

Adapting Instruction

Wallace H. Wulfeck II

Space and Naval Warfare Systems Center Pacific
San Diego, California
wally.wulfeck@navy.mil

Abstract. It is often claimed that adapting instruction to an individual's progress, personal characteristics or preferences will somehow increase learning, and there have been literally thousands of studies over at least the past 100 years exploring this idea. This presentation will review various approaches to adapting instruction, such as changing the rate, difficulty, sequence or structure, instructional strategy or instructional media on the basis of learner progress, prior knowledge, aptitudes or preferences, under various forms of instructor, learner, program, or opponent control. This paper gives an organizing framework, describes some of the theoretical underpinnings for particular adaptations, and describes experimental and practical criteria for evaluating claims of efficacy and efficiency of instructional adaptations.

1 Introduction

We have known for over 2000 years how to provide effective instruction to an individual: provide expert tutors who personally coach the learner in a shared workspace over a period of years. The tutors continuously adapt instruction to the individual, structure the subject matter to be learned, decide on activities to engage and motivate the student, determine the sequence of topics to be learned or tasks to be mastered, provide instruction and context, model correct performance through worked examples, focus practice, observe the student's performance, monitor progress, correct or remediate performance lapses, provide feedback and coaching for improvement, conduct dialogues about the task and provide amplification and meta-instruction. This was the model of instruction at the time of Aristotle and Alexander and it is still used in apprenticeships, coaching, and in graduate-level and professional education.

The problem, of course, is that one-on-one tutoring is expensive. In the last few hundred years, instruction for groups of students became more common, in order to achieve efficiency in mass education. In the 20th century, perhaps as a result of the industrial revolution, a view of instruction as assembly-line manufacturing emerged, and attempts were begun to automate instructional processes. Standardized testing began during the First World War, "teaching machines" were invented in the 1920s, instructional films in the 1940s, programmed instruction in the 1950s, and with the development of television and early computers came "educational technology" in the 1960s and 1970s.

Although the usual goal of these instructional technologies is merely to make the delivery of instruction less expensive but not less effective than conventional

instruction, sometimes a stated goal is to achieve learning gains in mass instruction comparable to those routinely achieved by one-on-one tutoring. Benjamin Bloom [3] famously described the “two-sigma problem,” noting that group instructional methods rarely achieve gains in performance comparable to the two-standard-deviation gains that are often observed in tutoring. In general, the idea is that if instruction could somehow be more responsive to individual students, that is adapted to individuals rather than to (the slowest members of) a group, then learning might be more efficient or effective.

2 Adapting Instruction

A modern general conceptualization of the control of instruction was first mapped out by Smallwood [29] in the context of control theory, and substantially formalized by Atkinson [1] in a now-classic paper describing “ingredients for a theory of instruction.” In Atkinson’s view, control of instruction, and therefore of adaptation involves (1) a model of the learning process, (2) specification of admissible instructional actions, (3) specification of instructional objectives, and (4) a measurement scale for costs of actions and payoffs of achievement of objectives.¹ The model of the learning process requires a reasonably precise characterization of an individual’s state of learning before and after an instructional action, and therefore, by implication, some measure of the student. More generally, characterizing the model of learning and the effect of instructional actions on learning in any precise way really requires some sort of theory of learning and/or behavior change.

There are many ways to modify or adapt instruction, and they may be mixed. Following Atkinson’s [1] characterization, we will describe some dimensions of adaptation in terms of models of learning, instructional actions, and implementation of control. In some cases there may be similarities or overlap across these dimensions.

2.1 Basis for Adaptation

Perhaps the most important dimension of adaptation is the characterization or model of the learning process. The model specifies some properties of the student’s learning process which we will observe and use as a basis for prescribing some instructional action or treatment. This at least requires some measurement of the individual, together with the theoretical expectation that variation in that measurement has some instructional importance. That is, observed differences for individuals on that measure will lead to differences in whether and how we will instruct, and therefore to a difference in outcome. Among the properties of individuals and/or their learning or performance to which adaptation may occur are at least the following:

¹ Here the term “objective” refers to a goal or overall outcome of instruction, not a “behavioral objective” in the sense of Gagne or Mager. Atkinson (1972) gave examples of alternative instructional goals such as: (1) maximize the mean performance of the whole class, (2) minimize the variance in performance for the whole class, (3) maximize the number of students who score at grade level, or (4) maximize the mean performance for each individual.

Individual preference. The easiest way to get a measure from individuals is to simply ask them whether they feel that they know a concept, or are ready to take a test, or are ready to move on, or need additional explanation or practice, or prefer one or another style of instructional presentation (Also, see *learner control* below.) Unfortunately, it has been known for at least half a century that students are not particularly good judges of their own states of knowledge [1] and therefore not very good at judging their needs for explanation, practice, or remediation.

Current progress / result / score on some measure. This may be as simple as whether the last answer to a probe test question was correct or incorrect, or some estimate of the likelihood that a student has learned a particular concept, or it may be a more complex measure, such as a learning rate or a pattern of responses. A very common adaptation strategy had its roots in early programmed instruction (cf. Skinner, 1954): present a “frame” or block of instruction which concludes with a question. If the response is correct, proceed to the next frame; otherwise inform the student of an error and present the frame again. This style is still used today in powerpoint-derived web-based training because it is easy to implement, if not very effective. Much more sophisticated approaches have been based on mathematical models of learning (cf. 1), or extensive cognitive analyses of tasks [e.g. 4; 2].

Traits or aptitudes. It is often claimed that different individuals have different learning styles or aptitudes, and that adapting instruction to them will somehow increase learning. There have been literally thousands of studies over at least the past 100 years exploring this idea. Proponents of one or another instructional method generally seize upon one supposed characteristic (usually a binary one) that might differentiate individuals, and then propose different instructional treatments depending on the individual’s classification according to that characteristic. For example, we see learners described as:

- Right-brain vs. Left-brain
- Active vs. Passive
- Wholist vs. Serialist
- Visual vs. Auditory
- Multi-tasking vs. Sequential
- Abstract vs. Concrete
- Convergent vs. Divergent
- Extravert vs. Intravert
- Type A vs Type B
- Sensing vs. Intuitive
- Thinking vs. Feeling

A quick tour through Wikipedia starting with topics such as “Learning Styles” or “Individual Differences” will lead to dozens of these sorts of dichotomies. More sophisticated theorists will combine two or more of these dichotomies into multi-dimensional constructs. Unfortunately, these oversimplified approaches rarely work.

An adaptation to an individual difference actually requires substantial analysis and experimentation in order to demonstrate effectiveness. First, there must be some

observable difference between individuals. Preferably there should be some reasonably scientific theory about why the difference exists and why adaptation to the difference should have any effect on an instructional outcome. Second, there must be some sort of test or measurement for the difference that reliably differentiates individuals. The key here is “reliably”. Further it must be possible to measure this difference quickly enough to affect instructional decision making. Also, the difference must be stable long enough for an instructional strategy to be applied and take effect. Then there must be some prescription for an instructional adaptation to the difference, and there must be a reliable post-instruction measurement so that differential outcomes could be observed. Finally, there must be an experimental or quasi-experimental evaluation of the effectiveness of the adaptation. Further, results of that evaluation ought to show a disordinal interaction between the individual difference variable and the adaptation variable.

Despite hundreds of studies over 40 years of research on what are now called “aptitude-treatment interactions”, and several major reviews [13; 12; 33, 30, 37] there is almost no evidence of effective and practical adaptation of instruction to individual traits or aptitudes.

According to Tobias [35]: “Instructional designers are often urged to adapt instruction to students’ learning styles. The persistence of the learning style concept is amazing—a testament to the gullibility of even well-informed individuals who ought to know better. It seems that advocates of learning styles have never heard of the history of ATI research, which attempted to provide a database for adapting instruction to student characteristics and found many thorny problems. It is probably fair to say that the popularity of adapting instruction to learning styles is matched only by the utter absence of support for this idea.”

Prior knowledge / skill or ability level / prior achievement. In contrast to the dismal results for aptitude-treatment interactions, good results have been observed when adapting instruction to prior achievement. It has been shown that students with low ability or low knowledge of a particular topic generally need increased instructional guidance or support for learning [33, 34, 36, 23]. Also, more complex or broader measures are often used for more macro-level instructional decisions. For example, completion of pre-requisites is often a condition for admission to an advanced course, or we may decide whether a student is ready for a particular topic based on an aggregate measure of prior achievement or prior knowledge.

2.2 Instructional Actions for Adaptation

Rate or Pacing. Instruction may slow down or speed up, for example by allowing more or less time for study on a topic, or by providing more or fewer examples or practice opportunities. Fletcher [16] notes that individualization of pace is by far the most common adaptation to individual differences in learning, and is so common that it is “frequently, although incorrectly, treated as synonymous with individualization of instruction.” Fletcher [18] describes a “Rule of Thirds” which is a statistical summary of meta-analyses of the use of computer-based adaptation of pacing: it “can either reduce instructional time to reach instructional goals by about one-third (a goal more characteristic of training than education), or increase the skills and knowledge

acquired by about one-third while holding instructional time constant (a goal more characteristic of education than training).”

Difficulty. Chunks of instructional content may be graded or calibrated for difficulty or ease of learning, and more or less difficult concepts may be presented. Topics may be skipped or reinforced. This approach is commonly taken in adaptive testing, where items are calibrated, then selected one by one, based on the correctness of previous answers, to converge quickly on an estimate of achievement or ability [cf. 38]. It is used less commonly to adapt instruction, because it is based on a normative approach while instructional content has structural relationships which can be exploited for sequencing.

Sequence or Structure. Instruction may be divided into separate topics on the basis of some logical order or content structure. Topics may be arranged in some heterarchy of superordinate-subordinate and relationship links, and instruction may proceed up, down, or sideways through the network. For example, topics thought to be prerequisite to others may be presented earlier, or conversely a holistic overview might precede more detail on particular topics. Surprisingly, however, changing the sequence of small chunks of instruction seems not to make much difference -- there were a number of studies in the 1960s that “scrambled” the order of frames in programmed instruction and found no differences in learning – unless there were strong dependency relationships among problems to be solved [39].

Method of Instruction. The instructional strategy may be varied. For example, a common instructional strategy called “Rule/Example/Practice” presents conceptual generalities or directions, followed by worked examples, followed by practice opportunity [cf. 24, 25]. Sometimes other orders of these components (e.g. “Example, Practice, Rule,” 21) may even work better. An extension of this is a “problem-based” strategy that might start with an overall task or problem to be solved, and then work on separable parts of the problem while building knowledge.

Mode or Medium. The method of delivery of instruction may vary. For example, instructional materials might be presented in verbal or written form, or pictorially, or via a computer animation. In general however, results of research on differential effects of media are very mixed. Clark and Salomon [9] ask “why should we expect media to teach anyone anything?” and give references to many prior reviews of literature on media effectiveness. Clark [8] concludes “The best ... evidence is that media are mere vehicles that deliver instruction but do not influence student achievement any more than the truck that delivers our groceries causes changes in our nutrition. Basically, the choice of vehicle might influence the cost or extent of distributing instruction, but only the content of the vehicle can influence achievement” (p. 13).

2.3 Control of Adaptation

Another dimension of adaptation involves the control of instructional alternatives, that is, how a control strategy for the instructional process is implemented.

Instructor control. Traditional instruction is usually directed and controlled by a teacher or tutor, who decides on rate of presentation, sequence, instructional strategy, and media, and most importantly, diagnosis, feedback, and remediation of performance problems and misconceptions.

Learner control. The learner might choose what topics to study, in what order, for how long, and may choose alternative delivery media or methods. There have been many studies of learner control, with very mixed results. Learners may be allowed to control the rate of instruction (often called self-pacing), the choice of instructional strategy or method, or control of sequence of topics or activities. In extreme forms, such as pure discovery or “constructivist” learning, students may explore instructional environments with little guidance. We referred above to Atkinson’s [1] caution concerning self-pacing. In a broad review of learner control, Lunts [22] notes: “Thus, the research studies on LC fail to confirm or disconfirm anything. Consequently, there are no right answers on whether LC is beneficial for students and whether a higher degree of LC implied in a computer program improves instructional effectiveness” (pg 68). Finally, Mayer [23] concluded: “Pure discovery did not work in the 1960s, it did not work in the 1970s, and it did not work in the 1980s, so after these three strikes, there is little reason to believe that pure discovery will somehow work today” (pg 18). Kirshner, Sweller and Clark (2006) conclude that constructivist approaches to instruction are less effective than direct instruction.

Program or machine control. In computer-based instruction, programs can be written to choose instructional events, present and score practice or test items, provide written or pictorial content, and implement different instructional strategies. Investigations of the use of automation in instruction for the last 80 years have involved one form or another of program control. Its roots are in Pressey’s [26] teaching machine, Skinner’s (1954) programmed learning, and Crowder’s [14] intrinsic programming. One approach, based on mathematical learning and memory theory and optimization was heavily investigated at Stanford University with good results [19]. Suppes, Fletcher & Zanotti [32] used extremely detailed analyses of mathematics curricula and research on mathematics learning to inform computer control of pace and sequence. Another approach is to design machine-based instructional systems based on analyses of tutoring. This approach began with early work by Carbonell, Collins, and colleagues. [cf. 7, 11, 31, 10] More recent approaches in intelligent tutoring systems involve extensive cognitive task analysis [cf. 28] and sophisticated logic for making control decisions [cf. 27]. The lesson learned from all of this work is that really deep content and cognitive analysis is necessary to construct effective instructional programs.

Opponent control. In competitive tasks, such as sports, war games, or business simulations, control of instructional events may be based on scripted scenarios, or at least on conventions. Ultimately, however, control of events may depend on what actions are chosen by an opponent. Often an instructor will act as an opponent in

order to present instructive events or tune the level of difficulty or provide meaningful consequences to a trainee's actions. There is little research on the effectiveness of such strategies, although it is difficult to see how instruction and practice on competitive tasks could avoid opponent control completely.

2.4 Other Dimensions of Adaptation

In addition to the basis, actions, and control, there may be other variables that affect adaptation. One might be the type of content – it is possible that different models of learning might apply depending on whether one is learning facts such as in basic arithmetic versus high-level rules for problem solving. There have been many schemes for describing different types of content, but only some that then connect with alternative instructional actions or adaptations. Merrill's [24] approach is better than most.

Another dimension involves training individuals versus teams. Most tasks in the world of work actually involve teams or groups working together. Some development has been done on models of instruction for teams, or team instructional strategies. [e.g. 6], but very little has been done on adapting individual instruction within team training.

3 Conclusion

So, what we know at this point? Several points are worth making in summary:

First, individual tutoring is the most reliable way to achieve individualization and adaptation. When intelligent tutoring systems are carefully designed, they seem to achieve some of the same benefits. Good tutors adapt the pace, sequence of instruction, instructional strategy, amount of practice, and feedback. They do this by having a deep understanding or analysis of the content to be learned, strategies for explanation, and techniques for diagnosis, feedback, and remediation.

Second, computer-based adaptation of pacing based on careful models of learning and memory works and reliably yields about 30 percent time savings or increase in amount learned.

Third, both computer control of pacing/sequence and intelligent tutoring work best when there has been deep analysis and careful characterization of the instructional content and of the tutoring process. It is clearly time to revisit the learning trajectory optimization approaches developed at Stanford in the 1960s and 70s, and update them in light of more recent cognitive and content analysis techniques. More research and development on understanding and implementing in programs what tutors do to achieve Bloom's two-sigma difference in effectiveness is clearly warranted.

Finally, while this paper considered Atkinson's [1] first two ingredients for instruction, models and methods for adaptation, it has not discussed the third and fourth ingredients relating to instructional goals and the cost/effectiveness of actions to achieve them, mainly because so little solid work has been done. Fletcher [e.g. 15, 17] is one of the few voices in this wilderness.

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