IN SEARCH OF THE TRAINABILITY QUOTIENT: BEYOND LEARNING CURVES

Charles C. Coker, Ph.D., CRC, CVE, CWA

Abstract

Assessment of employment potential plays an important role in the vocational preparation of handicapped students and adults. Indeed, within vocational rehabilitation programs, vocational evaluation services have long played an influential role in predicting the employment potential and training needs of handicapped individuals (Blakemore & Coker, 1982; Dunn, 1976; McCray & Blakemore, 1985; Schalock & Karan, 1979). Vocational assessment programs are also rapidly expanding within secondary school settings as schools increase their efforts to facilitate handicapped students' transition from school to work (Brolin, 1986; Meers, 1985; Peterson, 1986; Ashley, DuBose, Poplin, & Sinkewiz, 1986; LeConte, 1986). Prediction plays a critically important role in this process. Traditional assessment tools and techniques such as work samples or situational assessments are used to: (1) evaluate a handicapped individual's current performance levels; and (2) based on that information make predictions about future performance capabilities (Blakemore & Coker, 1982, 1983; Chan, Parker, Carter, & Lam, 1986; Gersten & Irvin, 1984; Irvin & Halpern, 1979; McCray & Blakemore, 1985). While vocational evaluation techniques have proven to be useful in establishing current performance levels, a number of authors have indicated that these procedures and the inherent limitations of the evaluation instruments currently available make the goal of prediction much more susceptible to error (Blakemore & Coker, 1982; Chan et al., 1986; Dunn, 1976; Irvin & Halpern, 1979; McCray & Blakemore, 1985). This error stems from the lack of measuring improvement in performance during assessment. Yet, evidence of such improvement can be one of the best indicators of trainability potential (Bellamy & Snyder, 1976; Blakemore & Coker, 1982; Chan et al., 1986; Gersten & Irvin, 1984; Irvin & Halpern, 1979). In many settings, trainability, rather than immediate employment potential, should be the key focus of assessment. This is particularly true in educational settings. Current evaluation practices do not adequately address the issue of trainability prediction. The research presented will examine the concepts of work sampling theory (Pruitt, 1970), trainability testing (Robertson & Downs, 1979), and learning curve analysis (Coker & Blakemore, 1985). It describes the research needed to develop a new computer system for analyzing critical measures that would lead to validation of the "Trainability Quotient" - an indicator of benefit from further training.

Introduction

Vocational assessment routinely involves the measurement of handicapped individual's capacity to function on repetitive motor tasks. In many instances, the assessment process is a static measure of current potential, and fails to use available technology to predict performance increases associated with learning. In recent years, the Research and Training Center at the University of Wisconsin-Stout has had a focus on "learning curve analysis" (LCA) and its application to vocational assessment through several research studies, development of training guides, and development of computer software (Blakemore & Coker, 1982; Coker & Blakemore, 1985; Coker, 1985; McCray & Blakemore, 1985; Coker, McCray, and Blakemore, 1987; Dolce, 1983). These activities have made considerable progress in making such technology available for application in vocational assessment. As is typical, the research has also found considerable problems in developing accurate prediction of vocational potential and current research is beginning that goes beyond plotting learning curves. Research both in South Africa (Taylor, 1982) and England (Robertson & Downs, 1979) refers to this problem in terms of measuring the ability of the individual to benefit from further training. This research refers to "Trainability Testing" and provides a more positive approach to assessment since it tends to focus more on the individual's responsiveness to training techniques rather than a one time determination of ability. Siegel and Bergman (1975) advocated a similar method to comply with EEOC guidelines.

This article summarizes the progress of the research at the Center in computer based learning curve analysis and potential for application in work sampling theory and trainability testing. New concepts are explored to advance prediction of trainability through computer based mathematical curve fitting techniques, summary statistics, and clinical judgement.

Previous Research

There are three potential and fundamental errors in drawing conclusions from static measures of an individual's functional capacity that stem from: differential practice, performance variation, and prediction (Coker & Blakemore, 1985).

Differential Practice. First, the client's performance measures are compared to individuals whose amount of prior training or practice on the task(s) may be totally different from that of the client being evaluated. There are a large number of studies demonstrating that performance on work tasks involving motor skills shows marked improvement with practice (e.g., Fitts & Posner, 1967; Schmidt, 1975). In addition, other research demonstrates that improvement continues to occur for many thousands (Cochran, 1968) and, in some cases, even millions (Crossman, 1959) of practice trials. The basic conclusion to be reached from studies of motor and industrial work skills is that these generally show progressive improvement with practice over a large number of trials and, perhaps, many years (Peterson, 1975).

The usual result of the traditional comparison of performance to normative information is an underestimation of the skill level of the client. Dunn (1976) found that only 15% of the males and 6% of the females reached the industrial standard in a single administration of a work sample; even though the subjects were non-disabled college undergraduates. In Chyatte's (1976) research, only 3.4% of the clients on one work sample and 1.2% on another reached the industrial standard at the end of a single administration. Blakemore and Coker (1982) found that only 5% of the clients in their study did. Both Dunn (1976) and Blakemore and Coker (1982) found significantly more individuals meeting the competitive norm with further practice. After three additional administrations, 55% of the males and 42% of the females were now meeting the industrial standard (Dunn, 1976). For Blakemore and Coker's (1982) client subjects, 55% were meeting the industrial standard after four additional administrations.

Performance Variation. Secondly, traditional assessment processes loses valuable data that could better determine the client's real potential. A static process of evaluating the level of functioning, such as using the mean or total production rate, fails to account for differential performance during the repetitions or cycles of the tasks within the work sample and the potential for further learning. Individuals functioning at the same average level on a work sample involving several repetitions are not necessarily performing comparably during the entire session.

Too often the assumption is that performance during several trials of the same task will follow the idealized learning curve where skill acquisition increase consistently over time. The problem is that the actual performance is not known. The same mean time could result from several different situations:

(1) Performance could begin at a high level and deteriorate over time as a result of fatigue, boredom, confusion, etc.
(2) Performance could be relatively stable except that there is a momentary decline in task performance due to distraction, forgetting of instruction, or perhaps lack of parts.
(3) There could be a rapid acquisition of the task because the task had been previously mastered and the individual rapidly returned to that level.
(4) Or it is possible that steady level task performance occurred from the very first attempt to the last one because the individual is currently practiced on the task and is at the optimal level.

The typical result is that the current and potential task performance is underestimated and additional valuable information about the client's ability is lost. It would not be lost, however, if an LCA approach was used.

Prediction Error. Thirdly, very often work samples are used to predict the individual's future potential. There are few, or no, work samples that have demonstrated their predictive validity. Work samples were developed not to predict, but to demonstrate that an individual could do the task in question by using the actual task as a work tryout. Norms are given simply to state where that performance level is relative to others who have been given the same task in the same situation. Typical work sample measures do not provide estimates of the training potential of the individual.

Learning Curves

A number of researchers (e.g., Tillman, 1971; Dunn, 1976; Blakemore & Coker, 1982; Chan, Parker, Carter, & Lam, 1986) have suggested that one way to overcome the problems of underestimating client potential on work samples is to plot the client's performance data in the form of a learning curve (or equation) and to extrapolate client potential using this data. The term "learning curve" usually refers to a graph representing changes in performance over time or trials. Though the changes in performance can be attributed, in part, to learning, variations in the curve also reflect variables other than learning which affect performance (e.g., environmental variables, motivation). Though these graphs of performance do not necessarily reflect the actual amount of learning that occurs, they do reflect how an individual actually performs, which is the most important aspect. Since the term "learning curve" is widely used in the literature, this research referred to the graphing of performance (and equations which describe such performance) as a learning curve, with the realization that such curves reflect the effects of many variables.

The research by Blakemore and Coker (1982) indicated that the use of the learning curve technique does have great potential for providing more accurate estimates of the level of performance than does a static assessment measure. They had vocational evaluation clients perform on the same work sample for five consecutive work days. On the average, performance was 30.68% better on the final day of practice (Day 5) than on the first day of practice (Day 1). Thus, if the performance level (total time score or average score) for Day 1 had been used as the estimate of the client's capacity to perform this task, their potential would have been underestimated by an average of 30.68%.

Statistical analyses demonstrated that learning curves could produce significantly more accurate predictions of Day 5 performance. They found that predicting Day 5 performance using the performance scores from Days 1-4 produced predictions that differed from the actual level of performance by only 6.78%, on the average. The use of Day 1 scores only resulted in Day 5 predictions differing from the actual scores by 17.15%. Both of these estimates were significantly better than the 30.68% average error made when using the total time score for Day 1 to estimate Day 5 performance level.

The major drawback to the use of the LCA is the fact that the manual application of this approach is simply too time consuming. In the traditional approach, the total number of pieces, the total time to complete a set number of pieces, or mean production rate are relatively simple to obtain. It is also very easy to administer the work sample and obtain the data in such cases. A timer is started when the client begins the task and is stopped when the client is finished. In the interim, the professional can be busy with other tasks.

This would not be the case, however, if data were to be collected for use in calculating a learning curve for a client. In this case, client's performance would have to be constantly monitored and the amount of time taken to complete each item would have to be recorded. In addition, a more complex analysis of the data would be necessary. This procedure would, of course, reduce the amount of time professionals could spend on other aspects of their work or with other clients. Thus, though analysis of performance through generation of learning curves has been advocated for a number of years, few professionals consistently employ them.

Performance Analyzer Software

One of the primary purposes of the previous research project by Blakemore and Coker (1982) was the development of a microcomputer system that automatically collects data on work sample performance and calculates a learning curve using the data which was collected. This system would have the advantage for applied use of learning curves in that it can be used to accurately reflect a client's present level of functioning and potential. At the same time, it does not have the disadvantage of increasing the work load. One purpose of this project involved determining the feasibility and utility of making learning curve theory a routine procedure for evaluating client potential through the development and testing of software for microcomputers.

The Performance Analyzer and Trainer (PAT) software (Coker, Blakemore, McCray, & Edwards, 1987; Coker, McCray, & Blakemore; 1987) that was developed involved the use of three concepts: learning curve analysis, performance feedback, and pacing of performance. For all three concepts the recording of the time it takes for a client to complete each repetition of a task on a work sample is required. The computer provides the timer, but the task must include switch closure to start and stop the timer. The closure can be obtained by including pressing a switch as part of the task elements, or task movements could automatically start and stop the timer (Blakemore & Coker, 1982; Kelk, 1986). In the latter case, a completed piece could be dropped into a box which closes the switch or breaks a photocell beam. There are a number of more creative and exotic ways that switch closure or opening could result in control of the timer that is part of the software program or computer. Once the task is appropriately tied to the computer, the professional or client can utilize the software.

The PAT software is based on the Commodore 64 system, has been used in several clinical situations, and in current Center research. The basics of the systems were field tested at the Leads Employment Rehabilitation Center in England (Kelk, 1986) and portions adopted from their PACE experiment. The software generates the following measures for LCA:

- MEAN TIME TO COMPLETE TASK CYCLE
- STANDARD DEVIATION OF ALL TRIALS
- MEAN OF THE BEST 20%
- FASTEST TRIAL
- SLOWEST TRIAL
- RANGE BETWEEN FASTEST AND SLOWEST
- TRIALS ORDERED FROM FASTEST TO SLOWEST
- POWER CURVE ON CURRENT TRIALS
- PREDICTION POWER CURVE (999)

The PAT software has the advantages of: 1) automatically collecting information; 2) providing summary of current performance; 3) analyzing data based on power learning curve formula; 4) displaying predicted performance through hundred of trials; and 5) shaping performance through four feedback and three pacing programs.

Problems with Learning Curve Analysis

The development of the PAT software and application in several settings indicated that the prediction of vocational potential mathematical modeling techniques has significant potential. The computer does much of the work and provides a summary report, learning curve on existing data, and projections of learning potential, and provides graphic programs for feedback and pacing of performance. Despite the attractiveness of the PAT features, significant limitations exist for making accurate decisions about the training potential of individuals with handicaps. First, only one learning curve formula is used and there is no research evidence clearly indicating either the accuracy of this curve as a predictor or the range beyond which predictive accuracy begins to deteriorate (e.g., 5 times the number of initial trials, 10 times, 15 times). The PAT does not indicate the extent to which the curve's accuracy may vary depending upon the complexity of the task or the number of initial trials administered. Despite the calculation of a learning curve, prediction success will also vary with the amount of prior experience on the task. There are indications that the learning curve of more practiced individuals will be more reliable than that of the unpracticed learner. As a result, learning curves based on inexperienced individuals with few trials often result in negative predictions because of inconsistencies between the training process and the mathematical modeling process. This result tends to render the information meaningless for predictions, though experienced users of the software can examine performance trends for clinical decisions. And in cases in which a positive curve can be projected, lack of an adequate research base calls into question the relative accuracy and reliability of individual projections.

Second, the limited memory and storage capacity of the Commodore system severely restrict the amount of data which can be gathered and analyzed, ability to compare performance over time and across different tasks and conditions, and provide practical reporting formats. All of these limitations have a deleterious effect on the accuracy of the predictions about training potential. Despite these limitations, however, this early research does suggest that existing microcomputer technology more powerful than the Commodore system (e.g., IBM PC's and Apple II's) would be likely to have sufficient storage and processing capability to manipulate the data and make the projections if the proper measures could be identified or derived.

Work Sample Theory, Trainability Testing, and Learning Curve Analysis

The assessment of performance during work sampling (Pruitt, 1970), trainability testing (Robertson & Downs, 1979), and learning curve analysis (Coker & Blakemore, 1985) are all inter-rated in that they have as their basic function the measurement of an individual's ability to perform a given task, but they also differ. In work sampling as an industrial personnel selection tool, the assumption is that the person is well trained on the task and therefore this technique will yield the information as to which individuals can best perform the tasks for which they would be employed. The underlying assumption is that the best predictor of future performance is past performance. The work sample is used as a measure of "past performance." Trainability testing goes one step further. Rather than accept the premise that the individual performing the work sample is well trained, the testing process provides training on the task through repeated performance under different instructional and learning strategies. In learning curve analysis, the assumption is made that there is no need to know the prior experience of the individual. Instead, precise measure of performance on repeated cycles of the task is obtained and mathematical modeling techniques are used to describe current ability and to predict future performance.

There are advantages to each techniques. Obviously, work sampling is the easiest, less costly, and less time consuming. Trainability testing can be time consuming and expensive with unclear guidelines as to what constitutes an valid training and testing procedure. Learning curve analysis is simply not practical without computer based software and predictions have not yet been validated. Taylor's (1982) comments on the problem of trainability testing could apply to all three:

> "... problems arise from a proliferation of tests, the limitation of predictions to the learning of motor skills, poor prediction of long term job performance, inter-rater reliability, and the need for an experienced instructor-assessor."

The one problem that is inherent in all three of these techniques is inability to accurately specify the ability of the individual to benefit from further training. Each technique makes assumption about the location of the individual on their learning curve. Work sampling theory is based on the assumption that the testee is at the plateau of the curve. Trainability testing assumes that after training the individual is at the plateau of the learning curve. Learning curve analysis assumes that several trials will yield sufficient information to generate the individual's learning curve. The problem still remains: Does the obtained information give reasonably accurate measure of ability on a task? The answer is yes, the closer the individuals are to the asymptote or top of their learning curve.

Mathematical Modeling: Learning Curve Fitting

Despite the appeal and sophistication of learning curve analysis, it must be remembered that it is basically a relatively simple and pure mathematical process. In learning curve analysis, the time to complete repeated cycles of a task is analyzed by using a curve that best fits the existing data. While the PAT software eventually used only one curve (power curve), the original research examined seven different potential curves. Three curves were incorporated into the initial versions and two were later eliminated because they would sometimes predict minus seconds to complete the tasks. There are a number of formulas to do curve fitting. For example, in the Curvefit software (Cox, 1987), there are no less than twenty-five formulas varying from a straight line through Hoerl function, Exponential, Geometric, Logarithmic, Beta, Gamma, Cauchy, and others. The problem in mathematical modeling is that the curve which best fits the existing data, and therefore, presumably yields the best predictions, does not necessarily coincide with common sense. The straight line formula will indicate that performance will never level off, thereby, overestimating the ability of the individual. A negative learning curve will be generated predicting that performance will decline. Yet, it is the rare individual whose true ability to do the task will decrease. And other mathematical models, as mentioned above, will include the impossible projection of minus time.

Despite the limitations of mathematical modeling, there is room for this technique in vocational assessment when combined with clinical judgment and training in the techniques. It is proposed that best use of the mathematical modeling process lies in first determining how experienced the individual is in relation to his true learning curve and then to make predictions based on his ability to benefit from further training. The problem may not be as complex as would be expected if certain assumptions are made about the phases of learning a task.

Phases of Learning

The idealized learning curve can be further divided into three phases which observations and measurement of performance suggest are fairly evident. First, the beginning of curve refers to the unpracticed individual which would be at the very beginning of acquiring the task during which time performance is typically erratic. As practice continues, the next portion of the curve has a steep accelerated slope indicating that the individual is rapidly mastering the task requirements, but with significant variation. Finally, the last portion of the curve is a plateau during which the individual displays consistent ability of the task with little variation. These phases can be termed "Beginning of Learning" (BOL), "Accelerated Learning" (ACL), and "End of Learning" (EOL).

During the phases of learning, each can be expected to be characterized by different performances that are readily identifiable. The first phase or BOL is characterized by inconsistent performance on the task. The individual's best performance tends to be significantly different from the worst performance. Both the ability to carry out the task motions and ability to sequence the task will be inconsistent. The measured performance will be far below the ultimate level of the individual. Prediction from information during this phase will be inaccurate. During the middle phase of learning (ACL), there will be significant increases in the best performance, reduction of worst cases, sequencing of task motions will become smoother, and speed of task motions will increase. Though slow cycles will occur, the major improvement will be in the elimination of the number of slow trials. Prediction from information during this phase would tend to yield positive and significant gains over time. More than likely, predictions will yield overestimation of ability. The last phase of learning has very definite characteristics. In EOL, the difference between fast trials and slow trials will tend to be small, motions and task sequencing smooth, and the fastest trials will tend to be similar to that in ACL but more frequent. Predictions from information during this phase will indicate gradual and small increases over time; and would be the most reliable and valid.

It may be possible to define the amount of error associated with prediction depending on the phase of learning. For example, if the information indicates that performance is consistent with BOL, it may be that is simply too early to predict because the prediction error would be large, while patterns consistent with EOL phase would have considerable validity. In ACL, it may be best to "wait and see," but important information is available including the fact that the individual is learning the task. Learning curves could be generated for high and low predictions with expectation that the individual will fall into the range of predictions. In EOL, the learning curve will relatively flat with performance at or near the individual's highest level.

Filters

The second concept that needs to be considered in development of the training quotient is the concept of filtering. In sound wave propagation through amplitude modulation (AM) and frequency modulation (FM), different filtering techniques are used to pick up the broadcast signal and to exclude interference and noise. The same can apply to measurement of motor skill performance. In the measurement and research on performance, it is clear that the major performance changes that occur is not the rapid gain in the ability of the individual to do the task, but rather in the increase in consistency and elimination of slower trials. Poor trials not only decrease in number, but these slow trials are less distant from the fastest. In prediction of performance, more accurate prediction can be accomplished if unusually slow trials are eliminated as interference is eliminated from a radio signal. Such trials may have resulted from atypical conditions such as distraction, dropping parts and other obvious accidents stopping task work, or inadequate supplies would not be used in the analysis, even though some of these conditions may be of importance to successful task completion and work behaviors. LCA could then be applied once these trials have been eliminated. This mathematical curve fitting could be viewed as an attempt to remove the "noise" from the true measurement of performance in order to predict potential.

The need for filters are required to increase prediction accuracy. Current research is examining the effects of different ways to reduce "noise and interference" from the base data. The problem is how to clearly define what is extraneous information from the "true" data, and then to use those paradigms in the computer program.

The Trainability Quotient and the Computer

The research efforts at the Center indicates that there is promise in pursuing the development of what might be called the "Trainability Quotient" which can be defined in two ways:

1) A measure indicating the amount of benefit from further training,

or

2) The difference between the current location on the learning curve and the predicted level at the plateau of the learning curve.

The first definition of the Training Quotient has the advantage of measuring the need for training and its relative benefit. The second definition is an operational one and its reliability and validity will be dependent on the research that is currently underway and being planned.

The computer age has brought forth many exciting possibilities. The research and concepts being proposed would have little utility to rehabilitation without the tools of the computer age. Now this research has application, because the computer can automatically collect data, analyze data, filter information, apply algorithms based on analyses and clinical judgments, and print reports and recommendations that no human service provider or teacher would have the time or talents to do. It has the ability to bring the laboratory directly into the practitioners hands. The "black box' that may one day generate a valid and reliable "training quotient" has been described, but it will require much research to program that black box with the proper perspectives. There is no need for the practitioner to wait, work sample testing, trainability testing, and learning curve analysis can be applied now by experienced individuals. These tools and knowledge should be used to measure the training potential of individuals with handicaps rather than relying on a static measure of performance and norming tables.

Summary

This article suggests that the use of pure mathematical modeling for accurate prediction of future potential has significant limitation if used in isolation from observation of client performance and lack of clinical judgments. The development of the Trainability Quotient as a measure of the individuals benefit from future training by locating the individual on his own learning curve is considered a viable concept. It has also indicated that identifying the phases of learning, the use of filtering techniques, and the selection of the proper curve fitting formula(s) are important steps to pursue in this endeavor. Combining this research with the principles of work sampling and trainability testing has the potential to better serve the individuals with handicaps in a variety of settings: Vocational Evaluation, Work Adjustment, Community Based Assessment, Career Exploration and Guidance, Supported Employment, and other settings. The techniques described here are also applicable to working with special populations such as the severely mentally retarded and traumatically brain injured.

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AUTHOR:

Charles C. Coker, Ph.D., CRC, CVE, CWA
Research and Training Center
Stout Vocational Rehabilitation Institute
University of Wisconsin-Stout
Menomonie, Wisconsin 54751