increases its arousal and learners experience emotions (affective states) such as confusion, frustration, irritation, anger, rage, or even despair. Cognitive equilibrium returns when discrepancies are resolved, misconceptions are discarded, and confusion is alleviated. At that point, learners resume with hope, determination, renewed curiosity, and maybe even enthusiasm. Given this link between affect and cognition, an agile learning environment that's sensitive to a learner's affective states will presumably enrich learning, particularly when deep learning is accompanied by confusion, frustration, boredom, interest, excitement, and insight." (D'Mello, Graesser, & Picard, 2007, page 53)

Pekrun (2011) argues that the focus of emotions can be on either the academic activity or the academic outcome. They can be experienced as having either a positive or negative valence and can lead to either an activating or deactivating outcome. For example, hope, pride and gratitude are positive activating emotions focused on outcomes, whereas enjoyment is a positive activating emotion focused on activity. Correspondingly, anxiety, anger and shame are negative activating emotions focused on outcome, whereas frustration is a negative activating emotion focused on activity. By contrast, relaxation is a positive and pleasant, deactivating sensation that tends to damp down further activity, as does boredom in the negative and unpleasant category.

Pekrun (2011) distinguishes a further category of emotion called "epistemic" emotions, so called because they can be "caused by [the] cognitive qualities of task information and of the processing of such information." These emotions include surprise, curiosity and confusion.

There are also longer lasting feelings such as moods, for example despondency, that also need to be included. Moods are without any particular object focus but have valences of simply "good" or "bad."

All these different kinds of feeling have a range of effects. First is the direct activating or deactivating effect of the experience of the feeling itself, as well as its valency. Second are the largely unconscious effects on cognitive functions such as, for example, attention and engagement (Linnenbrink, 2007). Third is the way that the learner interprets and appraises the nature of what is being felt and also its possible causes. In this respect, note Dweck's work, described earlier, on how learners with different implicit beliefs about learning may well feel, and then differentially interpret, contrasting emotions on experiencing failure.

Broadly, Pekrun (2011) argues that good learning outcomes are more likely to occur when the learner generally enjoys pleasant emotions and he also notes the difference between short-term and long-term effects.

> "For example, relaxed contentment following success can be expected to reduce immediate motivation to reengage with learning contents, but strengthen long-term motivation to do so." (Pekrun, 2011, page 28)

The consideration of the time-scales of motivation from the task, to the lesson, to the course, and into future life, takes us into the territory of "learning how to learn" and how systems might inculcate not just resilience in learners, but also strengthen their desire to engage in a lifetime of learning (Maehr, 2012).

Keller's ARCS & MVP Theories

Keller (2008a) offers an example of how motivational theories may be applied to the design of computer-based instructional systems. This paper built on his earlier "Attention, Relevance, Confidence, and Satisfaction" (ARCS) model of motivation

(Keller, 1979, 1983), and its updated version "Motivation, Volition, and Performance" (MVP) (Keller, 2008b). In both cases his theories offer a design rationale for the motivational strategy of a tutoring system. Because of the explicit focus on tutoring system design, Keller's motivational theory includes issues concerned with the learner's Attention. This overlaps with other more recent work on the HCI of learning materials, see for example Mayer (2014). Relevance and Confidence also play clear roles in motivation, as indicated earlier. So, for example, we can view different goal orientations as providing different kinds of relevance, and we can view self-efficacy as strongly related to confidence. Finally Satisfaction has strong links with Pekrun's (2011) analysis of academic emotions, in particular with contentment, pride and possibly gratitude.

Keller's ARCS model provides a "box and arrow" representation showing the major outputs of what the learner does in a lesson, or over a course, in terms of their effort, performance and the consequences of that performance, see Figure 1. Solid arrows indicate influences; so effort influences performance which in its turn influences consequences. There are two other kinds of influence: "person inputs" and "environmental inputs." Person inputs, such as the learner's motives and expectancies, influence effort, while individual abilities, skills and knowledge influence performance.

In relation to person inputs, Keller refers to a number of different theories of motives and expectancies under the generic term "expectancy-value theories." Here motives may include the desire for competence, the fear of failure, and innate curiosity, among others. Expectancy involves the learner's beliefs about their learning process and outcome, for example, the degree of agency that they may have in progressing it and its likelihood of success. So, expectancy includes the learner's self-efficacy.

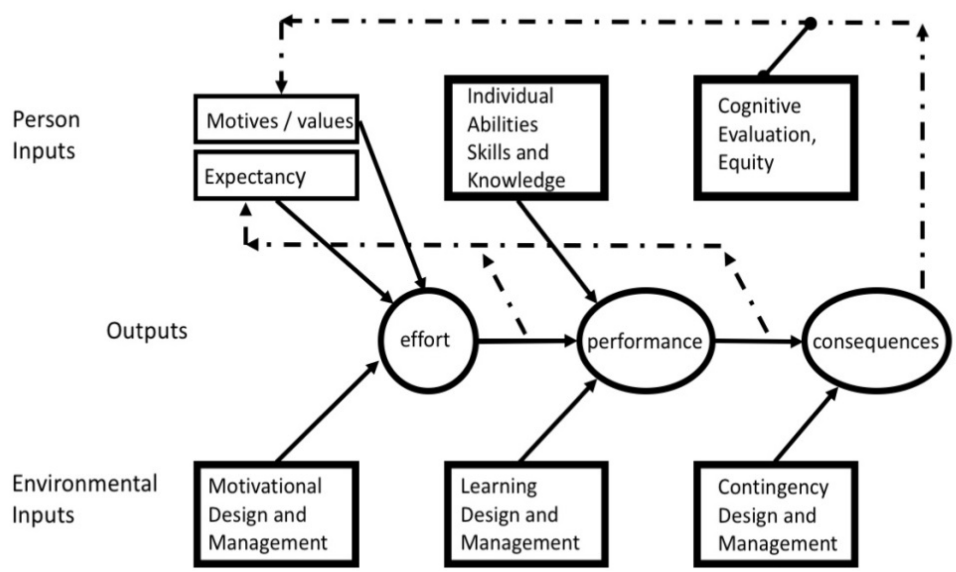

Figure 1. Keller's Attention, Relevance, Confidence, and Satisfaction (ARCS) model of motivation, adapted from Keller (1979, page 29).

The environmental inputs consist of various design elements of the computer-based teaching system itself. So motivational design might include methods to make the taught material interesting; while learning design might include issues of the sequence of learning tasks and feedback on performance and on effort. Contingency design is concerned with helping the learner manage the different possible consequences arising from different degrees of effort and performance.

The dashed arrows indicate feedback loops within the model. So, effort and performance provide feedback within the learner for expectancy, and consequences provide feedback to motives. These feedback loops hint at the idea of motivation being a process as well as a state, where the memory and perception of past learning affects both current and future learning.

Keller's later "Motivation, Volition, and Performance" (MVP) model elaborated on the ARCS model by paying greater attention to "volition": the choice of the direction of effort, its initiation and its persistence together with their own feedback loops to expectancies. This focus on volition is mirrored by Yeager and Dweck's interest in learner "resilience" and how it may be nurtured (Yeager & Dweck, 2012). The MVP model also elaborates the information processing aspects of learning that have a bearing on learning and performance, including cognitive load (De Jong, 2010).

MOTIVATIONALLY-INTELLIGENT TUTORING SYSTEMS

This section of the chapter describes six tutoring systems that have been designed to deal with the learner's motivation, either as a one-off adaptation or dynamically, see Table 1. These six were chosen to cover a reasonably broad range of motivational theories and to cover the history of the field of motivationally adaptive intelligent tutoring systems from its start to the present day. No attempt is made to cover the whole field of such systems, and this selection is designed to be illustrative rather than comprehensive.

Motivationally-intelligent tutoring systems take account of the learner's state of motivation and adapt, or are adapted, accordingly. This adaptation can be a one-off macro-adaptation prior to the session, or it can be dynamic, micro-adaptation that attempts to track the varying state of the learner's motivation over time.

Macro-Adaptation

In this section, we briefly describe two macro-adaptive systems that aimed to adapt to varying aspects of motivation, see the upper part of Table 1. The first system was built to explore the idea of goal orientation and the potential value of having the system provide feedback that matched the learner's individual goal orientation. The second example is of a system that was not itself motivationally adaptive but designed to provide data for later systems that would be motivationally adaptive in terms of the relevance of their feedback.

Goal Orientated Ecolab

Goal Orientated Ecolab is an example of a macro-adaptive system, see Martinez-Miron et al. (2005). They built two new versions of an existing tutoring system, Ecolab, (Luckin, 1998; Luckin & du Boulay, 2016) to introduce young learners to ecological concepts. The two new versions of Goal Orientated Ecolab addressed motivational issues because they were aimed at two contrasting kinds of goal orientation (see the earlier section on Learners beliefs about learning and goal orientation, as well as Ames, 1992; Elliott & Dweck, 1988; Hulleman, Durik, Schweigert, & Harackiewicz, 2008). One version provided feedback that was aimed to suit a mastery orientated learner, and the other version provided feedback that was aimed to suit a performance orientated learner.

> "For instance, if a student's persistence is low, her confidence is high and she has made an error, then the feedback provided promotes more persistence. In this case, the mastery system's motivational feedback might be *"Learning how to do it requires another attempt,"* whereas the performance feedback might say *"If you want to be the best, try again,"* in order to emphasize comparative judgements with other students. Along with the differences in motivational feedback, help is provided on demand in the mastery version, whereas the performance version offers help every time an incorrect action is performed. In addition, elements of the interface are used to emphasize a particular goal orientation." (Martinez-Miron et al., 2005, page 429)

While there are arguments as to how stable a learner's goal orientation is in different learning contexts, the assumption here was that at least the learner's goal orientation could be measured initially and would not change over the course of the interaction, so the adaption to the learner's matching goal orientation could be made once and at the start.

An evaluation of the two systems was conducted to explore the effects of matching or mismatching learners' goal orientations with the two different systems. Because of high variances in the data, it was hard to draw firm conclusions about the effectiveness of the system matching the way that it supported goal orientation to the goal orientation of the students themselves (Martinez Miron, 2008).

Animalwatch

A second example of macro-adaptation can be found in the work of Arroyo et al. (2000). This was a design study to create an effective set of macro-adapted tutoring systems, rather than an evaluative comparison between pre-defined macro-adapted systems, as in the case of Goal Orientated Ecolab. Note that the same version of

Animalwatch was used by all participants, and the different reactions of sub-groups of participants were collated to provide design insights for future macro-adaptable versions of the system. Arroyo and her colleagues observed a mixed gender cohort of 5th graders learning mathematics with a tutoring system called Animalwatch.

The link with motivation was the issue of young learners' ability to make effective use of help when it was provided (see Aleven, Roll, McLaren, & Koedinger, 2016 for a detailed discussion of this issue). This relates back to Keller's (1979) work on attention and relevance, described earlier. The researchers were interested in how the nature of the hints provided by the system might be differentially effective with respect to the gender of the learner and also with respect to their cognitive development, as measured by a pre-test. Hints were categorised in terms of their degree of interactivity and their degree of symbolism. By offering hints of different degrees of interactivity and symbolism on a random basis, the researchers were able to establish a number of interactions between gender, cognitive development and the most effective hint type. These interactions would have provided the basis for future macro-adapted versions of Animalwatch that would have, for example, provided low cognitive ability girls with low symbolic hints and the opposite for high cognitive ability girls.

Micro-Adaptation

The learner's motivational state is both complex, covering aspects of values, expectancies and feelings, and typically also largely hidden. This makes assessing the state difficult for the purposes of adaptation. Self-report by learners is always an option, though there are questions about its reliability as well as the possibility of disruption to the learning. Thus, a tutoring system usually has to rely on external clues or proxies for aspects of that internal state. For example, it might observe the learner's physiological measures, facial expression or posture as clues to feelings (Arroyo et al., 2009; D'Mello, Lehman, & Graesser, 2011), the amount of effort being exerted as a clue to beliefs and values (Arroyo et al., 2014), and the use of the help system as a clue to expectancies (Luckin & Hammerton, 2002). For a discussion of various real-time affect-sensing technologies, see Burleson (2011).

So, an initial question about any motivationally intelligent tutoring system is to what motivational aspect is the system trying to adapt. Second, we can ask what external clues are being used to detect that aspect. Third, we can ask what is the nature of the adaptation with respect to that aspect, see Table 1.

In almost all cases the motivational pedagogy consists of attempting to manage the values, expectancies and feelings of the learner such as to keep them in a state where learning is likely to occur. It is worth noting that some apparently negative feelings, such as frustration, can be spurs to positive learning outcomes (Baker, D'Mello, Rodrigo, & Graesser, 2010) as can deliberately fostered confusion (Lehman et al., 2013).

Table 1. Motivationally adaptive intelligent tutoring systems

System	Internal motivational aspects	External motivational clues	Way of adapting	Main Motivational Theory
Goal Oriented Ecolab Martinez Miron et al. (2005)	Mastery *vs* performance Orientation.	Pre-test questionnaire.	Macro-adaptation.	See section on Learner beliefs about learning.
AnimalWatch Arroyo et al. (2000)	Cognitive development, Gender.	Pre-test.	Macro-adaptation.	Attention Relevance.
MORE del Soldato & du Boulay (1995)	Self-efficacy, Independence, Confidence.	Problem-solving effort; Pre- and post-problem self report of confidence; Use of the help system.	Adjusts problem difficulty; Adjusts feedback and offers of help.	See section on Keller ARCS Theory.
Genetics Tutor Song & Keller (2001)	Attention, Relevance, Confidence (self-efficacy).	Pre-test values of attention, relevance and confidence; Quiz answers during learning.	See Section on Keller ARCS Theory.	See section on Keller ARCS Theory.
Affective AutoTutor D'Mello, Lehman and Graesser (2011)	Academic achievement emotions: boredom, frustration, anxiety.	Real-time measures of Posture and Facial expression; Dialogue log.	Adjusts facial expression of empathetic pedagogical tutor agent; Adjusts feedback and dialogue move.	See sections on Learner beliefs about learning (attribution theory) and Academic emotions.
Wayang Outpost Arroyo et al. (2014)	Engagement; Self- regulation; Academic achievement emotions: boredom, frustration, anxiety, excitement.	Effort, Performance, Use of the help system.	Adjusts problem difficulty and feedback emphasizing effort and perseverance; Learning companion provides supportive demeanour and comments.	See sections on Learner beliefs about learning and Academic emotions.

In this section, we briefly describe four micro-adaptive systems that aimed to adapt to varying aspects of motivation, see the lower part of Table 1. Two have been chosen from the early days of motivational research in intelligent tutoring systems, and two from more recent times. The two systems from the early days were one-offs and did not develop further. The two systems from more recent times were developed over a long period and many different versions were developed and evaluated. This chapter focuses on just one version in each case. As stated at the start, this chapter is not intended to be detailed review of the field but it is hoped that these four examples give a good sense of what has been achieved.

MORE

MORE (MOtivational REactive plan) was one of the earliest tutoring systems to adapt to the learner's degree of motivation *during* the learning process, i.e., it was micro-adaptive. The system was aimed at university students learning how to debug Prolog programs (del Soldato & du Boulay, 1995; du Boulay & del Soldato, 2016). It was much influenced by Malone and Lepper's (1987) and Keller's (1983) ARCS work described above. The system focused on the learner's self-efficacy and independence in terms of their self-reported confidence, their actual effort and their use of the help system. The system used self-reports of the learners' confidence, in particular when they were first offered a new problem and *before* they had made any attempt to solve it.

The *motivational* pedagogic strategy of the system was distinct from its *cognitive* pedagogic strategy (i.e., the strategy to ensure the learner covered all the material, respecting its pre-requisite structure and difficulty). So, the system might offer a problem that it had every reason to believe that the learner could already solve, not to improve their understanding, but in order to build their confidence. It also distinguished between offering corrective feedback from offering hints so as to respect the learner's sense of independence. The system might also refuse a request for help if it believed that the student did not need that help. Here we briefly describe how the system would deal with a student who gives up on a problem after a generally good performance. The motivational rule distinguishes four cases: effort (little or large) *vs* confidence (low or OK). For example, where both effort and confidence were low, the system would remind the student of earlier successes, provide a hint but suggest that they carried on working on the same problem. By contrast, where effort large and confidence was OK, the system would praise the student's effort, and choose a next problem of the same difficulty. For more details of the motivational strategy, see del Soldato and du Boulay (1995).

There was a limited evaluation of the prototype system in terms of leaners' reactions to it. These were generally positive, although the occasional refusal of help by the system was not liked, even though this is a tactic used by human teachers, and indeed now by some intelligent tutoring systems if they think that the learner is gaming the system

(Baker et al., 2008). MORE was just one many systems designed and evaluated by the group at Sussex, for an overview see du Boulay (2011a).

Genetics Tutor

Keller's ARCS model (described earlier) was implemented and evaluated in an experiment involving three tutoring systems that shared a common Hypercard system for teaching 10th grade students about genetics, but differed in the way that they dealt with the learner's motivation (Song & Keller, 2001). One version of the system was "motivationally saturated" in that it embodied all the motivational strategies included in the ARCS model and did not adapt to the learner, but with the designers' expectation that this might be annoying for learners who were already strongly motivated. Another version was "motivationally minimised" in that it included only those motivational strategies necessary to make instruction viable, such as including technical drawings, and again did not adapt to the learner. The third version was motivationally adaptive, in that it deployed only the relevant strategies, based on each learner's score on a pre-test of attention, relevance and confidence and on a quiz taken during the learning. The set of confidence enhancing strategies included "Use words and phrases that help attribute success to the learner's effort and ability" and "Clearly present the objectives and overall structure of the lesson." Confidence sustaining strategies included "Give the learner control over pacing" and "Match learning requirements to prerequisite knowledge and skills to prevent excessive challenge or boredom."

A small between-subjects evaluation was conducted over a short period. The results were generally positive in terms of the greater effectiveness of the adaptive model of motivation and the authors concluded that "CAI can be designed to be motivationally adaptive to respond to changes in learner motivation that may occur over time."

Affective AutoTutor

Affective AutoTutor is an intelligent tutoring system that includes a pedagogical agent playing the role of a teacher (D'Mello et al., 2011). The system uses natural language processing, semantic analysis of the learner's answers to questions, and a set of dialogue moves to test and develop the learner's understanding of a topic through dialogue. Many versions of this system have been implemented. In the version described here, additionally to tracking the learner's increasing understanding of the domain of computer literacy, it also tracked the learner's affective state and attempted to keep the learner in an affective state that was conducive to learning or move the learner into such a state if that was needed.

The main motivational focus of the system was on maintaining the user's emotional equilibrium: see the earlier section on academic emotions. The authors developed their motivational strategy from attribution theory (Weiner, 1986) and cognitive dissonance theory (Festinger, 1957) among others. In a series of separate studies, they identified confusion, frustration and boredom as the three negative affective states most likely to occur over the short timescale of lessons with the tutor, together with a "neutral" state. They used multi-modal methods to detect the learner's affective state with about 50% accuracy via posture monitoring, eye-tracking and dialogue monitoring.

The pedagogical agent added emphasis to what the underlying AutoTutor might choose as its next dialogue move by adjusting her facial expression and intonation. The facial expressions of the agent included approval, disappointment, scepticism and empathy. For example, the empathetic agent might behave as follows:

> ". . .consider a student who has been performing well overall (high global ability), but the most recent contribution was not very good (low current contribution quality). If the current emotion was classified as boredom, with a high probability, and the previous emotion was classified as frustration, then AutoTutor might say the following: "Maybe this *topic* is getting old. I'll help you finish so we can try something new." This is a randomly chosen phrase from a list that was designed to indirectly address the student's boredom and to try to shift the topic a bit before the student becomes disengaged from the learning experience." (D'Mello et al., 2011, page 120)

Affective AutoTutor's response in the above situation of changing topic is slightly different from MORE's response in a similar (though not identical situation) where MORE would suggest the learner stayed with the same topic. One of the strengths of motivationally intelligent tutoring system technology is that such discrepancies in pedagogical tactic can be empirically tested with relative ease.

Affective AutoTutor was evaluated against basic AutoTutor with positive results in terms of better learning gains for the affectively supportive version. There were two caveats however. First, this improvement was observed only for learners with low domain knowledge, and second, this improvement even for these students only occurred in the second and subsequent lessons. As a consequence, the authors suggest that "there is an appropriate time for affect-sensitivity" indicating yet another dimension that needs to be addressed by an effective motivational pedagogy. Affective AutoTutor is just one of many systems developed and evaluated by the group at Memphis, for an overview see Nye, Graesser, and Hu (2014).

The use of a pedagogical agent is now commonplace in tutoring systems, including intelligent tutoring systems. The presence of these agents adds extra complexity to motivational pedagogy in terms of the different roles that they can play (e.g., tutor or fellow student), the different emotional demeanours that they display (e.g., empathetic or concerned) and the choices about their age, gender and ethnicity. Overall however it appears that such agents promote effective learning (Heidig & Clarebout, 2011; Schroeder, Adesope, & Gilbert, 2013).

Wayang Outpost Mathematics Tutoring System

Wayang Outpost (now called Mathspring) is an intelligent tutoring system that aims to coordinate the cognitive, metacognitive and affective learning factors of K-12 young learners (Arroyo et al., 2014). Arroyo and her colleagues describe a number of versions of the system as well as a number of evaluations of it at different stages of its development. The system is a multimedia mathematics tutor that includes a pedagogical agent in the role of a tutor, and in later versions also includes an agent acting as a peer learning companion. The system organizes the mathematics curriculum by generic skill rather than by standard topic. It uses an apprenticeship model of learning problem-solving via the Vygotskian notion of adjusting the level of difficulty of tasks to maximise learning by keeping the learner within her Zone of Proximal Development.

From a motivational point of view the main foci of the version of the system described here were on the effort demonstrated by the learners, their developing metacognitive knowledge and skill, and their academic achievement emotions (Pekrun, 2006; Pekrun, Frenzel, Goetz, & Perry, 2007).

In terms of effort, the feedback from the system and its adaptations to the learner was derived from Dweck's work on learners' beliefs, often mistaken, about learning (Dweck, 1999b, 2002a, 2002b). These issues are discussed in more detail in the earlier section on learner beliefs about learning. The main components of its cognitive, affective and metacognitive strategy were based on eight generic learner behaviours, such as achieving mastery without much effort or its opposite, low mastery with high effort. These behaviours were themselves derived from logged information about the number of incorrect answers submitted by the learner, their use of hints and the time that they have taken.

For each of these behaviours the system made content-focused decisions (cognitive decisions) such as maintaining the current problem difficulty. It also provided affective and metacognitive feedback via the pedagogical agent who might verbally urge the learner to deemphasise the importance of immediate success. Thus we can characterise the overall strategy as one of attempting to build up the learner's perseverance and resilience, based on the idea that mathematics can be learned by anyone and does not depend on some special fixed cognitive attribute (Yeager & Dweck, 2012).

In addition to the effort-based tutoring strategy described above, the system also provided various means for the learner to build up an accurate sense of their progress, as well as to develop strategies to self-regulate their learning, in other words their metacognitive knowledge and self-regulation (Butler & Winne, 1995; Greene & Azevedo, 2007; Zimmerman & Moylan, 2009). These tools included an open student model that the learner could consult to see what progress they had made, together with suggestions for further work. The student model also emphasised the idea of skills and knowledge as something that could be developed through effort, in keeping with the overall effort-based training pedagogy. The system would also generate individual charts and tips that were aimed to develop the learner's ability to self-regulate, e.g., "Dear [student's name], We think this will make you improve even more: Read the problem thoroughly. If the problem is just too hard, then ask for a hint." Finally, the learners were encouraged to regard the tutor in the system as a helpful teammate, so as to emphasise the idea that seeking help from someone more skilled was a natural aspect of the process of learning a new skill.

In addition to focusing on effort and fostering self-regulation skills, the system also aimed to support a number of academic achievement emotions. These were confidence/hope *vs* anxiety, interest *vs* boredom, frustrated *vs* not frustrated, and excitement *vs* not fun. Initial versions of the system instrumented the learners, but later versions were able to infer the learners' emotions from their behaviour. In order to provide emotional support an empathetic learning companion was introduced who would display a range of emotions, similar to Affective AutoTutor. The companion would offer supportive affective and metacognitive advice, such as "Learning math is like riding a bike. We have to practice a lot before getting good."

Arroyo et al. (2014) describe a number of evaluations of both the complete system, as described above, as well as evaluations of individual aspects of its support. Overall these evaluations tell a positive story about the effectiveness of this system *vs* standard classroom teaching and also *vs* versions of the system without certain of the support features. They also found an interesting result in that a comparison of the system with the teammate tutor persona compared to a standard tutor persona did not improve performance but did improve help-seeking behaviour. Some of the subtleties of help mechanisms and their effect on help-seeking behaviour are explored by Aleven et al. (2016).

CONCLUSION

This chapter has provided a brief introduction to the issue of motivation in the context of intelligent tutoring systems. In addition to an overview of a small number of motivational theories, it has also described six tutoring systems that were designed to track and adapt to the changing motivational state of a learner over the course of one or more lessons.

In terms of the motivational leverage that such systems can exert through adaptation, we see three broad possibilities at present. Each of these cover, to different degrees, the three general areas on motivation research namely beliefs and values, expectancies and feelings.

First, systems can adapt the choice of what task to set the learner. In the context of systems designed to offer problems to solve or issues to explain, they can change the difficulty of the tasks, as in Wayang Outpost, or move on to a new topic (as in Affective

AutoTutor). They can also adapt their feedback to making it more effective in terms learner attributes such as their goal orientation (Goal Oriented Ecolab), gender (Animalwatch), or pre-test knowledge and skill (Animalwatch). However, what they cannot do at present is to make radical changes in the way that topics are introduced and presented as described by Rosiek (2003) in her work with human teachers.

Second, systems can indirectly track and then adapt to the feelings of the learner either by asking the learner, as in MORE, instrumenting the learner, e.g., by measuring posture, as in Affective AutoTutor, or by observing learning behaviour, such as the learner's use of the help system, as in Wayang Outpost, or their language, as in Affective AutoTutor. Again, the adaptation can be in terms of the system's choice of what task to set the learner, but there is also the possibility of the system referring to, or indirectly acknowledging the learner's feelings through the empathetic demeanour or comments of an on screen pedagogical agent, or indeed by changing topic, as in Affective AutoTutor. However, what such systems cannot do at present is deal with moods or with emotions whose focus is not directly on the activity in hand. While a human teacher can ask a despondent student about what the matter is, it is not at all clear at present on what basis an intelligent tutoring system could conduct such a conversation.

Third, systems can attempt to address the learner's potential misunderstandings about the nature of learning itself by praising effort and offering support for the idea that effort does in fact lead to learning, such as in Wayang Outpost. They can also assist the learner's metacognitive understanding of their increasing mastery of new skills through such devices as an open student model, and the learner's ability to regulate their learning behaviour through hints and suggestions, as in Wayang Outpost.

In some ways, intelligent tutoring systems have strengths in this area that human teachers do not have, in that they can log and analyse detailed data about the learner's activities and progress. This information, suitably organised and presented can then be made available to the learner. Research into motivation from within education and psychology provides broad-brush motivational pedagogic strategies (see for example, Schunk et al., 2008). However, the detailed work of designing, building and evaluating intelligent tutoring systems involving detecting learner emotions by a variety of means (see for example, Arroyo et al., 2009; Craig, Graesser, Sullins, & Gholson, 2004; D'Mello et al., 2007); analysing how those emotions change and evolve over the short term (see for example, Baker, Rodrigo, & Xolocotzin, 2007); and finding ways to help the learner manage those emotions, are some of the major contributions of this field.

In terms of the future, we have already hinted at two possible directions of travel, namely (i) systems being able to introduce, reorganize and present the material to be taught in ways to motivate individual learners; and (ii) systems being able to have a conversation with learners about their state of motivation and the reasons for it. We can also anticipate systems managing the motivation of their learners over a longer time-horizon than an individual lesson or even a whole course to try to build a long-lasting general desire to learn, such as espoused by Maehr (2012). In support of all of these goals we need a wide-ranging analysis of the space of possible motivational adaptation, in a manner similar to that provided for affective adaptation by Harley, Lajoie, Frasson, and Hall (2017).

ACKNOWLEDGMENTS

I thank Abrar Almjally, Veronica Cucuiat, Judith Good, Kate Howland, Charlotte Robinson and Anthony Trory and the anonymous referee for very helpful comments on an earlier draft of this chapter.

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