Development of a Training Effects Algorithm for Modeling the Impact of Training in IMPRINT for 21st Century Air Force Needs

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Abstract
The general aim of this project was to employ a model-based approach for aligning instructional strategies with technical task performance. The modeling system used in this effort was the Improved Performance Research Integration Tool (IMPRINT). IMPRINT has been used successfully by the United States Military to predict human performance in complex and dynamic operational environments. At the outset of this project, however, IMPRINT did not include a training component to determine the effects of instructional approaches on task performance within various learning taxonomic domains. In order to achieve the project goal, the project team carried out an extensive literature review on the effects of training on technical task performance and developed a training effects algorithm based on the meta-analysis of relevant studies. The training effects algorithm acts as a plug-in to the IMPRINT system and has been shown to effectively model training effects in a technical mission.

1.0 INTRODUCTION/PERSPECTIVE

The United States federal government has invested considerable resources over the last twenty years developing methods to model the impact of new systems on human resources and performance. By using human performance modeling systems, it is possible to predict the impact of various input factors such as personnel characteristics, environmental stressors, and task assignments on workforce performance and to plan for the selection and hiring of new personnel. The modeling system studied within this project is the Improved Performance Research Integration Tool (IMPRINT), which consists of a set of automated aids to conduct human performance analyses. The U.S. Army Research Laboratory, Human Research & Engineering Directorate developed the Improved Performance Research Integration Tool (IMPRINT) to support Manpower and Personnel Integration (MANPRINT) and Human Systems Integration (HSI). This tool had been used successfully by the U.S. Army to predict human performance in complex and dynamic operational environments in order to set realistic system requirements; to identify soldier-driven constraints on system design; and to evaluate the capability of available manpower and personnel to effectively operate and maintain a system under environmental stressors (U.S. Army Research Laboratory website, accessed July 2009).

IMPRINT has also been used to target warfighter performance concerns in system acquisition; to estimate soldier-centered requirements early, and to make those estimates count in the decision-making process. As a research tool, IMPRINT incorporates task analysis, workload modeling, performance shaping, degradation functions and stressors, and embedded personnel characteristics data. While previous versions of IMPRINT focused on Army missions, IMPRINT Pro is a tri-service tool with the capability to examine Army, Navy, Air Force, Marine, and Joint missions and systems (U.S. Army Research Laboratory website, accessed July 2009).
IMPRINT assists users in estimating the likely performance of a new system by facilitating the construction of flow models that describe the scenario, the environment, and the mission that must be accomplished. At the completion of a simulated mission, IMPRINT can compare the minimum acceptable mission performance time

and accuracy to the predicted performance. This allows the user to determine whether the mission met specific performance requirements.

The actual data input and analysis within IMPRINT occurs at the task level – analyzing high-level functions (e.g., troubleshooting a circuit board) in terms of smaller-scale tasks (e.g., determining whether or not there is desired resistance at a particular component), and then indicating the types of task skills required for proper execution of the smaller-scale tasks. IMPRINT has been used successfully to predict human performance in complex and dynamic operational environments.

Despite its capabilities for modeling human performance, IMPRINT does not include a sophisticated training component to determine the effects of instructional approaches on task performance within various taxonomic domains. The goal of this project was to determine whether and to what extent IMPRINT could predict the efficacy of alternative instructional approaches for different technical tasks. To accomplish this goal, the research team drew upon the technical training and human performance literature to develop a training algorithm that will interface with IMPRINT. This IMPRINT enhancement is designed to predict the efficacy of alternative training effects that include delivery media, learner characteristics, and instructional approaches for technical tasks such as those carried out by Air Force maintenance personnel within the cognitive, perceptual, motor, and communication domains.

Scientific modeling and computer simulation has played a role in both the social and natural sciences. There have been major advances with regard to computer modeling in fields such as economics, environmental and political sciences (Gilbert & Conte, 1995; and Krugman, 1996). Social science computer simulations are one of the most exciting applications that are supported by the increased computing power. However, most of these models and simulations are not setup to account for the effects of varying instructional strategies.

2.0 OBJECTIVES/PURPOSES

The main objective of this project was to draw upon the technical training and human performance literature to develop a training algorithm that will interface with IMPRINT. This IMPRINT enhancement is designed to predict the efficacy of alternative instructional approaches for critical Air Force maintenance and logistics tasks within the cognitive and psychomotor domains. The ultimate goal is to help transform Air Force training systems into flexible, responsive systems that develop individual and group problem-solving and decision-making abilities in the general domains of maintenance and air crew training.

The training effects algorithm developed as a result of our efforts allows us to determine how different instructional strategies impact performance on an individual as well as an organizational level. Models connected to the new system will be able to predict how training can influence the human agents of that system. For instance, the modeling outcome allows for the prediction of which instructional strategy (or grouping of strategies) enables the system to be fielded in the most cost effective and rapid way with the least amount of training. The ultimate goal is that modelers can apply the findings meaningfully in an IMPRINT model to account for instructional training effects on task performance.

3.0 TECHNIQUES

In order to develop a training effects algorithm, a meta-analysis was conducted to statistically synthesize the literature review findings in order to inform the algorithm development. Meta-analysis is a set of statistical techniques for combining information from different studies (as identified from an exhaustive literature review) to derive an overall estimate of a treatment's effect. Given that the results from different studies investigating different independent variables (instructional strategy effects) are measured on different scales, the dependent variable in a meta-analysis must be some standardized measure of effect size. Effect sizes are measures of the strength or magnitude of a relationship of interest and have the advantage of being comparable across all of the studies. To describe the results of comparative experiments reviewed in the literature, the usual effect size indicator is the standardized mean difference (d) that compares the treatment and control means, or an odds ratio if the outcome of the experiments is a dichotomous variable (success versus failure). With continuous variables as predictors, the correlation itself is the indicator of the effect size. We transform all other indices to the metric of the correlation coefficient, primarily via the transformation $r = d / \sqrt{(d^2 + 4)}$. A meta-analysis can then be performed on studies that describe their findings as correlation coefficients together with the transformed values that represent the impact of treatment interventions.

Since meta-analysis has a unique role in this study, some weaknesses were found. First of all, when we create the standardized regression models using predictors from different studies we will usually not have inter-correlations among those predictors. Thus we are essentially assuming that variables are not correlated, which is not the case for many of our predictors. Also as Becker and Wu (2007) have pointed out, one of the challenges meta-analysts face when intending to combine results from regression studies (or here from treatment and correlational studies) is that the predictors usually differ from study to study even when researchers are studying the same outcome. Such "unparallel models" make it difficult to combine the results directly because the effects of different predictors are held constant in different studies when computing the effect of a focal predictor. The third limitation is that studies have examined different populations of interest. In general the target populations are students but their education levels have a wide range, as do their initial levels of experience. This situation could be problematic when it comes to combining the research results, particularly if the various treatment interventions are differentially effective across populations.

The main purpose of doing meta-analysis in this project was to provide information necessary for algorithm development and modeling to show the relationship among all independent and dependent variables. Ultimately, combinations of treatment types, durations etc., will serve as inputs to the model in order to project potential outcomes of different training scenarios. To accomplish this, standardized regression models will be created for each outcome from the data obtained via effect-size calculations. In order to generate these models we must estimate standardized regression coefficients that will be represented by the mean correlations.

4.0 RESULTS

4.1 Algorithm Development and Modeling

The meta-analysis process resulted in a standardized regression model that allows prediction of the task performance time of an alternative instructional approach given: (1) the task performance time of the anchor instructional approach (M_{Anchor}), (2) its standard deviation (SD), (3) the task Taxons array, and (4) the meta-analysis *R-Values*. The *R-Values* represent the distance in standard deviations between the conditions. These mean *R*-Values are used to generate a training and task performance algorithm that is implemented in the current version of IMPRINT. The formula that is used to get the projected alternative group performance time is:

$$M_{\text{Alternative}} = M_{\text{Anchor}} + 2 \times R\text{-}Value \times \text{SD}.$$

For example, if a defined task has normal performance time with Mean=50 and SD=20 and the R-Value that represents the relationship between the anchor and alternative instructional approaches equals 0.615, than the new performance time will be:

$M_{\text{Alternative}} = M_{\text{Anchor}} + 2 \times R\text{-}Value \times \text{SD} = 50 + 2 \times 0.615 \times 20 = 74.6.$

As a first step to implement the algorithm within IMPRINT, we created an external plug-in that can be called by IMPRINT. In this method, the algorithm was coded to a plug-in function. In a C# environment, a new function named "GetAdjustedTime" gets the task mean, standard deviation, and Taxons array as inputs and returns a new adjusted time. In an external user interface, the modeler can select an anchor and alternative to be compared and change the *R*-Values for each category. Figure 1 presents an overview of the plug-in, the users' interfaces, IMPRINT, and two text files, and shows how those elements connect with each other.

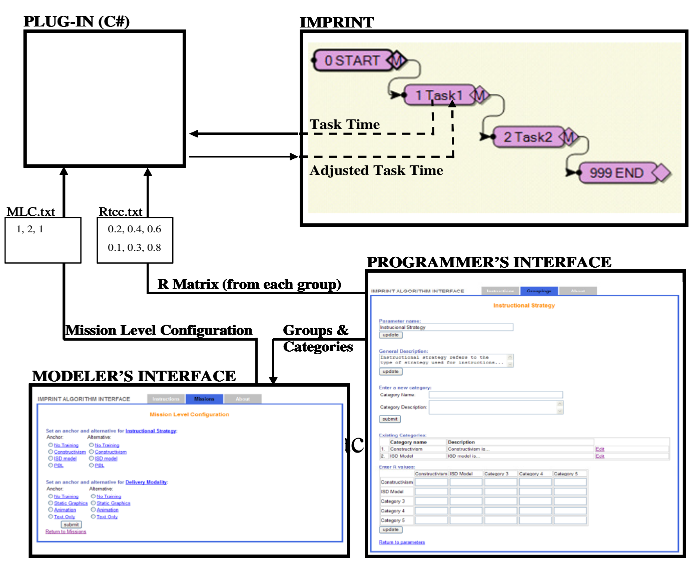

Figure 1. Plug-in interfaces and communication with IMPRINT

The plug-in is called from IMPRINT tasks expressions with the task mean, standard deviation, and taxons array as parameters. The plug-in then uses the parameters and two text files (MLC.txt and Rtcc.txt) to calculate a new adjusted time for a task, given the particular sort of training or instructional intervention envisioned. This time is returned as the task performance time.

Even though this plug-in enables a comparison between two instructional strategies, there are a few limitations that needed to be addressed. First, the modeler has to change the tasks in the model to use expression (i.e., code) instead of distributions (i.e., concrete values of Mean and SD in case of normal distribution). Because it is not possible to use both the "Use Distribution" mode and "Use Expression" mode at the same time, the modeler needs to code the mean and standard deviation, and then call the plug-in function (see Figure 2 for a typical expression).

A second limitation to the first implementation is that the plug-in could not get direct access to the task Taxons. In IMPRINT, tasks can be broken down into categories called Taxons. This categorization is used to describe the workload composition of a task. There are nine IMPRINT Taxons (Visual, Numerical, Information Processing, Fine Motor-Discrete, Fine Motor-Continuous, Gross Motor Light, Gross Motor Heavy, Communication (Read & Write), and Communication (Oral)) grouped into four domains (Perceptual, Cognitive, Motor, and Communication).

The algorithm multiplies the effect of the cognitive categories by the percent indicated for the cognitive Taxons (including perceptual, cognitive and communication) and the effect of the motor categories by the motor Taxon. Thus, if the specified task is defined as motor, only the motor categories effects will influence the task performance time. To be used, in this implementation the Taxons need be coded in the expression and sent as parameters to the plug-in.

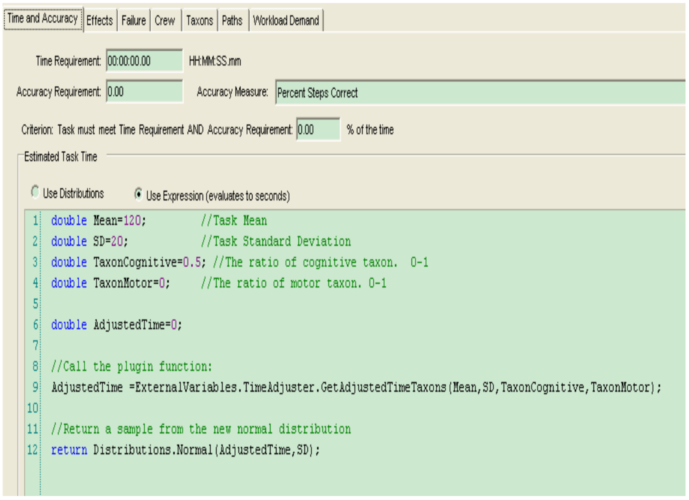

Figure 2. Expression code used to call the plug-in function

To overcome these limitations, a newer version of IMPRINT was developed to include the plug-in algorism as an integral part of IMPRINT. The current version of IMPRINT includes a Training Effects Calculator (TEC) that uses the algorithm developed by the FSU team.

The Training Effects Calculator includes the following features:

(1) Ability to apply the effects of changing training characteristic (i.e., anchor vs. alternative) within a specific category to an existing mission without having to code each task manually.

(2) Ability to see and modify the relationship (i.e., *R*-Value) between two specific training characteristics within the IMPRINT environment

(3) Application of Taxon Characteristics to determine level of training effect for a specific mission task.

(4) Ability to print out a comparison report for mission level performance for two training characteristics within a specific category.

5.0 SCIENTIFIC SIGNIFICANCE OF THE PROJECT

Through consolidating and synthesizing evidence linking training methods and strategies to performance, it was possible to develop meaningful, analysis-driven IMPRINT training algorithm. We have evidence that it is possible to take existing literature and transform it into a dataset and consequently an algorithm to be used within the IMPRINT system. This algorithm works as an IMPRINT plug-in that is capable of modeling the effects of instructional training effects on technical task performance within the cognitive and psychomotor domains. This plug-in can be continually updated as new training and performance literature emerges. It is also possible to extend the algorithm to model training effects on performance within the perceptual and communication domains.

While we have demonstrated the concept that empirically based training strategy effects drawn from the existing literature can be modeled within IMPRINT, there is future work to carry out in order to finalize a training effects (TE) algorithm. Key research and development tasks include: fleshing out the other taxon characteristics r-matrices to allow for additional comparisons; IMPRINT / Plugin interfacing to automatize the linking of the TE Algorithm with in IMPRINT missions; further develop the interaction effects of multiple TE categories; and carrying out a validation study to verify current algorithm assumptions.

With current findings from this study and future research and development, the TE Algorithm can have a strong impact for systems designers by providing them with empirically based results to help them make decisions about appropriate training strategies as integrated into systems operations. Ultimately, these results allow designers to see the effectiveness and efficiency of different training methods. This work further provides a model to conduct related work in other areas such as analysis of training and development strategies effects for first responders or even terrorist organizations with the intent of understanding the impact of training strategies on organizational operations and performance.

6.0 REFERENCES

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Biography

Tristan E. Johnson is a member of the research faculty in Human Performance Research Center at the Learning Systems Institute. He is an Assistant Professor of Instructional Systems in the Department of Educational Psychology at Florida State University. Dr. Johnson has several years of experience studying team cognition, team-based learning, measuring shared mental models, team assessment and diagnostics, and team interventions. He is also involved in the development of agent-based modeling and the creation of data-driven algorithms for modeling training and instructional effects within performance models.

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Rinat B. Rosenberg-Kima is a doctoral student at Florida State University, pursuing a Ph.D. in Educational Psychology and Learning Systems under the direction of Dr. Tristan E. Johnson. She received her BS degree in Computer Sciences and MA degree in Psychology from Tel-Aviv University, Israel. For the past three years, Ms. Rosenberg-Kima Rinat has worked as a research assistant at the Learning Systems Institute at Florida State University. She has programmed a plug-in algorithm and interface to be used by the United States Air Force Research Lab (AFRL), and is involved in the development of agent based modeling algorithms.