What Is Adaptivity? Does It Improve Performance?

Jacqueline A. Haynes[1], Jody S. Underwood[1], Robert Pokorny[1], and Amit Spinrad[2]

[1] Intelligent Automation, Inc., Rockville, Maryland, USA
{jhaynes,junderwood,bpokorny}@i-a-i.com
[2] The Hebrew University of Jerusalem, Jerusalem, Israel
amit.spinrad@mail.huji.ac.il

Abstract. Asking *whether* adaptivity improves performance is the wrong question. The right question is *what kinds* of adaptivity should be used to tailor the interactions between learner, context, objective, and instructional approach to maximize learning and performance. Most research on adaptive learning has focused on learning in intelligent tutoring systems and other digital learning environments. However, there is a lack of research that focuses on retention and deeper learning. This paper will define adaptivity, review different types of adaptivity used for instruction and their effects within the learning environment and longitudinally, and give some examples of how we have used adaptivity for short- and long-term improvement in performance and learning. We conclude that adaptivity in learning environments should be used to focus on deep conceptual learning promoting long term results.

Keywords: adaptivity, intelligent tutoring systems, digital learning environments, learning, pedagogy, individualized instruction.

1 Introduction

Among educators, the cry to "individualize instruction" has been heard for many years. The currently used variant of the term, "adaptive learning," implies the same type of individualization in an e-learning environment, where the instruction is adjusted in response to an individual learner's responses to stimuli. The desired outcome of adaptive e-learning is to achieve learning gains that are as effective as one-to-one human tutoring, for example, Bloom's [1] 2-sigma effect, which has become the holy grail of e-learning research. Corbett [2] reports that the Cognitive Tutors (Anderson, Corbett, Koedinger, & Pelletier [3], achieved Bloom's 2-sigma effect of learning gains. It was a great result for an intelligent tutoring system, using immediate feedback as its adaptive mechanism. However, they did not look at long-term retention of a skill that was meant to be long term, nor at the appropriateness of immediate feedback to the student or the context.

Researchers and practitioners alike continue to develop instructional methods that employ different strategies for presenting information, motivating and engaging students, providing feedback (in different forms and on different schedules), and countless variations of the normal components of an instructional event. We assert that

D.D. Schmorrow and C.M. Fidopiastis (Eds.): AC 2014, LNAI 8534, pp. 224–235, 2014.

asking *whether* adaptivity improves learning and the resulting performance is not the right question. The right question to ask is *what kinds* of adaptivity should be used to address the interactions between learner, domain, context, objective, and teaching approach to maximize the effect on learning and/or the resulting performance?

In this paper we suggest broadening the concept of “adaptivity” to include a greater variety of methods that may be used to enhance the performance of different types of tasks. Durlach and Ray [4] provide a comprehensive list of adaptivity types for instruction and training and present analyses and meta-analyses of studies indicating the effectiveness of different approaches. Like Durlach and Ray, we propose that instructional adaptations should consider not only the learner and their responses, but the content and target tasks as well.

Second, we discuss research showing that some commonly-accepted beliefs about effective instruction do not hold up in many situations. For example, when comparing massed vs. distributed practice, most practitioners accept the position that distributed practice is the preferred method; however, there is considerable research showing that the benefit of one over the other depends on the content and context of instruction.

Third, we present two different adaptive learning applications with empirical evidence of performance improvement approaching the desired 2-sigma level. Each application has implemented a method of instruction known to be effective in individual coaching/tutoring in an e-learning environment. The effectiveness of these methods stems from their focus on using adaptive features to engage learners in deeper processing of the material.

Finally, we conclude that effective instruction should have the goal of promoting deep conceptual understanding and long-term benefits of the learning. Adaptive instruction can do this by focusing on a number of important factors such as features of the performance task and context of use.

2 What Is Adaptivity?

A good way to define adaptivity is through examples. There have been many approaches to adaptivity in digital learning environments. Some focus on monitoring student activity, interpreting the results, understanding students’ requirements and preferences, and using the newly gained information to facilitate the learning process [5]. Others focus on adapting to the student's goals, preferences, capabilities, and knowledge [6]. Durlach and Ray [4] identified these types of adaptivity used in intelligent tutoring systems (ITSs):

1. *Mastery.* In a mastery condition, students need to master one module before being able to move onto successive levels. This has also been called prerequisite learning [7].
2. *During-problem guidance.* While solving a problem, hints are provided after a period of time passes without the student taking a correct action, after an incorrect action, or as requested by a student. Typically, each successive hint gives more information, with the final level giving the correct answer.

3. *Tutoring dialogs.* Natural language processing techniques have been used to engage students in interactive dialogs to encourage them to elaborate on the reasoning they used in solving a problem.
4. *Error-sensitive feedback.* This type of feedback goes beyond simply whether an action was right or wrong, but tries to correct student misunderstandings.
5. *Self-correction.* Feedback is delayed a few steps to allow the student to detect and correct any errors that may have been made.
6. *Fading worked examples.* This method starts by showing a worked-out example, gradually reducing the amount that is shown, and increasing the amount the student has to do to solve entire problems.
7. *Hyperlink annotation and direct navigation support.* Used in non-linear educational systems, this technique guides students to other sources based on the goals, knowledge, and other characteristics of the individual learner.
8. *Metacognitive prompts.* Prompts are provided to help students do such things as self-explanation and self-evaluation. The prompts are similar to tutoring dialogs, but with a focus on domain-independent thinking such as whether the student understood the main point of a text.
9. *Spacing and repetition of domain problems.* This refers to the time between practicing a skill and how much to repeat it in order to retain it.

In their review, Durlach and Ray [4] focused solely on model-based adaptivity, where student models or others (e.g., expert or instructional) are used to guide adaptation. While effective, we posit that model-based adaptivity is not as useful a category as it could be. The following categories use Durlach and Ray's adaptivity types to expand on the pedagogical approaches used to adapt learning environments to individuals, and focus solely on feedback and activity selection [8].

1. Provide custom feedback to learners during the experience. Most intelligent tutoring systems (ITSs) provide feedback after each step of problem-solving [9]. One form of this type of feedback is "local adaptation," defined as feedback that is sensitive only to the current response features and not to a history of responses [4]. This category includes the following adaptivity types from Durlach and Ray [4]: during-problem guidance, tutoring dialogs, error-sensitive feedback, fading worked examples, and metacognitive prompts.
2. Provide custom feedback to learners after the experience. In computer-aided instruction systems where students work out how to solve the problem somewhere else and then enter an answer, the system provides a final score, and right/wrong feedback in response to a solution [9]. This category includes Durlach and Ray's [4] self-correction adaptivity type, extending the idea of the type of feedback given after the experience.
3. Tailor which activities a learner experiences. Some systems move learners to a problem that contains skills they need to work on [3, 10]. This has also been called model-based adaptation [4], a strategy in which rich information about student differences, such as concept accuracies and how long ago the learner interacted with this concept, are used to adapt content by selecting an appropriate next space to move to. This category includes the following adaptivity types from Durlach and Ray [4]: mastery, hyperlink annotation and direct navigation support.

4. Tailor how learners experience the environment. Some systems provide interface features to make things accessible to hearing- or vision-impaired people [11] or simplify content to meet the needs of the learner. This category does not include any adaptivity types from Durlach and Ray [4].
5. Schedule and distribution of practice. Spacing and repetition of problems in the learning environment extends the prior focus on feedback and activity selection in very important ways, and comes directly from Durlach and Ray [4].

Adaptivity has also been effective in other digital learning environments, some of which take on the flavor of games. For example, Barab, Gresalfi, & Arici [12] found that students learn best when they take part in "transformational play." Transformational play, a type of simulation, occurs when players engage with the content to make choices that transform the situation, get to see the consequences, and get the opportunity to try again. While games offer countless other approaches to learning and instruction, our focus in this paper is not on games, but on tutor-initiated instructional adaptivity.

We next present a summary of additional research that will define the types of adaptivity that may be most effective, and the conditions in which they should be used.

3 Extending the State of the Art of Adaptivity

In this section, we discuss research showing that some commonly-accepted beliefs about effective instruction do not hold up in many situations. Effective instructional solutions with unique characteristics have been found to be linked to specific types of tasks.

The nature of a learner's engagement with the instruction is important. A series of studies by Chi [13] led to a conclusion that tasks requiring deeper understanding are best taught when the learner must actively interact with content, rather than passively 'accepting' the content. Some learners may prefer to read or watch videos to help them with what they are learning, but it is unclear whether the learner is actively engaged. Further, research has found that grounding tasks in authentic environments helps learners to integrate the knowledge and skills needed for effective task performance [14]. More generally, people learn better when new information is based on what they already know [15], when they have an opportunity to apply new knowledge or skills [16], and when the instruction is organized in increasing order of complexity [15].

Wulf & Shea [17] specify a set of instructional dimensions for simple and complex skills: organization/schedule of practice, distribution of practice, feedback, guidance procedures, focus of attention, and observational learning. These dimensions provide a rich resource for designing adaptive instruction to address individual learners' needs.

Organization/Schedule of Practice. While randomly ordering skills in practice compared to blocked practice of a single skill usually results in better performance and transfer later, some studies show that novices learn better when they have blocked practice of component skills before combining skills (e.g., learning how to hit a tennis ball). More difficult skills (with high memory, attention, or motor demands) are learned better with blocked practice since complex tasks may cause working memory overload during learning. Randomly ordering short blocked practice sometimes works well. In general, random practice works better for learning simple skills or when learners have some experience; blocked practice works better for complex skills and for novices.

Distribution of Practice (massed vs. spaced). A very common finding in review articles [18] is that spaced practice (practice at intervals) leads to faster learning than massed practice (a lot of practice all at once). However, in a meta-analysis of 63 studies [19], spaced practice produced different results for each task type studied. As shown in Table 1, the effect of spaced practice varies according to the complexity and requirements of the task. The effect is strong for tasks of low complexity (Cluster 1), moderate for tasks of average complexity (Cluster 2), and low for tasks of high complexity (Clusters 3 and 4). In this meta-analysis, mental and physical requirements were not significantly correlated with effect sizes; overall complexity was the only factor found to be a key determinant for overall effect of spaced practice over massed practice. In another example, Lakshmanan, Lindsey and Krishnan [20] found better learning results both in terms of time to learn and ability to transfer learning across tasks when practice was massed rather than spaced. They ascribed the unusual finding

Table 1. Cluster analysis for tasks (adapted from Donovan & Radosevich [19])

Cluster	Overall Complexity	Mental Requirements	Physical Requirements	Tasks	Spaced Practice Effect
1	Low	Low	High	Rotary pursuit, typing, ball toss, ladder climb, peg reversal, bilateral transfer, crank turning	Strong
2	Average	Low	High	Free recall task, video games, slide bar task, sound localization, maze learning, upside down alphabet printing	Moderate
3	High	Low	High	Gymnastic skills, balancing task	Low
4	High	High	High	Air traffic controller simulation, airplane control simulation, hand movement memorization	Low

of superiority for massed practice to three factors. First, the task was of medium difficulty, which was more complex than most tasks. Second, the study measured task performance by skill in performing a task rather than recall. Third, the content to be learned was presented by a video showing task completion rather than by a set of verbal instructions. Under these conditions, the usual superiority of spaced practice over massed practice disappeared.

Feedback Provided to the learner (frequency, organization, form). Feedback has generally shown to be effective in helping learners. However, feedback has also been shown in a meta-analysis to reduce performance for more than 1/3 of the cases [21]. Some research since this meta-analysis was performed has attempted to determine what kinds of feedback are helpful, and for what types of tasks.

Empirical studies have shown that students learn rule-based math skills faster when provided immediate feedback consisting of short and directed error messages [3]. However, studies with motor skills show that performance during a learning session was better when students were given feedback after each trial (consistent with the math tutor result), but long-term learning was better if the feedback was given after many trials (e.g., 5 or 15). Moreover, the larger the number of trials in the feedback set, the better the long-term retention results [22]. This result can be explained because the learner tries to make sense of the feedback allowing them to integrate the information more deeply.

Wulf & Shea [17] report that for simple tasks, giving feedback about knowledge or performance after every few tasks has resulted in improved learning compared to giving feedback after each trial. Delaying the feedback for a few seconds, compared to immediately after or concurrently during practice, has also shown to produce more effective learning. That is, immediate feedback results in better performance during practice, but the effects degrade over time. One explanation for this is that learners come to rely on the feedback for their performance, and do not learn to figure out for themselves the correct way to perform. Frequent feedback also seems to help learners plan for the next response, instead of relying on memory retrieval, which is more often needed during the actual performance.

For more complex tasks, feedback after a small number of trials is better than after each trial, and also better than feedback after a large number of trials, whereas feedback after each trial was better for novices. There have also been studies that show that feedback after each trial is effective for complex tasks.

How should feedback be organized? Should the learner's attention be focused on a single feature (e.g., what one hand is doing during a two-handed task), or on many features at once? Some studies show confusion and degraded learning if the feedback focuses on many features at the same time.

The form of feedback is also important. Feedback form has many dimensions, including positive vs. negative, specific vs. general, and the amount of feedback [23]. Feedback is more effective when it is constructive, giving details of how to improve (often perceived as positive), not just telling the learner what was wrong (often perceived as negative). Telling a learner what went well is also appropriate and helpful in building learner confidence. Learners like and react well to a balance of top-down and bottom-up feedback; being specific about what needs to improve is more helpful than being general. Even when feedback is positive and specific, it can still fall short of being helpful if it is either cryptic or too long.

Physical Guidance Procedures. Results about physical guidance (e.g., setting a mechanical stop to indicate a target position, or putting a leg or arm into a position) are similar to those about feedback. For simple tasks, guidance often has strong effects during practice, yet when it is withdrawn, performance is often worse than that of learners who practiced the task without or with less guidance. For more complex tasks, physical assistance has shown good effects in the long run. For example, learning with ski poles has been shown to help students find their balance better when tested in situations where they are not using ski poles, compared to those who learned without ski poles. On the other hand, the same results were not found for people learning to maintain their balance on a wooden board pivoting to the left and right over a fulcrum. The poles in the skiing example allowed more extensive exploration, where poles in the balance example apparently limited what people would try. This is an area ripe for research.

Focus of Attention (watching your hands vs. watching the outcome, or following instructions). Learners who focused on the effect of a movement learned a task to a higher degree of automaticity and with fewer errors than learners who focused on the movement itself. Accordingly, studies have also shown that instructions that direct learners to attend to their body movements, as opposed to the goals of the movements, are detrimental to learning.

Observational Learning. Learning through observation is more effective for complex tasks than simple tasks [17]. For simple tasks, there have been mixed results of observation either helping or having no effect. Observational learning is effective for complex tasks for a few reasons. There is essentially a lot to look at, and hence to be extracted, as a complex task is being performed. Second, observation is more effective when there is a high informational load. Third, people seem able to learn coordination patterns from watching. Finally, learners can glean a better picture of how the subcomponents of a task fit together in the whole task. Other studies have shown that it's better to allow people to watch as others go through physical instruction, and then switch, rather than just have physical instruction. In addition, having teams work together (e.g., dyads) where they switch off between doing the task and observing it helps reduce fatigue; when they share thoughts with each other, it has been more effective than individual instruction; and it can be done in the same amount of time.

Now the question is, when should these methods of adaptivity be used? Are there contexts in which they are more appropriate and effective than others? We next present a summary of situations for effective adaptivity to be applied.

4 Applying Adaptive Instruction

This section combines the results of sections 1 and 2 into guidelines for adaptive instruction. Wulf and Shea's research on instructional dimensions [17] introduced some new ideas and informed some changes to the Underwood, Kruse, & Jakl [8] adaptivity guidelines (AG). For example, since it is more effective to look at immediate and delayed feedback at the same time, we collapsed the two “feedback” categories.

1. Provide custom feedback to learners.
   (a) For simple tasks, while immediate feedback and directed error messages can provide quicker learning times, long-term learning is better if feedback is given after many trials. The reasoning is that learners come to rely on the immediate feedback for their performance, and do not learn to figure out for themselves the correct way to perform. Feedback after many trials fosters deeper understanding of the problem and its solution.
   (b) For complex tasks, while feedback after a small number of trials is better than after each trial, it is also better than feedback after a large number of trials. Some studies also show that feedback after each trial is effective for complex tasks.
   (c) Feedback should focus on one feature at a time. Focusing on many features at the same time can confuse students and degrade learning.
   (d) Feedback is more effective when it is constructive, giving details of how to improve, not just telling the learner what was wrong.
2. *Tailor which activities a learner experiences.*
   (a) Mastering prerequisite modules before moving onto successive modules have been shown to result in improved student learning in many studies.
   (b) Providing direct navigational support for going to modules for which students are ready has resulted in improved learning.
3. *Tailor how learners experience the environment.*
   (a) Scaffolds that allow exploration help people learn complex skills in the long run.
   (b) Guiding students to focus on the effect of a movement, rather than on the movement itself, has the effect of learning the movement better.
   (c) Learning through observation is more effective for complex tasks than simple tasks. For simple tasks, it can either help or have no effect; more research should be done to determine how this adaptivity method can best be applied.
4. *Schedule and distribution of practice.* Overall complexity of the task is the key feature that determines the effect of practice schedule.
   (a) Random ordering of practice tasks works better for learning simple skills or when learners have some experience; massed practice works better for complex skills and for novices.
   (b) Distributed practice works better for tasks of low complexity, moderately well for tasks of average complexity (massed practice can also work fairly well), and has low effects for tasks of high complexity. There are also some conditions where the superiority of spaced practice disappears, for example, where a skill has to be performed rather than recalled.

5 Two Adaptive Learning Examples

In this section we describe two adaptive learning applications that we developed. Each has shown empirical evidence of performance improvement approaching the desired 2-sigma level. One application is directed at improving performance of procedural maintenance tasks; the other at improving comprehension of workplace-related text. The instructional method implemented in each of these e-learning environments focuses on enhancing the learner's conceptual understanding and deep processing of the material. Where relevant, each method is annotated with the adaptivity guidelines (AG) outlined in the previous section (e.g., AG2: tailoring which activities a student experiences).

5.1 Adaptive Visualization Training

Adaptive Visualization Training (AVT) was designed to help Navy technicians improve their performance of maintenance activities on complex radar equipment by fostering their ability to visualize how the equipment functioned.

In the e-learning environment, the student executed procedural maintenance steps on simulated equipment. Occasionally, when AVT determined the student could benefit (AG2), an instructional module presented the student with a question and then led the student through the process of constructing an answer. Constructing answers to questions helps the student develop conceptual understanding of the equipment and how the steps of the maintenance procedure works. The questions took one of three formats. The student was asked (1) to identify the relevant section of the equipment; (2) to provide an open-ended answer; or (3) to respond to a multiple-choice question and provide an open-ended justification. Students were given immediate feedback or hints on their answers (AG1a). In addition:

- Students were provided perspectives of how the equipment is physically seen, how it is depicted in documentation, and how it functionally operates. These views provided the opportunity to create a mental model, which allowed more conceptual reasoning about the system's operation. (AG3)
- The design was mindful of how instructional time should be scheduled to result in improved performance and meet practical schoolhouse requirements. (AG4)
- The instruction took into account learning (and decay) over time.

The resulting instruction was delivered and tested by the Navy as part of a 12-day instructional module. On a post-test, the students with the AVT intervention performed 24% better than the control students (a statistically significant difference), with a standard deviation improvement of 1.3 [24].

5.2 GradAtions

GradAtions® [25] is an adaptive web-based intelligent reading comprehension tutor designed to help people who already know how to decode. GradAtions uses the concept of "reading ladders," where a reader begins reading materials at an appropriate level of difficulty [26] and subsequent passages are selected at gradually increasing difficulty levels (AG2), allowing the reader to gain background knowledge and vocabulary, and to avoid reading experiences that are frustrating due to difficulty. In sum, learners read a passage, write a summary that is automatically assessed by an artificial intelligence algorithm, and receive feedback related to their comprehension (AG1b, AG1d). GradAtions also models how to write summaries if the student prefers to observe the method before beginning to write one (AG3c) and provides explorative scaffolds for creating summaries (AG3a).

A large-scale independent study of three reading tutors [27], conducted with high school students (including some 6-8 grade students), and participants at a community technology center. The study found two interesting results: (1) After using GradAtions for only 15 hours, reading performance improved about 0.4 grade level (see Table 2); and (2) When trying to optimize the ordering of three reading tutors, used for a combined total of 35-40 hours, using GradAtions first provided the best effect in reading improvement (an average increase of 1.1 and 0.8 grade level reading scores; the best result when another tutor was used first was a 0.5 grade level increase). We attribute this finding to the practice of deep semantic processing of text required by GradAtions®.

Table 2. Adjusted means (M), standard errors (SE), reading grade level equivalents (GL) for times 1 and 2, gain scores (means and grade level equivalents) across conditions

	ACCUPLACER 1			ACCUPLACER 2			Gain	
Condition	M	SE	GL	M	SE	GL	M	GL
Read-On! (*n* = 50)	48.1	3.4	8.7	52.2	3.6	8.9	+4.1	+0.2
STAR (*n* = 46)	48.1	3.4	8.7	50.5	3.5	8.7	+2.4	0
Gradations (*n* = 43)	45.2	3.2	8.5	52.0	3.4	8.9	+6.8	+0.4
Lifetime Learning (control group; *n* = 20)	56.3	6.3	9.0	50.6	6.6	8.7	-5.7	-0.3

In addition, the Navy conducted a longitudinal study with Navy recruits who read at or below 8th grade level [28]. Using a method similar to the one described above, these low-performing readers showed an increase of two grade levels in reading comprehension after a 37-hour instructional period. Eight weeks later, a skill-retention assessment was conducted. The results indicate that the students who used GradAtions® maintained a 1.7 grade level increase in reading comprehension skills, compared to virtually no retention among students receiving the instructor-led program. This stunning gain in reading comprehension performance and the retention of the gain are attributed primarily to (1) adapting the instruction to give the learner reading passages at the correct level(s) throughout the instructional period (AG2); and (2) deep processing of the material at a semantic level, which is required to write a good summary (fostered by AG1b, AG3a, and AG3c).

6 Conclusions

The two IAI applications resulted in strong learning effects by focusing on deeper semantic levels of interactions with the content, shown by the post-test differences and longitudinal effects in their respective studies. Superficial treatment of the content will not allow students to answer the questions well in AVT, nor to write a good summary in GradAtions®. The instructional tasks are designed to require deeper processing, which we believe should be the goal of any learning environment. Various methods of adaptivity can be used in a well-designed system to promote more active learning.

While Durlach & Ray's review [4] showed many positive results of different forms of adaptivity, more research needs to be done on how these adaptive features foster deeper learning at a semantic level, and support longitudinal results. We have provided a summary of potential adaptive features that could be used to create an environment that fosters deeper semantic processing of information.

References

1. Bloom
2. Corbett, A.T.: Cognitive computer tutors: Solving the two-sigma problem. In: Bauer, M., Gmytrasiewicz, P.J., Vassileva, J. (eds.) UM 2001. LNCS (LNAI), vol. 2109, pp. 137–147. Springer, Heidelberg (2001)
3. Anderson, J.R., Corbett, A.T., Koedinger, K., Pelletier, R.: Cognitive tutors: Lessons learned. The Journal of Learning Sciences 4, 167–207 (1995), http://act-r.psy.cmu.edu/papers/129/CogTut_Lessons.pdf (retrieved March 2, 2006)
4. Durlach, P.J., Ray, J.M.: Designing adaptive instructional environments: Insights from empirical evidence. U. S. Army Research Institute Technical Report (2011)
5. Jones, V., Jo, J.H.: Ubiquitous learning environment: An adaptive teaching system using ubiquitous technology. In: Atkinson, R., McBeath, C., Jonas-Dwyer, D., Phillips, R. (eds.) Proceedings of the 21st ASCILITE Conference Beyond the Comfort Zone, pp. 468–474 (2004)
6. Melis, E., Andres, E., Budenbender, J., Frischauf, A., Goguadze, G., Libbrecht, P., Pollet, M., Ullrich, C.: ActiveMath: A generic and adaptive web-based learning environment. International Journal of Artificial Intelligence in Education 12, 385–407 (2001)
7. Underwood, J.S., Underwood, I.M.: Immediation: Automatically diagnosing what students know, to teach what they are ready to learn. Paper presented at the National Meeting of the American Educational Research Association, Chicago, IL (2007)
8. Underwood, J.S., Kruse, S., Jakl, P.: Moving to the next level: Designing embedded assessments into educational games. In: Zemliansky, P., Wilcox, D. (eds.) Design and Implementation of Educational Games: Theoretical and Practical Perspectives. IGI Global, Hershey (2010)
9. VanLehn, K.: The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. Educational Psychologist 46(4), 197–221 (2011)
10. Falmagne, J.-C., Cosyn, E., Doignon, J.-P., Thiery, N.: The assessment of knowledge, in theory and in practice (2004), http://www.business.aleks.com/about/Science_Behind_ALEKS.pdf (retrieved February 20, 2006)

11. Shute, V.J., Hansen, E.G., Almond, R.G.: An assessment for learning system called ACED: Designing for learning effectiveness and accessibility, ETS Research Report, RR-07-26, Princeton, NJ, pp. 1–45 (2007)
12. Barab, S.A., Gresalfi, M., Arici, A.: Why educators should care about games. In: Educational Leadership (September 2009)
13. Chi, M.T.H.: Active-constructive-interactive: a conceptual framework for differentiating learning activities. Topics in Cognitive Science 1, 73–105 (2009)
14. van Merriënboer, J.J.G., Kirschner, P.A., Kester, L.: Taking the load off a learner's mind: Instructional design for complex learning. Educational Psychologist 38, 5–13 (2003)
15. Reigeluth, C.M.: The elaboration theory: Guidance for scope and sequences decisions. In: Reigeluth, R.M. (ed.) Instructional-design Theories and Models: A New Paradigm of Instructional Theory, vol. II, pp. 425–454. Lawrence Erlbaum Associates, Mahwah (1999)
16. Merrill, M.D.: First principles of instruction. Educational Technology Research and Development 50(3), 43–59 (2002)
17. Wulf, G., Shea, C.H.: Principles derived from the study of simple skills do not generalize to complex skill learning. Psychonomic Bulletin & Review 9(2), 185–211 (2002)
18. Carpenter, S.K., Cepeda, N.J., Rohrer, D., Kang, S.H.K., Pashler, H.: Using spacing to enhance diverse forms of learning: Review of recent research and implications for instruction. Educational Psychology Review 24, 369–378 (2012)
19. Donovan, J.J., Radosevich, D.J.: A meta-analytic review of the distribution of practice effect: Now you see it, now you don't. Journal of Applied Psychology 84(5), 795–805 (1999)
20. Lakshmanan, A., Lindsey, C.D., Krishnan, H.S.: Practice makes perfect? When does massed learning improve product usage proficiency? Journal of Consumer Research 37(4), 599–613 (2010)
21. Kluger, A.N., DeNisi, A.: The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. Psychological Bulletin 119(2), 254–284 (1996)
22. Schmidt, R.A., Bjork, R.A.: New Conceptualizations of Practice: Common Principles in Three Paradigms Suggest New Concepts for Training. Psychological Science 3(4), 207–217 (1992)
23. Underwood, J.S.: Effective feedback: Guidelines for improving performance. In: Proceedings of the International Conference of the Learning Sciences, Utrecht, The Netherlands (2008)
24. Pokorny, R., Haynes, J., Gott, S., Chi, M., Hegarty, M.: Infusing simulations with expert mental models, adaptivity, and engaging instructional interventions. In: Interservice/Industry Training, Simulation, and Education Conference Proceedings (2013)
25. Haynes, J., Fowler, D., Mayhew, S.: Intelligent reading tutor for improving reading comprehension and content learning. In: Interservice/Industry Training, Simulation, and Education Conference Proceedings (2009)
26. Vygotsky, L.: Thought and language. Trans. Alex Kozulin. MIT Press, Cambridge (1986)
27. Atkinson, R.K.: An experimental evaluation of three computer-based reading comprehension tutors. Final report to the Office of Naval Research, ONR N00014-05-1-0129 (2007)
28. Chapman, R.A.: Computer-based reading-comprehension tutorials: An experimental evaluation. Final report for ONR N00014-07-AF-00002 (February 18, 2009)