Finding an Empirical Basis for Personalizing Training

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ABSTRACT

Personalization has often been described as the gold standard of training, but the research establishing a basis for personalization is limited. In this paper, we report results from comparing six factors that appear in current theories about personalization: generation; education; exposure to technology; knowledge pre-test; skill pre-test; and skill testing during training. Participants in this study were randomly assigned to two groups, allowing us to evaluate the hypothesis that younger, more technically sophisticated students will benefit more from active, technology-based training. One group studied traditional multimedia instruction (IMI) that explained the tasks; the second group received hands-on practice from an intelligent tutoring system (ITS). Results from analysis of covariance indicated that differences in age, education, exposure to technology, initial knowledge, and initial skill were not strongly related to final performance, when training treatments were taken into account. Skill testing during training proved somewhat more consistently related. None of the treatment by covariate interactions, however, yielded a statistically significant effect, so there was no support for changing instructional methods based on any of the factors studied. Instead, the hands-on practice provided by the ITS had a consistent, positive effect. The practical implications for personalized training are discussed.

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INTRODUCTION

Every generation is different from the last. Or so the saying goes. But for the training community, the implications of that statement are not clear.

For the generation born after the mid to late 1980s, whether you label them genM (Wallis, 2006), the Net Generation (Tapscott, 1998), or Digital Natives (Prensky, 2001a), most in the training community would agree that there are significant differences between their world and that of the previous one. This generation has always had computers, cell phones, video games, and the Internet, and much of their "face-to-face" has been replaced by Facebook, texting, and Twitter. There is, however, virtually no agreement on what these differences mean in practice to training. Some have argued that their immersion in technology has produced distinct characteristics that are relevant for how they can be taught. They are, the argument goes, technically sophisticated and proficient in multitasking; they learn best from active search and investigation; they believe learning should be fun; and they are dependent upon technology for acquiring knowledge and interacting with others (Oblinger & Oblinger, 2005, Prensky, 2001a, b). Some have even suggested that their cumulative experiences may have changed the way they learn, perhaps even at the level of altering brain structure (Prensky, 2001a). According to these views, traditional teaching methods, step-by-step instruction, and antiquated technology will fail to intellectually challenge them and will only serve to alienate them. Personalizing training based on age is seen as a necessity.

This perspective, however, has come under considerable fire. Many argue that the notion is too simplistic to be of value. A number of studies have documented that there is considerable variation in technology usage among university and high school students, particularly when more advanced forms of technology are considered (Kvavik, Caruso & Morgan, 2004; Kennedy, Krause, Judd, Churchward & Gray, 2006; Oliver & Goerke, 2007). Clearly, the implication that technology skills and experience will be universal among digital natives is not well supported by the data. Some studies have even indicated that it is the 35-44 year olds who show the heaviest technology use (Bayne & Ross, 2007).

Generally, these critiques fall short of providing contrary evidence; rather, they generally argue that other factors, such as the extent of technology use or education (Helsper & Eynon, 2010) may be as or more important than generation *per se* in determining the appropriate instructional approach. In effect, they shift the focus for personalization from generation to differences in technical sophistication, education, or other factors. Direct studies of the relationship between these student characteristics and instructional approach, however, are rare (Pashler, McDaniel, Rohrer & Bjork, 2009).

This study directly addresses the hypothesis that younger and/or more technically sophisticated students will benefit from advanced training technologies. It compares learning using traditional interactive multimedia instruction (IMI) to learning achieved when students are actively engaged in problem solving exercises and supported by a state-of-the-art intelligent tutoring system (ITS). As the ITS involves active search and investigation of solution spaces, supported by expert knowledge on problem solving approaches and strategies, younger and more technically sophisticated students should be able to more fully leverage its capabilities. The IMI, on the other hand, allows the students to study and review all of the knowledge at their own pace, characteristics that may, some argue, favor older or less technically sophisticated learners. If this hypothesis holds, we would expect significant interactions between these student characteristics and the training approach that is used.

Traditional instructional design, on the other hand, makes a different prediction. Traditional design does consider student background, but generally limits this analysis to the required knowledge, skills, and abilities (KSAs) the population may lack. Approaches to instruction are then based on this analysis of the KSAs to be covered and the strengths of different approaches relative to this gap. The best suited methods are optimal given the state of the learners and the nature of the task to be taught. Personalization occurs, then, by adjusting the use of an instructional approach rather than by implementing different approaches for different student populations. As we will see in the section that follows, traditional design would recommend the use of an ITS to train the task selected for this study.

THE TRAINING TASK AND TRAINING TREATMENTS

For this study, the task we trained was that of coordinating and directing an in-stride breach of a minefield as the commander of a mechanized infantry-tank team. Although the in-stride breaching tactic is relatively well defined, it is cognitively complex. It requires initial planning and continuing, time-critical problem solving as the scenario unfolds. Abilities to assess situations, to evaluate alternatives, and to coordinate actions are critical. Additionally, formative studies supported the premise that the skill was cognitively complex. High rates of error, particularly errors of omission, were common initially, as the problem-solving skill built through practice (Biddle, Perrin, Dargue, Pike, & Marvin, 2006).

ITSs have been designed specifically to train cognitively complex, ill-structured problems, and when they are coupled with cognitive task analysis methods, they can be used to build problem-representation and problem-solving abilities (Hall, Gott, & Pokorny, 1995). These capabilities of the ITS will be instrumental to providing training for the selected task. Consequently, if traditional design practices are predictive, we would expect the interaction of student characteristics and training treatment to be relatively unimportant, compared to the use of the ITS for training these problem-solving abilities.

Skill learning was demonstrated in the Marine Air Ground Task Force XXI (MAGTF XXI) simulation. MAGTF XXI is a real-time, High Level Architecture (HLA) conformant, tactical simulation built for the U.S. Marine Corps. It was developed by MAK Technologies under the Program Manager Training Systems (PM TRASYS) Tactical Decision-making Simulation (TDS) program to facilitate expeditionary warfare training.

Interactive Multimedia Instruction

The IMI used in this study covered all of the in-stride breaching tactics and the MAGTF XXI interface. The instruction included descriptions, photographs, and graphics of the equipment; annotated screen shots and narrated video clips of the MAGTF simulation displays and commands, and annotated screen shots illustrating breaching operations and tactics. As part of the instruction, participants were then given a knowledge test. The knowledge test consisted of 63 multiple-choice or matching questions. The tests were scored and returned to the participants with corrections, so they could review their performance and improve their understanding of the breaching tactics and simulation displays and controls.

Intelligent Tutoring System (ITS)

An Intelligent Tutoring System (ITS) lesson was the second training treatment. Commonly, ITSs are made up of three primary components – a student model, an expert model, and an instructional (or tutor) model, with a user interface to provide a skill practice environment. The instructional model applies the chosen instructional strategy, including selecting the problems to be solved. The expert model contains solutions for problems within the training domain, while the student model represents the ITS' estimate of what the student understands and the areas where this individual needs more practice. Beyond this generic, three-component architecture, however, there is considerable variation in how these capabilities are built. Figure 1 overviews our implementation of the ITS.

Our student model implements a profile of dynamically maintained variables, with each variable corresponding to one learning objective. These variables are estimated as weighted averages over a specified number of observations. As a result, changes due to learning are reflected across exercises, as the average increases with correct performance, or decreases as errors are made. The amount that scores are changed is adjusted according to the degree to which the action reflects mastery of the learning objective and the degree to which the ITS provided guidance in selecting the action. These updates are also applied to every learning objective that is implicated by a given action.

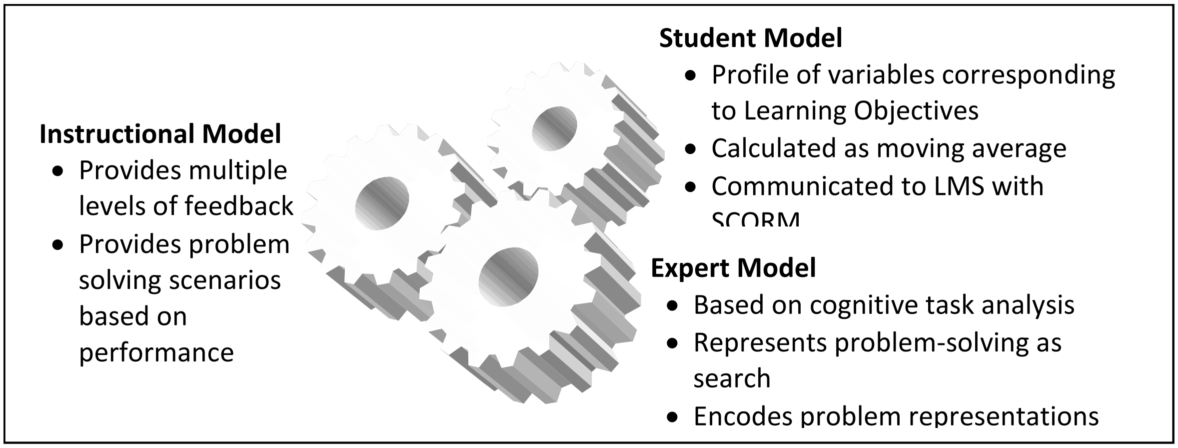

Figure 1. Specific Implementations in the ITS

With student requests for assistance or student errors, our instructional model responds with information on problem-solving strategies and/or problem representation derived from cognitive task analysis. The specificity of the information increases as additional requests are made or additional errors occur. The instructional model is also tasked with selecting follow-on exercises. By examining current student model scores, the instructional model identifies exercises that represent the next step in skill development or that are needed to clarify learning needs diagnoses (see Perrin, Buck, Dargue, Biddle, Stull & Armstrong, 2007 for additional detail).

Our implementation of the expert model is based on the cognitive task analysis technique known as PARI, for Precursor, Action, Results, and Interpretation (Hall, Gott, & Pokorny, 1995). Although PARI was developed for the analysis of maintenance troubleshooting tasks, it is based on a more general view of problem-solving as search through a problem space (Newell & Simon, 1972). PARI includes standard procedures that can be used to identify representative problem sets for ITS exercises. It also provides methods to elicit detailed information from experts on how they represent a given state of a solution (what issues have been resolved and what issues remain), optimal and alternative paths to a solution, and their strategies for selecting actions at each step along those paths. Our expert model directly encodes these solution paths. For each path, the model also encodes the expert's summary of the situation (representation of the problem) and the rationales for the possible next steps (see Figure 2). Additional detail on our ITS architecture and implementation can be found in Perrin (2009).

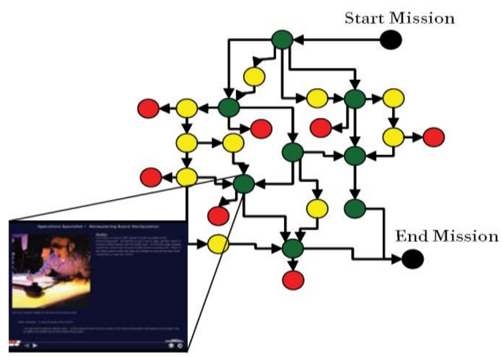

Figure 2. Optimal and Alternative Decision Paths in the Expert Model

METHOD

Participants

Twenty-four Boeing employees volunteered for the study. The group was composed of 20 males and 4 females. Six had prior military experience, but individuals with previous experience with infantry-tank task force operations were disqualified from participation.

Procedure

Participants first read and signed an informed consent form. It described their rights to anonymity and to withdraw at any time, as well as the general features of the study. Next, they completed a brief demographic questionnaire that included questions on age, education, and the frequency of computer game use. Age was recorded as an integer value. Education was coded into 5 categories; the groups and the number of participants in each were as follows:

1. High school degree - 1
2. Some college - 4
3. College degree - 8
4. Some graduate school - 3
5. Graduate school degree – 8

We use the frequency of computer and video game use as an indicant of technical sophistication. This measure is commonly used and has significant similarities to the technology that was used to assess skill learning. Computer and video game use was coded into 4 categories; the groups and the number of participants in each were as follows:

1. No or extremely limited use - 12
2. One to three hours per month - 2
3. One to six hours per week - 6
4. One or more hours per day – 4

All participants then received Interactive Multimedia Instruction (IMI) that covered the in-stride breaching tactics and the MAGTF XXI interface, to give them a basis for initial, baseline performance. Next, each participant used the MAGTF XXI simulation to conduct the initial phases of an in-stride breach. Each scenario ended when the units were positioned for the breach and when fire to suppress the opposing force and mask your units' movements was established. The scenarios were limited to these steps so that they would be short enough to allow multiple trials. Participants were given 10 minutes to complete these actions. To this point, all participants had received the same instructions and training; this initial trial established a performance baseline. After it, the participants were randomly assigned to one of two training treatments as follows.

IMI Review

Under this training approach, participants were given 20 minutes to conduct a self-directed review of the IMI. The IMI review allowed them to focus on any aspects of the breaching tactics or the simulation controls and displays that they wished, based on problems they had experienced during the baseline trial. This review was followed with another test, which was scored and returned to provide feedback, as before. This test had the same questions as the first, but in a different order.

Following the self-directed review and test, participants in the IMI Control group conducted a second in-stride breach using MAGTF XXI. This trial was followed with a final round of self-directed IMI review, knowledge testing with feedback, and an in-stride breach using MAGTF XXI. Thus, overall, each participant conducted three breaching operations, the first providing a baseline followed by two test trials. Each scenario was identical, so improvement in performance would represent a combination of study of the declarative knowledge in the IMI, knowledge testing feedback, and practice on the simulation.

It is also noteworthy that the IMI was created prior to this study, in support of a separate project (see Biddle, Perrin, Dargue, Pike, & Marvin, 2006). It was developed by a subject matter expert in the field who had extensive background and experience in training. As it is an independent product, designed originally for the objective of fully preparing students to perform the tactic in MAGTF XXI, concerns that these materials were given little emphasis, should be reduced.

Intelligent Tutoring System

Following the baseline trial, participants in this group studied an ITS lesson built using the architecture described previously. The ITS lesson did not repeat the declarative knowledge covered in the IMI. Rather, it presented a mission that required an in-stride breach that was similar to, but different from one used in the test trials. It required that the participants select an action to implement. It provided hints on the next actions, based on the expert's preferred solution strategy, when the student asked for assistance. It also provided feedback on the student's actions, including the impact on problem resolution and the optimal action, if it was different from what the student had selected. The ITS required the students to apply their knowledge of the MAGTF XXI interface and breaching tactics. For example, the IMI described how to use light vegetation and terrain features to help mask the movement of units. It also provided screen shots and interpretations of terrain displays. The ITS lesson, on the other hand, reached points in problem solutions where a unit needed to be moved, and asked the student to select a route. That selection, of course, depends upon the student applying his/her knowledge of terrain masking (see Figure 3).

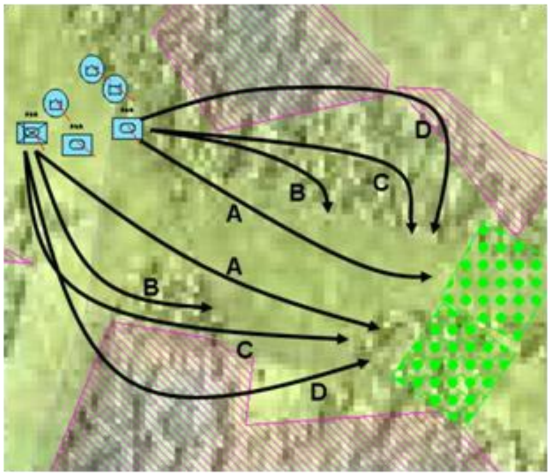

Figure 3. Selecting Routes in the ITS

After completing the ITS lesson, this group conducted a second in-stride breach using MAGTF XXI. This trial was followed with a final round of ITS study and a final in-stride breach. Similar to the control participants, each participant in the ITS group conducted three breaching operations, with one providing a baseline and two test trials.

The average time students took to study the ITS lesson was about 20 minutes the first time and about 15 minutes the second time. These study times were approximately the same as the time the control participants spent reviewing the IMI and their knowledge test results. Overall, the study times between the groups were approximately equal.

Data and Analysis

Measures of skill acquisition were provided by a set of automated performance assessment algorithms that had been designed and built for a previous project (see Biddle, Perrin, Dargue, Pike, & Marvin, 2006). For the scenarios used in this study, the automated assessment algorithms could detect and evaluate 21 distinct student actions. These actions, in turn, defined performance for 6 in-stride breaching tasks, as follows:

1. Establish Support by Fire: Assign and position units to provide support by fire for the breaching units.
2. Coordinate Movement: Coordinate arrival times of the support by fire units.
3. Position for Breach: Assign assets and position them to perform or support the breach.
4. Identify safe route: Establish route that minimizes exposure to hostile fire by taking advantage of the terrain and likely enemy force positions.
5. Control Suppressing Fire: Select the location and frequency for suppressing fire.
6. Control Obscuring Fire: Select the location and frequency of fire to help obscure your unit movements.

Scores on these tasks were the proportions of correct actions to the total number of opportunities achieved during each trial. Use of the automated performance assessment capabilities of this system is noteworthy as it eliminates experimenter bias as a possible threat to the internal validity of the study. Simply put, experimenter expectations could not influence final performance data, if those data are automatically generated by the system.

Previous analyses of these performance data indicated that learning occurred for 4 of the 6 measures. Specifically, the first 4 measures listed above showed significant trials effects. Measures for the other two tasks, dealing with the control of suppressing or obscuring fire, indicated that this skill was performed accurately in the baseline trial and so, changed little over trials (Perrin, Buck, & Gehr, 2010). Consequently, we limited our analysis for this paper to the first 4 performance measures, where personalizing the training could possibly affect the efficiency of skill acquisition.

Six measures were used as covariants in an analysis of covariance (ANCOVA). These variables included the student characteristics discussed previously (generation, education, technology exposure) and variables related to adjusting the amount of time spent in training (i.e., pre-tests on knowledge and skill, tests embedded with training). The statistical analysis tested for treatment and covariant main effects and for treatment by covariant interactions. As noted previously, significant covariant by treatment interactions will support theories that hold that training approaches should change with age, education, or technical sophistication. Significant treatment main effects, on the other hand, support more traditional design approaches, which advocate adjusting the time spent using the selected approach.

It is important to remember that there are two different ways that the measures we are discussing can be used to personalize training. The individual difference variables (generation, education, and technology exposure) and pre-test results (knowledge and skill), if the interactions are significant, can be used to select an optional method of training delivery based on their value. The performance measures (knowledge and skill pre-test, and in-training performance) if the main effect is significant, can be used to adjust the amount of training that is delivered. For example, poor mid-course performance might signal the need for remediation content to be presented.

RESULTS

The results from the ANCOVA are summarized in Figure 4.

For the four performance measures that showed learning, two were rather consistently affected by the training treatment – Identify Safe Route and Coordinate Movement. For these two performance measures, 10 of the 12 analyses yielded significant main effects of training treatment. One additional ANCOVA involving the Establish Support by Fire measure also yielded a significant training treatment main effect. These results largely parallel those reported previously (Perrin, Buck & Gehr, 2010), and reflect the increase in final performance of the group that was provided ITS-based training.

For the covariants related to student characteristics (generation, education, technology exposure), main effects were rare. Neither Education nor Exposure to Technology yielded any significant main effects. Age, on the other hand, produced one significant main effect. Final performance of the Coordinate Movement skill was significantly related to age, with older students performing more poorly than younger students.

For the covariants related to learning performance, the Knowledge Pretest and the Skill Pretest each produced one significant main effect, while the In-Training Performance covariant yielded two significant main effects. Three of the four main effects involved the Establish Support by Fire skill, with each covariate (the two pre-tests and the embedded test) showing a positive relationship; that is, higher test scores on the covariants were associated with higher final performance scores. The remaining main effect involved the Coordinate Movement skill and the In-Training Performance covariate, with the relationship also being positive, i.e., higher covariant scores were associated with high final skill scores.

		Analysis of Covariance Summary		
Personalization Factor	**Performance Measure**	**Training Treatment**	**Covariate**	**Interaction**
Generation	Establish Support by Fire			
	Identify Safe Route	F=15.511, p<.001		
	Coordinate Movement	F=5.931, p<.05	F=4.620, p<.05	
	Position for Breach			
Education	Establish Support by Fire			
	Identify Safe Route	F=12.680, p<.01		
	Coordinate Movement	F=4.419, p<.05		
	Position for Breach			
Technology Exposure	Establish Support by Fire			
	Identify Safe Route	F=11.076, p<.01		
	Coordinate Movement			
	Position for Breach			
Knowledge Pre-Test	Establish Support by Fire		F=10.081, p<.01	
	Identify Safe Route	F=14.281, p<.01		
	Coordinate Movement	F=5.082, p<.05		
	Position for Breach			
Skill Pre-Test	Establish Support by Fire		F=5.123, p<.05	
	Identify Safe Route	F=12.414, p<.01		
	Coordinate Movement	F=4.821, p<.05		
	Position for Breach			
In-Training Performance	Establish Support by Fire	F=5.882, p<.05	F=22.081, p<.001	
	Identify Safe Route	F=5.123, p<.05		
	Coordinate Movement		F=6.431, p<.05	
	Position for Breach			

Figure 4. ANCOVA Results

Finally, none of the covariant by training treatment interactions reached statistical significance.

DISCUSSION AND CONCLUSIONS

For the cognitively complex, problem-solving task that we studied, there was no support for personalizing training by changing instructional methods, but tailoring the training by adjusting the emphasis on the selected approaches was indicated in some cases. Let us consider this positive result first.

Of the student characteristics evaluated, only age yielded a significant effect. In this case, younger students' final performance on one measure (movement coordination) was superior, on average, to that of the older students. These results are, by and large, consistent with the research on age. In general terms, verbal abilities stay relatively constant over the years, while performance abilities (e.g., problem solving) tend to decline (Salthouse, 1992). In practice, however, these differences are often minimized, and may even be reversed, due to the accumulated knowledge and experience of older workers (e.g., Chi, 1978; Kail & Park, 1990). For this study, one could argue that personalizing the training by increasing the exposure to the Coordinate Movement skill for older students might have produced more consistent outcomes. Assuming that all older students require more time, however, might not be the most effective personalization strategy, especially as there are more direct indicants of this need. The In-training Performance measure also produced a main effect with the Coordinate Movement skill. As the correlation between this within training measure and final performance was 0.54, and the correlation between age and performance was only 0.34, personalizing on the within-training scores should yield more focused and efficient personalization.

The covariants reflecting learning performance (the knowledge and skill pre-tests and the within training tests) provided a more consistent basis for personalization, compared to the student characteristics. Each of the learning performance factors showed a significant relationship to one or more of the final measures of task skill. Final performance on one task in particular, Establish Support by Fire, was associated with each of these covariants. Presumably, the emphasis given to this task in training could have been readily personalized by monitoring one or more of these covariants. By monitoring these measures, students who scored high in skill and knowledge could be given scenarios that started with the units in position, reducing unnecessary repetition and decreasing overall training time without a loss of proficiency.

Our results also suggest, not surprisingly, that performance measures that were closer in time to the final skill assessment tended to be stronger and more consistent predictors of final skill, and thus, a better basis for personalization. The knowledge and skill pre-tests yielded significant effects on one task performance measure each, while the within training performance covariant yielded two significant effects and a third approached statistical significance. Essentially, this result reflects the fact that the best predictor, and so, the preferable means to achieve personalization is a previous assessment of the same skill in the same environment.

These results also suggest that there can be substantial variation in when skills become predictable, and therefore, personalization strategies can be applied. As noted, previous analyses (Perrin, Buck, & Gehr, 2010) showed that performance on each of the four skills improved significantly over the course of training. Of these, one skill seemed readily predictable with pre-test data, either on knowledge or on skill, or using within training performance data. Two more skills were generally predictable during the course of practice. The fourth, however, was not significantly associated with any of these covariants. The most likely explanation of this result seems to be that this skill was still developing. Where the within training performance measure correlated with final performance at levels of 0.54 or greater for the three other tasks, the correlation of within training to final performance was only 0.25 for the fourth task. Additionally, in terms of the general sequence of events in the training scenarios, this task is mostly performed in the latter phases, and so, would logically be the last to receive a student's focused attention.

One of the key hypotheses addressed by this study was that students of differing generations, education, or exposures to technology should be trained using different methods. This study yielded no support for this hypothesis. Our intelligent tutoring system (ITS) lessons involved immersion into problem-solving situations and collaborative learning supported by an expert, problem-solving model. As such, this high technology, active investigation of problem-solving techniques should have been preferred by younger or more technically sophisticated students, according to the corresponding theories. In fact, students trained with these ITS lessons produced the highest level of final performance, without regard to their generation, educational background, or exposure to technology.

Presumably, aspects of the skill to be learned and where the students were in the acquisition of the skill were more important than the characteristics of the students. Simply put, the "right" training approach was right for everyone. In her summary of the research on another factor that has been suggested for training personalization, that of "learning styles", Clark (2010) draws a similar conclusion. She calls the notion of personalizing training based on the student's preferred learning style one of the more pervasive myths of training. While it may be premature to consider personalizing the training approach based on differing generations, education, or exposures to technology a myth, this study provides data to suggest that the effect is, at a minimum, not as pervasive and/or as strong as some have argued. And perhaps it is indeed just another training fad that further research will soon dispel.

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