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ABSTRACT

The primary purpose of this monograph is to describe how learning curves can be applied to vocational evaluation procedures to enhance the reliability and accuracy of performance prediction. Particular emphasis is placed on describing two techniques known as the "best 20 percent method" and the "Performance Analyzer and Enhancer." The latter is a computer software program designed for use with inexpensive microcomputers in both vocational evaluation and work adjustment services. Together, they represent an effective and practical approach to learning curve applications in typical vocational evaluation settings. Three other approaches to learning curve use are also described. They range in complexity from Tillman's simple notion of constantly readministering a task and plotting performance until "peak performance" is achieved, to sophisticated learning curve equations. Each of these techniques, while having significant limitations, also has much to offer current vocational evaluation practice. However, learning curve technology should be viewed as a complement to current vocational evaluation practices. It provides an additional means for better understanding client capabilities and limitations. Continued research and field testing, along with an increased emphasis among educators on providing training in learning curve technology to professional evaluation personnel, will perhaps lead to a wider use of learning curves in vocational evaluation programs as well as further refinement and improvement of many of the methods and techniques presented in this monograph. (KC)

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A GUIDE TO LEARNING CURVE TECHNOLOGY TO ENHANCE PERFORMANCE PREDICTION IN VOCATIONAL EVALUATION

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A GUIDE TO LEARNING CURVE TECHNOLOGY TO ENHANCE PERFORMANCE PREDICTION IN VOCATIONAL EVALUATION

by

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INTRODUCTION

Vocational evaluation is a comprehensive assessment process which uses a variety of techniques including psychological assessment, work samples, medical, vocational, and educational information, as well as other methods and resources to not only assess the existent functional levels of individuals with disabilities, but also, in many cases, to make predictions about future functional capacity. These predictions are used for a variety of purposes.

On a macro level, Shalock and Karen (1979), for example, indicated that much of the data derived from vocational evaluation services is often used to make decisions about a severely disabled individual's feasibility for vocational rehabilitation services within the State-Federal vocational rehabilitation system. Implicit in this process is the assumption that this data can be used to make reasonably accurate predictions about the likelihood that a program of vocational rehabilitation services will lead to employment or other acceptable outcomes identified by the State-Federal system. This assessment of "rehabilitation potential" is often difficult with severely disabled individuals, particularly if they have had little or no previous work experience or rehabilitation training. To overcome this difficulty, at least in part, specialized services such as vocational evaluation have been developed and utilized extensively during the last decade.

On a micro level, data derived from vocational evaluation techniques such as work sample testing and job-site-evaluation in particular, is often used to make specific predictions about employment potential for a given job or job area, as well as the likelihood the client will benefit from related training. A client's performance on one or two administrations of a work sample may be used to either screen a client out of further consideration for that job cluster, or recommend that the client receive technical training for the job, or be placed in the job area immediately.

The performance measures themselves are most often represented by what Blakemore and Coker (1982) described as "static measures." Examples of these types of static measures include mean time to complete a task such as a work sample, total time, number of pieces produced and so on.

The essential characteristic of these static measures is that they do not effectively take into account changes in an examinee's performance during the actual assessment process. Performance scores on individual trials are typically lumped together resulting in a mean score which is then compared to a norm group or production standard. Rarely is any systematic effort made by the evaluator to contrast changes in performance that occur during the actual testing itself. As a result, a client may show dramatic gains in performance during the latter stages of testing on a given task, but because the scores are then combined with initial scores which may be significantly lower, the end result is a depressed mean score which may not accurately reflect the client's performance capability. In other words, no systematic effort is made to take into account variation in performance during the fixed testing period.

The inherent assumption with this approach is that performance is highly stable. A client's performance after a small number, or in many cases only one administration of a task, is considered to be a reliable benchmark for not only establishing his current capabilities, but also his future performance potential. This assumption has been widely-accepted, at least implicitly, within the practice of vocational evaluation despite the fact that research in psychology, education, and industry has shown quite clearly that on most tasks, and indeed psychomotor tasks in particular, performance improves significantly with practice (Bilodeau & Bilodeau, 1961; Blakemore & Coker, 1982; Chyatte, 1976; Crossman, 1959; Dunn, 1976; Fitts & Posner, 1967; Newell & Rosenbloom, 1981).

While current definitions of vocational evaluation do not explicitly indicate the predictive component of this service (VEWAA, 1977), there should be little doubt, as previous authors have suggested, that prediction is an important component of vocational evaluation with many clients. Indeed, as early as the 1960's, leading vocational evaluation authorities were suggesting that prediction is an important focus of vocational evaluation.

Nadolsky (1969) defined vocational evaluation as "a process which attempts to assess and predict work behavior primarily through a variety of subject-object assessment techniques and procedures," (p.23). Gellman (1967) noted that vocational evaluation is primarily concerned with assessing an individual's present level of functioning and making predictions about future levels of functioning. More recently, Dunn (1976b) indicated:

> ...the predictive use of vocational evaluation underlies much of current practice (although) there seems to be considerable confusion among evaluators and others as to what prediction is all about and how it is done.
>
> (p. 41)

If one accepts the premise that prediction will continue to play an important role in vocational evaluation, then it is important to carefully examine this practice. Are the static measures typically used in current practice adequate to ensure reliable and accurate predictions about client capabilities? The research literature is relatively sparse in this regard. However, it would appear that based on what evidence is available, the current emphasis on using static measures as a basis for prediction is uncertain, at best. Blakemore and Coker (1982), for example, in conducting research which focused on comparing the accuracy of work sample measures versus learning curves to predict future performance found:

> ...the traditional static work sample measures provided consistently worse estimates of the final performance level than did any other techniques used in this study. This finding clearly supports the need to use learning curves or other indices reflecting

learning for prediction purposes rather than the traditional static measures such as mean or total score.

(pp. 35-36)

Others (Feuerstein, 1979; Schalock & Karen, 1979) have suggested that with regard to the assessment of individuals with mental retardation, the focus should shift from the current traditional psychometric approach, one which does not take into account dynamic changes in performance during the assessment process, to an "edumetric" approach. The edumetric approach to assessment would focus on measuring dynamic changes in performance as a result of learning which occurs during the assessment process itself. These changes in performance would then be taken into account whenever predictions are made about future functional capabilities.

This approach is in direct contrast to the current psychometric orientation of vocational evaluation services. This orientation often relies on using one or two administrations of a task as a basis for making predictions about future performance. And even within these administrations, little effort is made to take into account learning and improvements in performance which may occur as a result of increased experience with the task. Instead, the client's total performance is combined and a mean score is developed and then compared to that of a norm group or in some cases an industrial standard - once again based on two important assumptions: performance is stable and therefore initial performance is a reliable indicator of future practiced performance levels; and secondly, the performance of an inexperienced worker or examinee can be reliably compared to that of experienced performers to determine both short and long-range suitability for employment. Yet, as Dunn (1976a) indicated, comparing the performance of inexperienced, unpracticed examinees to that of experienced workers can lead to erroneously screening the first group out of future employment despite the fact that continued practice can lead to significant advances in performance levels to the extent that the examinees may eventually achieve competitive performance levels if allowed an adequate period for practice and learning.

Feuerstein (1979) also suggested that reliance on traditional static measures of performance, particularly with regard to mentally retarded individuals "... can only result in a tautological process in which a manifest level of functioning, already known to be low, is once again demonstrated by poor results obtained by the examinee" (p. 89).

Clearly, it is vitally important that vocational evaluation practices attempt to take into account changes in client performance which are a direct result of learning and experience with a task. This is particularly true with regard to assessment of individuals with severe disabilities who have relatively little work experience and often find themselves engaged in work sample, situational assessment, and other psychomotor tasks as part of the vocational evaluation process. Where dynamic changes in performance are evident, it is essential that these changes be considered when making predictions about an individual's performance capability.

Recognizing the important role prediction is likely to continue to play in vocational evaluation, both in terms of serving as a basis for making decisions about specific occupational outcomes, and training potential, as well as feasibility for vocational rehabilitation services through the State-Federal system, it is obvious that every effort must be made to ensure that the tools and techniques used as a basis for making such predictions be as reliable and accurate as possible. One approach that has been shown to be a relatively accurate predictor of performance potential is the learning curve. Learning curves have been used in industry, education, psychology, and other fields for several decades, as a basis for making predictions about human performance potential on a variety of tasks. They also appear to hold much potential for use within rehabilitation services.

The primary purpose of this monograph is to describe how learning curves can be applied to vocational evaluation procedures to enhance the reliability and accuracy of performance prediction. Particular emphasis is placed on describing two techniques known as the "best 20% method" and the "Performance Analyzer and Enhancer." The latter is a computer software program designed for use with inexpensive microcomputers in both vocational evaluation and work adjustment services. Together, they represent an effective and practical approach to learning curve applications in typical vocational evaluation settings. Both approaches were developed through research conducted at the Research and Training Center at the University of Wisconsin-Stout. This monograph is designed to enhance the utilization of this research in applied rehabilitation service delivery settings.

Finally, it should be noted that while learning curves have much to offer the practice of vocational evluation, they are certainly no panacea. As will become evident in later sections of this monograph, learning curves are not without their limitations. Indeed, they are to some extent, a misnomer. Learning curves actually indicate changes in performance. These changes may or may not be indicative of the extent of learning that has occured. For example, an individual may quickly learn a repetitive task, but because of boredom or fatigue, his performance scores do not reflect the amount of learning that has taken place. As a result, they should be regarded as useful tools which can further enhance existing vocational evaluation techniques rather than substitutes for current practices. When used wisely by properly trained vocational evaluation personnel, learning curves have much to offer in further enhancing the evaluator's expertise and his or her ability to successfully evaluate the widely varying capabilities of the clients served.

THE LEARNING CURVE

A learning curve is basically nothing more than a graphic depiction of changes in performance or output during a specified time period. The term learning curve is also used to refer to mathematical equations which describe the relationship between practice and performance. Learning curves provide a concrete measure of the rate at which an individual or group of individuals are learning a task. In their simplest forms, learning curves are generally depicted in either one of the forms shown in Figure 1 and Figure 2.

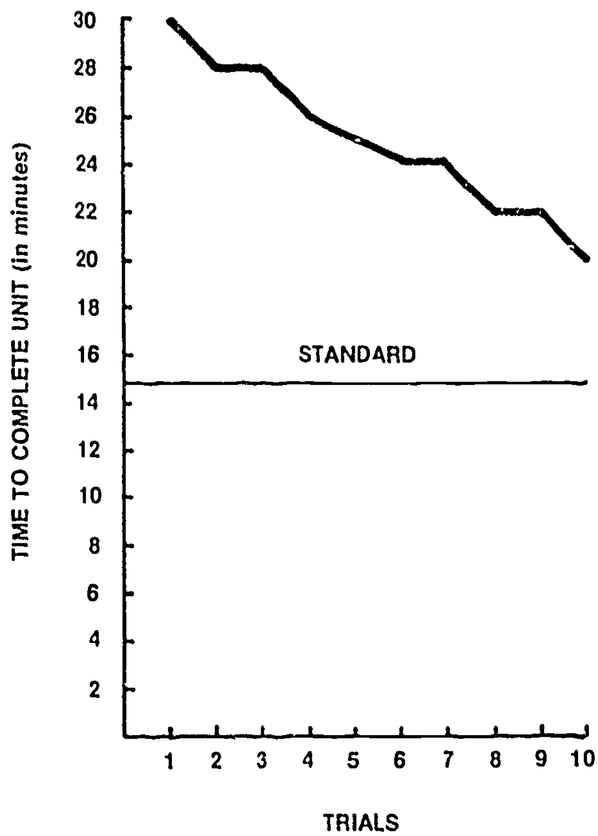

FIGURE 1

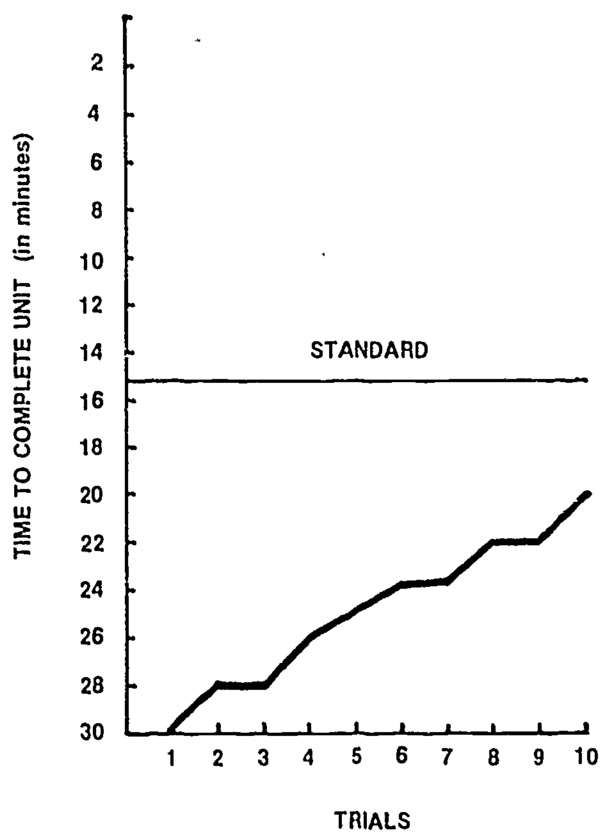

FIGURE 2

It is important to note that both Figures are based on the same data. However, as is readily apparent, one curve slopes downwards while the other curve slopes upwards. Both are correct. But in most cases, the upward sloping curve with the X (horizontal) and Y (vertical) axes depicted as shown is preferred because it is generally regarded as less confusing. People tend to assume that improvement in performance should be associated with an upward swing in a graph.

Another common way to express a learning curve is to use percentages instead of time values for the Y axis. For example, in both Figure 1 and Figure 2, time values are expressed on the Y axis with trials expressed on the X axis. However, as is indicated in the example provided in Figure 3, these time values can be replaced by another measure, the percent of standard. This is a useful approach because it indicates quite clearly the extent to which an individual's performance is approaching the production standard or norm.

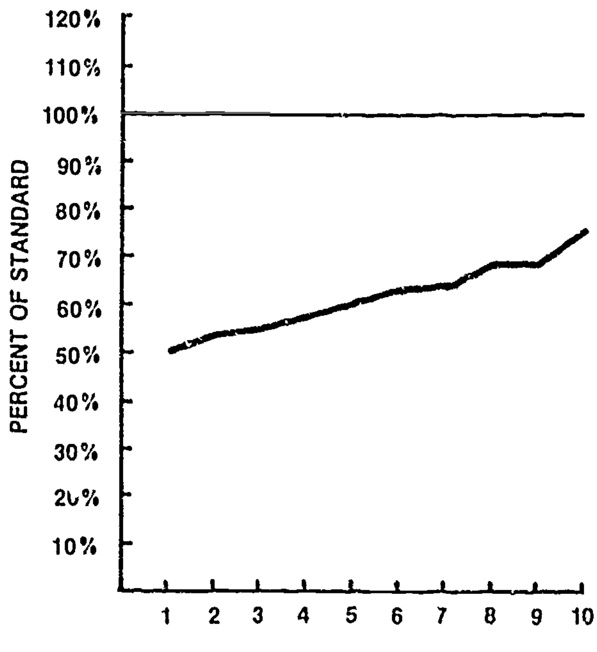

FIGURE 3

To convert an actual time score to a percent of standard value, the following formula is used:

$$(\text{Standard} / \text{Time Obtained}) \times 100\% = \%\ \text{of Standard}$$

For example, if the industrial standard for a simple work sample assembly task is 15 minutes then it is possible to determine the percent of standard for each of the time values shown in Figures 1 and 2. Using the formula, 30 minutes would convert to 50% of the standard and 20 minutes would convert to 75% of the standard and so on. Thus, it is apparant that the data displayed by this type of learning curve would provide an evaluator with a readily useful tool for assessing not only changes in a client's performance as a result of learning, but also the relationship of the client's performance to the standard.

Learning curves are useful because they clearly indicate changes in performance based upon learning. Some important characteristics of learning curves in general are worth noting. First, performance tends to improve with practice. Second, the rate of improvement is often very rapid when someone first begins learning a task. This rate, however, tends to slow as the amount of practice increases. This is the leveling off phenomenon observed in most learning curves. Finally, there is some point beyond which further significant increases in performance will not occur. It should also be noted that other factors besides learning can influence performance. These include factors such as environmental concerns, fatigue, distraction and others.

Learning curves have been used to not only measure the rate at which an individual or group of individuals learn a task, but also to compare that rate to an existing standard. Thus, it is not surprising that learning curves have been used to a limited extent, in industry, as performance appraisal tools (Stevenson, 1982). They have also been used in industry to make predictions about long-term improvements in performance that can be expected as a result of the curvelinear relationship that exists between performance level and the amount of practice an individual has. In other words, industry has long-recognized that as workers' gain experience with a task, performance can be expected to increase significantly. These increases can be taken into account and predicted relatively early on for some tasks, resulting in improved production scheduling, better labor cost estimates and so on. The same principles can be applied, to some extent, to the use of learning curves in education, psychology and vocational evaluation. A brief review of how learning curves have been used in industry may be useful in better understanding the diverse ways in which they can be used in rehabilitation facilities.

To date, the primary application of learning curves has been in manufacturing. They have been used extensively since the 1930's to help manufacturers better plan and schedule work. They have proven to be a useful tool for not only better controlling manufacturing costs but also for increasing efficiency. Learning curves have been developed for specific industrial applications where research has shown that a relatively stable relationship exists between changes in labor input and unit output. In other words, when first learning a task, the more experience individual workers have with a job, particularly those that involve psychomotor tasks, the more likely it is that they will show significant improvement in performance. This improvement is often quite dramatic during the intitial stages of learning and then begins to level off and eventually stablize over extended periods of time.

The Boeing Company is perhaps best known for having recognized the 80% learning curve effect for the manufacture of airframes. This effect is based on their own research which indicated that for this specific activity, each time unit output is doubled, there is a corresponding 20% decline in labor input or the time needed to produce the end product.

For example, if 10,000 hours are needed to produce the first airframe (1 unit), it can be projected with the use of the 80% learning curve, that only 8,000 hours will be needed to produce the second unit, 6,400 hours to produce the third unit and so on. Of course, the curve begins to level off with poduction reaching a point where improvements in unit output begin to stablize. However, the value of such a predictive tool is obvious in terms of enhancing manufacturing efficiency.

An important distinction should be made between different learning curve rates. An 80% learning curve, for a given job, indicates that the typical worker will show a 20% improvement in performance on that particular job. A 90% learning curve, for a specific job, indicates that only a 10% improvement in performance can be expected from the average worker. A 100% learning curve reflects the fact that for that particular job, workers will not show any significant improvement in performance even as they gain experience with the task. Thus, it is apparent that if one were to draw a learning curve representing the tradional static approach to work sample performance assessment, an approach which assumes performance is stable and therefore will not change with additional trials, a "learning curve" much like the one presented in Figure 4 would result.

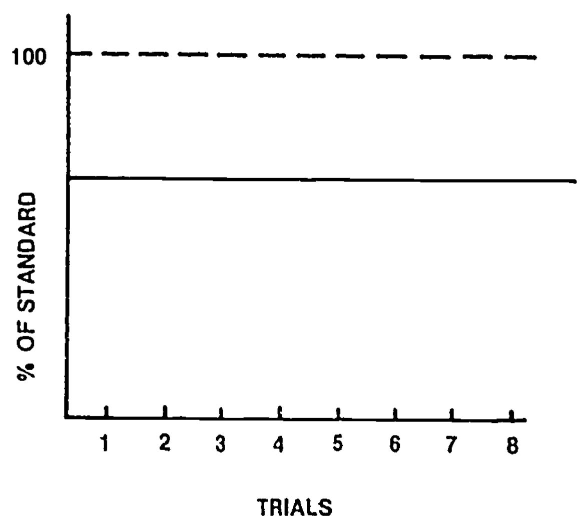

FIGURE 4

Tillman (1971) was one of the first proponents to suggest that learning curve principles could be applied to vocational evaluation activities in rehabilitation. He summarized the problem of using work samples as predictive tools in the following manner:

> Most often work samples are used on a single administrative basis. This provides information on the client's present level of functioning. From this information attempts are often made for prediction of ability to succeed on a job. There is, however, some doubt that knowledge of a client's present level of functioning sufficiently indicates his potential for absorbing experience and improving. Can we assume, for example, that a client who has had no exposure to woodworking hand tools and does poorly on a work sample involving these tools has no potential to learn? The answer

is no. Would it be feasible to give him a number of trials on the task and note any level of improvement on progressive trials? The answer is yes. If we plotted improvement on a graph we would have a learning curve.

(p. 1)

Tillman (1971) went on to provide an example of how a learning curve might be plotted for different clients involved in the same task. It is presented in Figure 5.

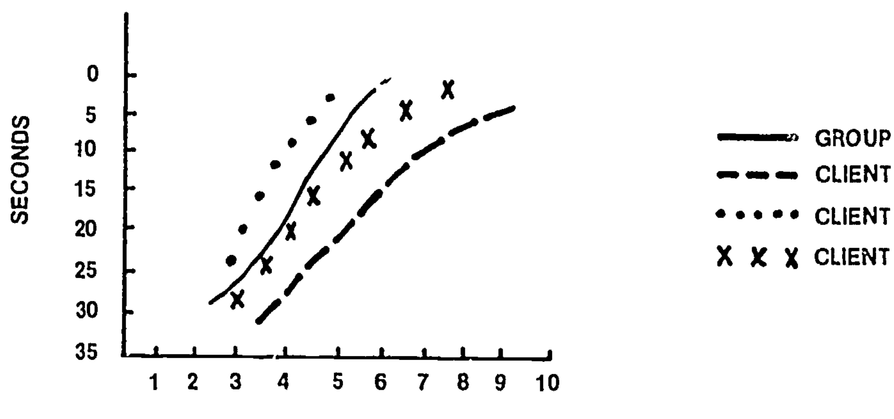

FIGURE 5

More recently, Coker and Blakemore (1984) used five different types of hypothetical learning curves to indicate how this dynamic approach to assessment differs from the more traditional static psychometric approach. They indicated:

> The advantage of the learning curve approach to evaluating work sample performance is that this method reflects what changes occur in the client's work sample performance during testing. 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 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. Figure (6) illustrates this point.
>
> In Situation A, the idealized learning curve is presented where skill aquisition increases consistently over time. In Situation B, performance deteriorates over time rather than steady improvement. It is clear that the client initially performed well, but performance deteriorated; and may have been caused by fatigue, boredom, confusion, etc. In Situation C, performance is relatively stable

except that there is a momentary decline in task performance due to distraction, forgetting of instruction, or perhaps lack of parts. In Situation D, there is a rapid reaquisition of the task. It is indicative of having previously mastered the task and of the ability to rapidly return to that level. Finally, steady level task performance from first to last repetition is graphed as is assumed under traditional work sample administration. Only in Situation E is the true current and potential level of task performance of 67% of the normative criterion accurate. In other situations, current and potential task performance is underestimated and additional valuable information about the client is lost. It would not be lost, however, if a learning curve analysis was used.

(p. 5)

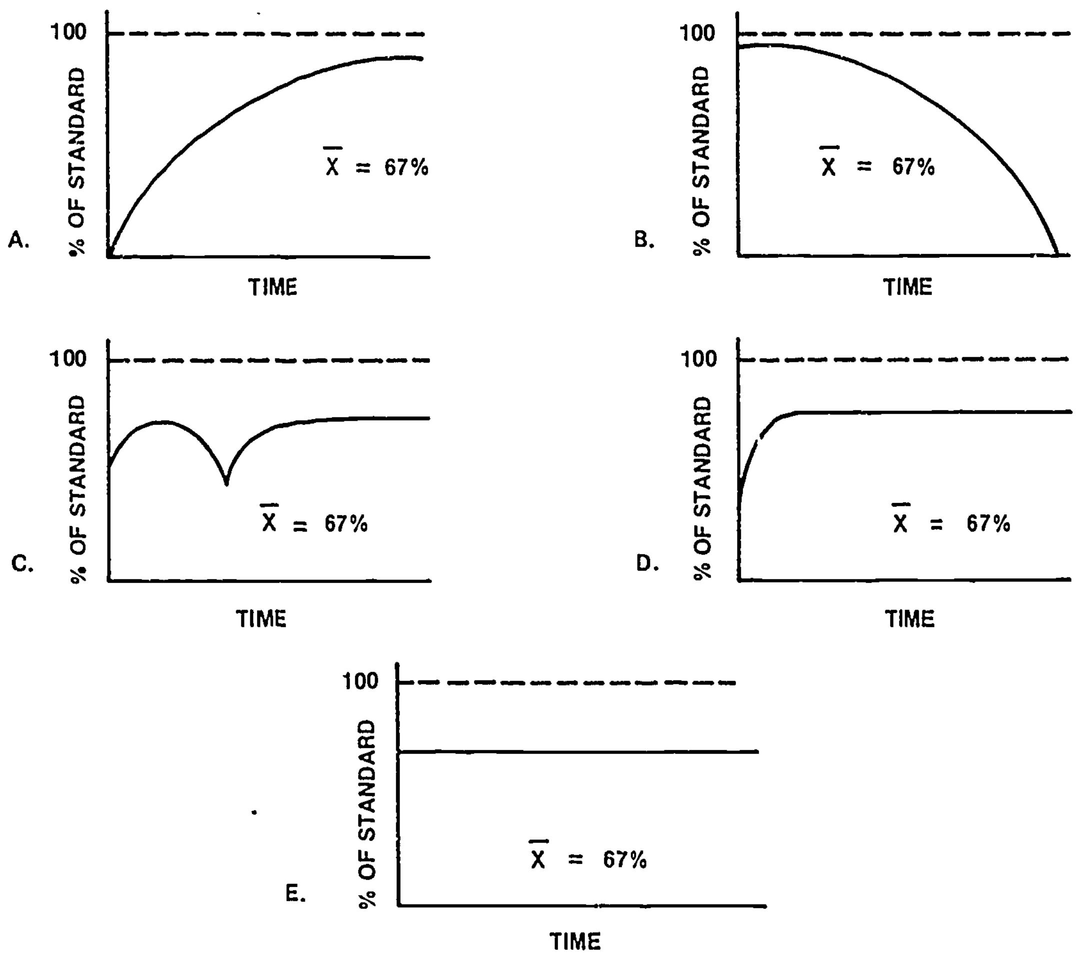

FIGURE 6

The previous learning curves represent examples of differential performance during a work sample with the same normative score of 67%. They may be summarized as follows:

A. Normal acquisition under an idealized learning curve.

B. Decline in performance due to fatique or lack of motivation.

C. Acquisition and reacquisition due to temporarily forgetting tasks, disruption, lack of attention, etc.

D. Rapid reacquisition to steady state indicating the relearning of a previously mastered task.

E. Idealized practiced worker performance assumed under traditional work sample administration.

Tillman (1971) suggested a method for developing learning curves with individuals as well as standardized learning curves for use with groups. He indicated:

> If it is desired to establish a standardized learning curve for a group, the steps to be taken are as follows: (1) The task must be administered to a number of subjects and their time recorded for a set number of trials. (2) The average (mean) time taken for each trial must be calculated. (3) Each trial's average time is plotted on a graph. (4) The final average curve is drawn through the points determined by the average curve. The larger the number of subjects the smoother the curve will be.
>
> The number of trials needed to establish a peak of client performance will depend upon the complexity of the task. It would be difficult to establish a peak with less than four trials; six to ten trials may be needed for more complex tasks. For any given work sample, the most practical method of determining the optimum number of trials is through the administration of the work sample to a number of people. The important point is to give the client enough trials to indicate his competency in a given task.
> (p. 2)

Plotting a learning curve by this method is a relatively simple task. However, Tillman's suggestion that clients be allowed to repeat work sample performance until supposed "peak performance" is achieved, is a major drawback to this approach. Learning and improvement in performance may continue almost indefinately on some tasks. Indeed, studies in industry (Crossman, 1959; Peterson, 1975) have shown that for some routine, repetitive tasks, Tillman,s notion of "peak performance" may not be achieved until several thousand trials have been completed. Obviously, such an approach is not feasible within vocational evaluation programs. Dunn (1976a) rejected

Tillman's approach, suggesting instead that learning curve equations offered a viable method for predicting performance potential based on a relatively small number of trials. He indicated:

> A possible solution to this problem would be to predict an estimated practiced performance level of the client from learning curve data. Data from a relatively small number of trials could be used to establish the equation for the individual's learning curve on a work sample. Once this equation has been developed, the vocational evaluator could use it to predict the client's estimated performance level after being provided with a certain number of practice trials (such as the number of trials provided to new workers by the industry for learning) or the number of trials needed for the client to reach the established industrial standard or norm.
> (pp. 3-4)

Dunn conducted research to test this hypothesis with regard to work sample testing (1976a). Using data collected by Botterbusch (1974), Dunn used the performance scores collected during the first three days of testing to predict performance on Day 4, the final day of testing. He found that the final performance level could be predicted with less than 1% of error on the average.

The results of this research were very encouraging; however, a major drawback to this approach is that it requires evaluators to use relativley sophisticated mathematical equations to make the predictions. Dunn indicated that mathematical skills "at least adequate to develop and solve logarithmic equations are required of the evaluator" (p. 11). In addition, this method requires substantially more administration time as well as time needed to make the actual calculations. These problems obviously tend to limit the practical utility of this approach.

As a result of these problems, Blakemore and Coker (1982) conducted research to determine if a simplified, yet accurate and reliable approach to the predictive aspect of learning curve use could be developed and applied to vocational evaluation activities.

As part of their research, they studied and compared eight different learning curve formulas with regard to accuracy and ease of use in predicting work sample performance. The accuracy of each of these methods was also compared to the use of traditional static measures used to predict performance capability (e.g. mean time, total time, norm reference). Subjects were administered a work sample task which consisted of 50 trials per day for five consecutive work days. Learning curve equations were applied to the data collected during day one of testing, and predictions were made regarding the level of performance expected at the conclusion of day five of testing.

Two major findings resulted from this research. First, all eight learning curve methods were superior performance predictors in comparison to the predictive accuracy of traditional work sample measures. Secondly, while the learning curve methods varied greatly in terms of their complexity and ease of application, the "best-20% method" was as accurate as the other more complex techniques. Because of its ease of use, the best-20% method appears to hold significant potential for use in work evaluation settings although additional research is needed to confirm the efficacy of this approach. In addition, the feasibility of using inexpensive microcomputers to gather data and perform the actual learning curve equation calculations was confirmed. These findings and the actual processes involved in applying learning curve equations and techniques to vocational evaluation practices are discussed in the following section.

LEARNING CURVE UTILIZATION

Recognizing that prediction is an important component of vocational evaluation and that learning curves can provide an effective means for enhancing the accuracy of these predictions, it is now important to examine how learning curves can actually be applied to the vocational evaluation process and related facility operations. In this section, five different approaches to learning curve utilization are described along with cautions on each ones' use.

METHOD NUMBER 1

Perhaps the simplest approach to learning curve use in vocational evaluation and manpower selection in general was suggested by Tillman (1971). As briefly indicated in section 2 of this monograph, this approach essentially involves providing the examinee or worker with several repetitions of the task and plotting the individual's performance on a graph. The end result is often a learning curve much like the one indicated in Figure 7. As long as the client continues to show improvement, additional administrations may take place until Tillman's notion of "peak performance" is achieved.

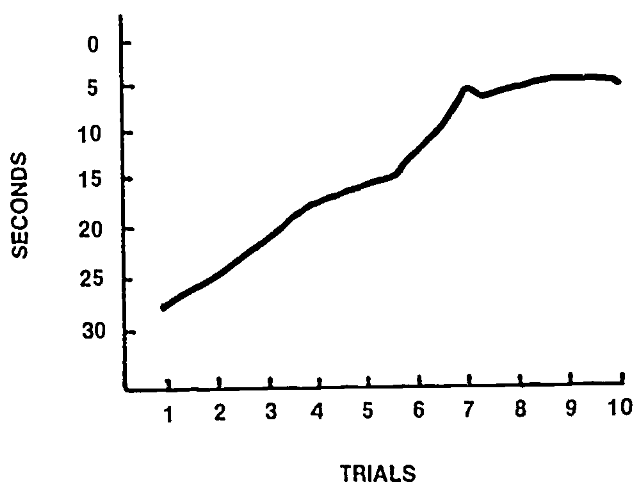

FIGURE 7

The main disadvantages of this approach have already been briefly discussed in Section 2. First, many hundred or even thousands of trials may be needed for certain tasks before the client begins to approach "peak performance." Indeed, Cochran (1968) found that punch press operators continued to show improvement through 8,000 trials. And Crossman (1959) found that approximately four million trials and four years were needed for this group to achieve peak performance.

Secondly, since there is little scientific basis for this approach, it is difficult to reliably predict when peak performance has been achieved. For example, learning curves typically show a series of improvements followed by plateus in which performance levels off. However, given additional opportunity to continue with the task, significant advances in performance may continue with new plateus resulting. Because of this, it is difficult for the evaluator to reliably predict when the client's final ultimate level of performance has been achieved.

These two major problems not withstanding, this approach also is limited in that it does not necessarily take into account the base performance level needed to actually do the job. For example, a client's performance might continue to improve as reflected in the learning curve. However, unless the evaluator knows the industrial standard or norm for the job, it will be difficult for him to reliably determine when this improvement has reached a competitive level.

Industry has provided one limited solution to this problem. Stevenson (1982) has suggested that learning curves can be useful in work settings to evaluate new workers during training periods.

This approach can be achieved by recording the new worker's performance in much the same manner as suggested by Tillman. However, an addition is made to the graph so that the new worker's performance is compared to the typical performance improvements shown by other workers who previously performed the task. The new worker's performance may also be compared to the standard time or production standard developed for the task through industrial engineering techniques such as stopwatch time study, predetermined motion time systems or other methods. In this way, the new worker's performance can be readily compared to the expected rate of learning, which is a dynamic measure, rather than the usual static measure such as mean score, alone. It can also be compared to the production standard to provide a more concrete basis for decision-making about a client's employability. An example of this approach is depicted in Figure 8. It indicates that at the end of the first week of training the average worker is expected to achieve 75% of the

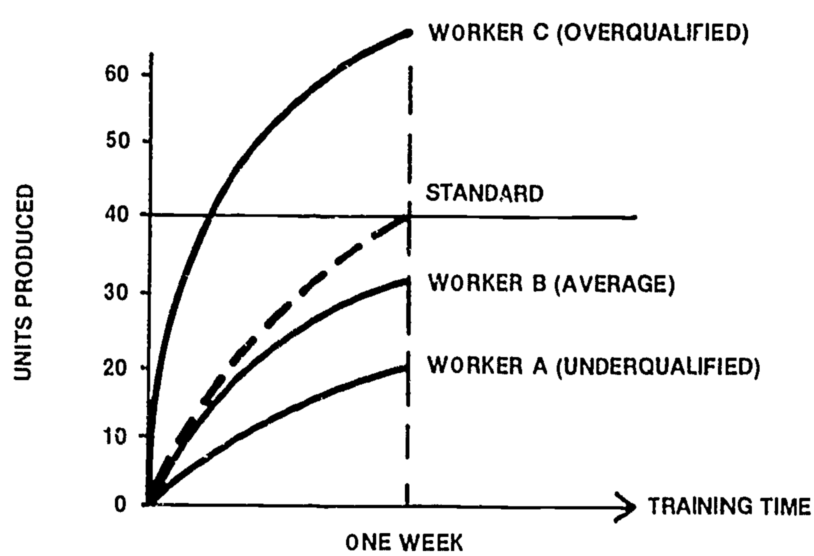

FIGURE 8

industrial standard (or produce 30 individual units when the standard for a fully trained worker is 40 units). As a result, Worker A's performance is far below this level and therefore he may be regarded as underqualified for the task. Worker B is viewed as qualified and Worker C is overqualified in that he far exceeds the normal level of performance.

While this approach has advantages over that offered by Tillman, it still has many of the same limitations. For example, for a disabled client, the rate of learning may be slower than the average rate as compared to a nondisabled group of new workers. However, this does not necessarily ensure that the disabled worker will not be able to reach the standard. Additional training time may make it possible for the disabled worker to achieve the standard within a reasonable period of additional training. If this factor is overlooked, it may result in incorrectly screening clients out of jobs they might otherwise be able to perform. In this regard, this approach has many of the same limitations of traditional static measures of performance.

Additional problems with regard to the time needed to develop the worker learning curves as well as the reliability of such curves and probable shortage of workers on which to develop and test such curves also limits the feasibility of this approach. Yet if the evaluation team has the time and resources needed to overcome these obstacles, this approach can provide useful data for decision-making. It certainly provides valuable information not typically offered by the traditional static measures. It might be especially useful in job site evaluations where it is possible to develop worker learning curves or use existing data provided by the employer. Additionally, it would also appear to have potential for use with many work sample applications. It could provide learning curve data for comparison purposes.

At the present time, this data is not normally available with either commercial work sample systems or individual work samples developed independently in facilities. However, given the large number of clients who typically engage in work sample tasks during the course of a year, and the relative ease with which this data can be accumulated and synthesized, it would seem feasible to develop this type of learning curve data for specific work samples or entire commercial work sample systems. Yet, time constraints, costs, and the need for the evaluation staff to develop the learning curves, as well as test them on nondisabled as well as disabled individuals alike, once again limits their widespread use. Further, it is doubtful whether commercial work sample system developers will be willing to make the investment needed to develop this data for complete work sample systems, despite its usefulness to practitioners.

METHOD NUMBER 2

The second major technique involves the application of predetermined learning curve rates to client performance. For example, it might be known that a certain activity typically shows a learning curve rate of 80%. Another activity might typically reflect a learning curve rate of 70% and so on. Once these rates have been established for the assigned task, it is then possible to use learning curve formulas and coefficients which can be applied to an individual client's performance in order to predict future performance levels.

For example, let's assume that a work sample task is known to have a learning curve rate of 80%. Once we have established the client,s initial level of performance, we can then estimate future performance using a formula, like the one noted below (Stevenson, 1982), along with the data presented in Table 1.

$$Tn = T1 \times nb$$

Tn = Time for the nth unit
T1 = Time for the first unit
b = Log learning percent/log2

Let's assume in this example, that the client is involved with an assembly work sample task. As indicated previously, an 80% learning curve rate is considered appropriate. In other words, past experience has demonstrated that on this task, examinees typically show a 20% improvement in performance with practice. Let's assume it took the client 10 minutes to produce the first unit. The evaluator would now like to predict how long it will take the client to produce the 20th unit, without having to administer the task another 19 times. To do this, he works through the following process.

$$T20 = 10 \text{ minutes } (20 \quad \log .8/\log 2 \quad)$$

The evaluator may now use a calculator with a logarithmic function to work through the entire formula. However, a more convenient technique is to use the predetermined learning curve coefficients offered in Table 1.

To use the table, the evaluator works through the following process.

Step 1: Find the desired number of units on which the prediction is to be based by simply reading down the unit number column. In this case, the units are equal to 20.

Step 2: Now read across to the appropriate learning curve percentage; in this example it is 80%.

Step 3: Select the applicable UNIT TIME from the appropriate column. In this case it is .381

Step 4: Plug the numbers into the formula noted previously (Tn = T1 X nB)

Predicted time 20th unit = 10 minutes(.381)

Predicted time 20th unit = 3.81 minutes

Table 1

TABLE 12S-1
Learning curve coefficients

Unit number	70% Unit time	70% Total time	75% Unit time	75% Total time	80% Unit time	80% Total time	85% Unit time	85% Total time	90% Unit time	90% Total time
1	1 000	1 000	1 000	1 000	1 000	1 000	1 000	1 000	1 000	1 000
2	700	1 700	.750	1 750	.800	1 800	850	1 850	900	1 900
3	568	2 268	634	2 384	702	2 502	773	2 623	816	2 746
4	490	2 758	562	2 916	610	3 112	723	3 315	810	3 556
5	.437	3.195	.513	3 459	.596	3 738	.686	4 031	.783	4 339
6	398	3 593	.475	3 934	562	4 299	657	4 688	.762	5 101
7	.367	3 960	416	4 380	534	4 834	.631	5 322	.744	5 845
8	313	4 303	422	4 802	.512	5 316	.614	5 936	729	6 574
9	.323	4 626	.402	5 204	493	5 839	.597	6 533	.716	7 290
10	.306	4 932	.385	5 589	.477	6 315	.583	7.116	.705	7 994
11	291	5 223	370	5 958	.462	6 777	.570	7 686	695	8 689
12	278	5 501	357	6 315	.419	7 227	558	8 244	685	9 374
13	267	5 769	.315	6 660	.438	7 665	518	8 792	.677	10 052
14	257	6 026	.334	6 994	.428	8 092	.539	9 331	670	10 721
15	.218	6 274	.325	7.319	.418	8 511	.530	9 861	.663	11 384
16	210	6 514	316	7 635	.410	8 920	522	10 383	656	12 010
17	233	6 747	309	7 914	.402	9 322	.515	10 898	.650	12 690
18	226	6 973	301	8 215	.391	9 716	508	11 405	614	13 331
19	220	7 192	295	8 510	.338	10 104	.501	11 907	.639	13 974
20	214	7.407	288	8 828	.381	10.485	.495	12.402	.634	14 608
21	209	7 615	283	9 111	.375	10 860	.490	12 892	.630	15 237
22	204	7 819	277	9 388	370	11 230	484	13 376	625	15 862
23	199	8 018	272	9 660	364	11 591	.479	13 856	621	16 483
24	195	8 213	267	9 928	359	11 954	.475	14 331	.617	17.100
25	.191	8 404	263	10 191	.355	12.309	.470	14 801	.613	17.713
26	187	8 591	259	10 419	350	12 659	.466	15 267	609	18 323
27	183	8 771	255	10 704	.316	13 005	462	15 728	606	18 929
28	180	8 954	251	10 955	342	13 347	.458	16 186	603	19 531
29	177	9 131	247	11 202	338	13 685	.454	16 640	599	20 131
30	174	9 305	244	11 416	335	14 020	.450	17 091	.596	20.727
31	171	9 476	210	11 680	331	11 351	417	17 538	.593	21 320
32	168	9 644	237	11 924	328	14 679	414	17 981	590	21 911
33	165	9 809	234	12 158	324	15 003	411	18 422	588	22 498
34	163	9 972	231	12 389	321	15 324	437	18 859	585	23 081
35	.160	10 133	229	12 618	318	15 643	.431	19 291	.583	23 666
36	158	10 291	226	12 811	315	15 958	.432	19 723	.580	21 246
37	156	10 447	223	13 067	313	16 271	429	20 151	578	21 824
38	154	10 601	221	13 288	310	16 581	426	20 580	575	25 399
39	152	10 753	219	13 507	307	16 888	421	21 001	.573	25 972
40	150	10 902	216	13 723	.305	17 193	421	21 425	571	26 543
41	148	11 050	214	13 937	303	17 496	419	21 844	569	27 111
42	146	11 196	212	14 119	300	17 796	416	22 260	567	27 678
43	144	11 341	210	14 359	298	18 091	414	22 674	565	28 213
44	143	11 484	208	14 567	296	18 390	412	21 086	563	28 805
45	141	11 625	206	14 773	294	18 681	.410	23 496	.561	29 366
46	139	11 764	201	14 977	292	18 975	408	23 903	.559	29 925
47	138	11 902	202	15 180	290	19 265	405	21 309	557	30 482
48	136	12 038	.201	15 380	288	19 532	403	24 712	555	31 037
49	135	12 173	.199	15 579	286	19 838	402	25 113	553	31 590
50	.134	12 307	.197	15 776	281	20 122	400	25 513	.552	32.142
51	132	12 439	196	15 972	282	20 404	398	25 911	550	32 692
52	131	12 570	194	16 166	280	20 681	396	26 307	518	31241
53	130	12 700	192	16 358	279	20 963	394	26 701	517	31 787
54	.128	12 828	191	16 549	277	21 239	392	27 094	515	31333
55	127	12 955	.190	16 739	275	21 515	391	27.484	514	31877
56	126	13 081	188	16 927	274	21 788	389	27 873	512	35 419
57	125	13 206	187	17 141	272	22 060	388	28 261	541	35 960
58	121	13 330	.185	17 299	271	22 331	386	28 617	519	36 499
59	123	13 453	.184	17 483	269	22 600	.381	29 031	538	37 037
60	.122	13 574	.183	17 666	268	22 868	383	29 414	.537	37 574

Source: Stevenson, Production/Operations Management pp.521-522

The evaluator can also use the table to predict the total time that will be needed to produce all 20 units, based on the time needed to produce the initial unit alone. To do this, he works through the following process:

Step 1: Read down the unit number column and identify the number of units to be produced. In this example, 20.

Step 2: Now read across to the appropriate learning curve percentage; in this case it is 80%.

Step 3: Select the applicable TOTAL TIME from the appropriate column. In this case it is 10.485

Step 4: Plug the numbers into the formula noted below:

Expected TOTAL TIME for all 20 units = T1 X nB

Expected TOTAL TIME all 20 units = 10 min.(10.485)

Expected TOTAL TIME all 20 units = 104.85 minutes

With this information, the evaluator now has a relatively reliable estimate of the client's expected performance level at the end of 20 trials, without having to administer the task all twenty times. The advantages of this approach are quite obvious and once the predictions have been established, it is then possible to compare these performance levels to the applicable norm groups or production standards. In this way, the evaluator might observe that based on the client's initial level of performance, he was not able to meet the production standard for experienced workers; however, through application of the learning curve, it is then possible to determine if additional trials are likely to result in the client achieving the production standard.

However, it is also evident that there are numerous limitations to this approach. First, it is necessary for the evaluation team to establish learning curve rates for certain work sample, situational assessment or job site evaluation tasks. This would obviously be a very time consuming task and it is unlikely that in the near future commercial work sample system publishers will provide this data as part of their systems, despite its value. With regard to job site evaluation, however, this problem may be overcome in the few instances where employers have enough experience with the task to have developed their own learning curves.

A secondary problem of equal importance is the fact that in most cases, the established learning curve percentage is based on the learning rate typically displayed by average, nondisabled workers. The extent to which this rate corresponds with that of disabled examinees in a vocational evaluation setting is difficult to estimate. In many cases, it may be possible that while an 80% rate for nondisabled workers is appropriate, it may be necessary to allow for additional trials for the average client to achieve the expected 20% gain in performance. Unless this problem is recognized, it could lead to errors in predicting client performance.

It should also be reemphasized that for a given job, the lower the assigned learning curve percentage, the more improvement may be expected from the typical worker performing this specific job. For example, a 70% learning curve for a specific job indicates that a 30% improvement in performance may be expected from the average worker, while a 90% learning curve indicates that only a 10% improvement in performance should be expected for the average worker. A 100% learning curve indicates no expected improvement at all. These expected levels of improvement are based on the specific job task and cannot be arbitrarily assigned to other tasks.

Thus it is apparent that while this approach has many advantages over conventional static measures, it too has significant limitations in terms of practical implementation. If the problem of the time and related resources needed to develop learning curve percentages for certain tasks can be overcome, it is evident that this approach has many advantages over the current practice which primarily relies on the intuitive judgement of the evaluator or, in some cases, little more than educated guesses to predict future performance levels for clients.

METHOD NUMBER 3

This method is somewhat similar to the previously discussed method in that it involves using learning curve formulas to predict performance. The major difference is that these formulas may be used without the need to have a task or job already classified as either having a 70% curve, 80% curve, 90% curve and so on.

Thus it would appear that this method has an important advantage over method number two. However, in actual practice, the use of these learning curve formulas is limited due mainly to the complexity of most of these formulas and the resulting difficulty most evaluators would have in applying them, as well as with regard to the time required to manually collect and manipulate the data.

Many different learning curve formulas have been developed. Some are more appropriate for certain kinds of tasks than others. Blakemore and Coker (1982) for example, studied six different learning curve formulas with regard to their predictive use in vocational evaluation. They included:

$$Y = K\left(\frac{X + C}{X + C + r}\right) \qquad Y = \frac{A}{X} + B$$

$$Y = AB^{X} \qquad Y = AX^{B}$$

$$Y = A + (B \cdot \log X) \qquad Y = (LX)/(X-A)$$

Blakemore and Coker's research indicated that each of these formulas was a more accurate predictor of performance capability than were traditional static measures such as mean score. The following example illustrates the use of one relatively simple learning curve equation for a client involved in a work sample task.

CALCULATING A LEARNING CURVE EQUATION

The instructions below describe how to calculate the hyperbolic learning curve equation (Y=LX/X-A) developed by Thurstone (1919) using the least-squares method described by Barlow (1928). The data used in the example were taken from the research study conducted by Blakemore and Coker (1982). The data represent a client's performance on the first 25 trials of a work sample task. The client eventually completed 250 trials on the task, 50 trials per day for 5 consecutive work days. The original scores were response times but they have been converted to a percentage of (industrial) standard measure.

Although the method described below looks somewhat complex, the calculations involved are really quite simple and can easily be done with a hand held calculator. The process can become quite time consuming, however, with a large amount of data (more than 25 scores or so). For that reason, we recommend the use of a microcomputer to perform the calculations if one is available. This can simplify the task and speed it up greatly.

To calculate the learning curve equation, you need to determine the values for L and A in the equation Y = (LX)/(X - A). These values, sometimes called parameters, are calulated using equations 1 and 2 below:

$$L = \frac{EY2(EX2Y) - (EXY)(EXY2)^{*}}{EY2(EX2) - (EXY)2} \qquad \text{Equation 1}$$

$$A = \frac{EX2Y - L(EX2)}{EXY} \qquad \text{Equation 2}$$

The first step in calculating the learning curve is to enter the data into a table such as Table 2 and to calculate the values in the table. (Note that we have included a blank table in the appendix for you to use with your own data. Simply photocopy that form whenever you wish to calculate a learning curve). As you can see from examining Table 2, there are 7 columns. The values in the first 2 columns, labeled X and Y, you already have after you have collected some data. The X values represent the trial numbers (starting at 0 - that is, the first trial is labeled 0, the second is 1, etc.). The Y column contains the scores the individual obtained on each trial. The remaining values in the table, columns 3 - 7, are calculated using the values in columns 1 and 2.

* The E in the formula represents a summing procedure, e.g., 2+2+5 = 9, and the 2 represents a squaring procedure, e.g., 2x2 = 4.

TABLE 2

Table to be Used When Calculating the Hyperbolic Learning Curve Equation (Y = (L x X)/(X - A))

			Values Used in the Calculation			
X	Y	X2	Y2	XY	XY2	X2Y
0	39%	0	1521	0	0	0
1	41%	1	1681	41	1681	41
2	52%	4	2704	104	5408	208
3	52%	9	2704	156	8112	468
4	56%	16	3136	224	12544	896
5	52%	25	2704	260	13520	1300
6	51%	36	2601	306	15606	1836
7	65%	49	4225	455	29575	3185
8	68%	64	4624	544	36992	4352
9	68%	81	4624	612	41616	5508
10	65%	100	4225	650	42250	6500
11	72%	121	5184	792	57024	8712
12	59%	144	3481	708	41772	8496
13	70%	169	4900	910	63700	11830
14	67%	196	4489	938	62846	13132
15	59%	225	3481	885	52215	13275
16	76%	256	5776	1216	92416	19456
17	79%	289	6241	1343	106097	22831
18	66%	324	4356	1188	78408	21384
19	63%	361	3969	1197	75411	22743
20	76%	400	5776	1520	115520	30400
21	74%	441	5476	1554	114996	32634
22	74%	484	5476	1628	120472	35816
23	79%	529	6241	1817	143543	41791
24	84%	576	7056	2016	169344	48384
Total	1,607%	4,900	106,651	21,064	1,501,068	355,178

Follow the instructions below to calculate the values in the table and to use the results of those calculations to compute the learning curve equation. We assume to begin with that you will already have created (or copied) the table and have entered the X and Y values and added the Y values.

Step 1. In the column labeled X2 (Column 3) put the square (the number times itself) of each X value (found in Column 1). Then add the X2 values and place the sum at the bottom of the column.

Step 2. In the column labeled Y2 (Column 4) put the square of each Y value (Column 2), add all of the Y2 values, and place the sum at the bottom of the column.

For example:

Y	Y2
39	1521
41	1681, etc.

Step 3. Multiply each X value by its corresponding Y value and place the results in the XY (for X times Y) column (# 5). Then add all of these values and place the sum at the bottom of the column.

For example:

X	Y	XY
0	39	0
1	41	41
2	52	104, etc.

Step 4. Take each X score and multiply it by its corresponding Y2 (Column 4) value. Add all of these XY2 values and place their sum at the bottom of the column.

For example:

X	Y2	XY2
0	1521	0
1	1681	1681
2	2704	5408, etc.

Step 5. Take each X2 value (Column 3) and multiply it by its corresponding Y value (Column 2) and place the result in the X2Y column. Add the X2Y values and place the sum at the bottom of the column.

For example:

X2	Y	X2Y
0	39	0
1	41	41
4	52	208, etc.

You have now completed the table and are ready to use the values in the table to calculate the values of L and A (Equations 1 and 2).

Step 6. Take the sum of the Y2 values (Column 4) and multiply it by the sum of the X2Y values (Column 7).

106,651 x 355,178 = 37,880,088,800

Step 7. Take the sum of the XY values (Column 5) and multiply it by the sum of the XY2 values (Column 6).

21,064 x 1,501,068 = 31,618,496,350

Step 8. Take the value obtained in Step 6 and subtract the value obtained in Step 7 from it. This is the numerator (top part) of Equation 1.

37,880,088,800 - 31,618,496,350 = 6,261,592,450

Step 9. Take the sum of the Y2 values (Column 4) and multiply it by the sum of the X2 values (Column 3).

106,651 x 4,900 = 522,589,900

Step 10. Take the sum of the XY values (Column 5) and square it.

21,064 x 21,064 = 443,692,096

Step 11. Take the value obtained in Step 9 and subtract the value obtained in Step 10 from it. This is the denominator (bottom part) of Equation 1.

522,589,900 - 443,692,096 = 78,897,804

Step 12. Divide the value obtained in Step 8 by the value obtained in Step 11. This is the value of the L parameter in the learning curve equation.

6,261,592,450/78,897,804 = 79.36

Step 13. Multiply the value of L times the sum of the X2 values (Column 3).

79.36 x 4900 = 388880

Step 14. Subtract the value obtained in Step 13 from the sum of the X2Y (Column 7) scores. This is the numerator in Equation 2.

355,178 - 388,880 = -33702

Step 15. Divide the value obtained in Step 14 by the sum of the XY (Column 5) scores. This gives you the value of the A parameter.

-33702/21,064 = -1.599

You have now completed the computation of the L and A parameters in the hyperbolic learning curve equation. You can now use these values to compute the Y value predicted using the learning curve equation for any value of X (i.e., any amount of practice). To do this you simply plug the X, L, and A values into the equation and compute the resulting Y value. For example, using the values we arrived at in the example given above we can make a prediction of where performance would be after 30, 40, and 50 trials of practice at the task. These would be calculated as shown in A, B, and C below:

A. The predicted Y value after 30 trials would be

$$Y = (79.36 \times 30)/(30 - -1.599) =$$

$$2380.8 / 31.599 = 75.34$$

B. The predicted Y value after 40 trials would be

$$Y = (79.36 \times 40)/(40 - -1.599) =$$

$$3174.4 /41.599 = 76.31$$

C. The predicted Y value after 50 trials would be

$$Y = (79.36 \times 50) / (50 - -1.599) =$$

$$3968 / 51.599 = 76.90$$

These calculations indicate that the individual who was being tested on this work sample could, based upon performance during the first 25 trials of the task, be expected to perform at about 75% of standard during trials 30, 40, and 50. The individual could also be expected to still be showing some improvement on the task, as well.

As mentioned above, the data used in this example represent an individual's actual performance on the initial 25 trials of a work sample task. As part of the research that Blakemore and Coker (1982) conducted, the data from the initial day on the task was used to predict the average performance level attained on the last day of practice (Day 5). The prediction was then compared with the actual level of performance that was attained on Day 5. The same was done with the data that was analyzed above. Using the parameter values (L = 79.36 & A = -1.599) from above, the predicted average score for Day 5 (Trials 201 - 250) is 79% which is 12% lower than the actual average score (91%) for those trials. The difference between the predicted and the attained scores represents prediction error. This difference is considerably less than that which would have been obtained used the average score (64%) for the first 25 trials been used, however. Thus, the benefit of using learning curves to make predictions can be seen.

It is important to note that while the results of the research conducted by Blakemore and Coker (1982) clearly indicated that each of the learning curve formulas they tested was more accurate in predicting eventual performance levels than were traditional static measures used with work samples, the authors noted the difficulty the average evaluator is likely to have in readily applying these formulas because of the relative compexity of the mathematics involved as well as the time needed to apply the formulas. In addition, it must also be noted that any learning curve formula tends to lose accuracy and reliability the further into the future the evaluator attempts to predict. For example, while it might be realistic for an evaluator to attempt to predict a client's performance at the twentieth trial or after 10 days of job training, based on a relatively small number of initial trials, it would be unrealistic to try and predict performance on the 1,000th trial or after 6 months of training, based on these formulas alone. Some researchers in this area (Blakemore & Coker, 1982 ; Trussell, 1966) have suggested that a general guideline to be followed is that it is only safe to predict approximately five times as many trials into the future as the number of trials on which the data is based. Thus, if predictions are to be based on data gathered from 10 trials, they should not go beyond the client's fiftieth trial. Beyond this factor, the reliability and accuracy of the predictions can decline substantially depending on the tasks involved.

Another important point for evaluators to keep in mind when using these formulas is that it is generally advantageous to administer the task during several discrete sessions, separated by rest periods for the examinee. This will result in the accumulation of data which will, in most cases, better reflect the client's potential for improvement. In this way, problems of fatigue, distractability, and outright boredom with the task can be better managed. If a learning curve is based on one continuous sitting over a period of several hours, obviously the client is more likely to become fatigued and this will generally depress performance. Using more sessions, with breaks in between, often results in a learning curve like the one noted in Figure 9. The fact that people tend to show significant performance improvements and then level out followed by additional improvements in the next session, with a new stabalizing level established and so on indicates the advantage of this approach in terms of obtaining more accurate data on client learning.

Finally, it should also be recognized that with regard to the use of any of these formulas, the more trials the client actually engages in, the more data can be accumulated, and the accuracy of the learning curve projections are then enhanced. However, this can have practical limitations. For example, administration of a single work sample or situational assessment task which requires several hours to complete obviously limits the number of times it will be repeated and the resulting improvements in performance that can be plotted. On the other hand, some tasks that require only a few minutes to perform might be repeated several dozen times, thereby providing a wealth of data. Even in this case, however, there is a tradeoff. For as the example in this section suggested, the more data that is accumulated, the more time that will be required to compute all the data. Thus time considerations must be considered in relation to not only the number of trials, but also the additional time that will be needed to collect and analyze the resulting

FIGURE 9

wealth of data. One practical solution to this problem is the use of microcomputers to process the data in such cases. This method is described in method 5 discussed later in this section. It provides a viable alternative to gathering large amounts of data reflecting client learning, without overwhelming evaluators with manually computing all of the data and translating it into a learning curve.

It should also noted that the example presented in this section represents one of the simplest learning curve formulas available. Other formulas are much more complex, require more data, and also more mathematical training among users. This problem tends to severely limit their use in most evaluation settings. Dunn (1976a) for example pointed out that evaluators would need, in most cases, mathematical skills that would at least, as a minimum, allow them to solve logarithmic equations. These skills are not normally part of a vocational evaluator's training at the present time. One solution to this problem is, however, as suggested earlier, to use microcomputers to process much of the data.

Of perhaps more significance, Blakemore and Coker (1982) found that another technique termed the "best-20% method" was as accurate a predictor as any of the learning curve formulas mentioned, and equally importantly, it was relatively easy for evaluators to use. The researchers indicated:

> ...if one were to make a recommendation about which prediction method to use, based upon the present findings, the best-20% method would probably be the most reasonable choice. This method was found to be as accurate as any of the learning curves yet is easier to compute and requires data from only one practice session. This conclusion should be tempered, however, by the possibility that future research might demonstrate deficiencies in the accuracy of the best-20% method.
>
> (p. 32)

In the following section, the best-20% method is described and an example of how to use it is presented.

METHOD NUMBER 4

The so-called "best-20% method" was developed and described by Blakemore and Coker (1982) with regard to their work on learning curve use in vocational evaluation. As the researchers indicated, this method was developed in an effort to find a "practical yet accurate prediction technique that was based on the well-demonstrated fact that performance improves with practice" (p. 9). It was described by the researchers as follows:

> this method consisted of using the mean of the fastest 20% of the trials during the first practice session as the estimate of the individual's final performance level.
>
> (p. 9)

For example, in the case of Blakemore and Coker's (1982) work, the examinee was administered a single work sample task each day for for five consecutive work days. Each one of the administrations consisted of 50 trials. Using the best-20% method then, the average score for the fastest ten trials, during the first day of administration, was calculated. This score represented the predicted performance level which the client would achieve by the end of the fifth day of work on the task; or, in other words, after another 200 trials.

Suppose a client was involved in a simple assemby work sample. One administration of the work sample involved assembling 50 units and recording the time score for each unit assembled. The following data depicted in Table 3 might then result.

TABLE 3

TRIAL	RAW SCORE (in seconds)	RANK	TRIAL	RAW SCORE (in seconds)	RANK
1.	27.5		26.	15.8	
2.	26.4		27.	20.1	
3.	16.7		28.	14.0	8
4.	16.8		29.	23.2	
5.	15.2		30.	16.5	
6.	20.6		31.	13.3	4
7.	21.3		32.	32.5	
8.	16.7		33.	22.3	
9.	14.8		34.	14.2	9
10.	41.9		35.	15.8	
11.	16.0		36.	22.6	
12.	16.6		37.	13.3	4
13.	14.8		38.	16.5	
14.	19.4		39.	14.7	
15.	15.4		40.	15.7	
16.	16.2		41.	15.7	
17.	18.4		42.	16.5	
18.	13.2	3	43.	16.5	
19.	12.6	2	44.	14.8	
20.	26.4		45.	14.7	
21.	17.2		46.	18.5	
22.	24.2		47.	13.9	7
23.	20.7		48.	17.2	
24.	14.5	10	49.	11.7	1
25.	13.7	6	50.	15.1	

Using the best-20% method, the evaluator would now take the 10 fastest scores and determine the mean. In this case the ten fastest scores in seconds are: 11.7, 12.6, 13.2, 13.3, 13.3, 13.7, 13.9, 14.0, 14.2, 14.5.

To find the mean, or the average, the evaluator now simply adds each of the time values and divides the total amount by 10. The result is a mean value of 13.44 seconds. This would then be considered the predicted performance level which the client could be expected to achieve given additional trials and opportunity to learn the task.

In some cases it may be necessary to modify this approach somewhat. For example, in this research, a single administration of the work sample actually resulted in 50 trials for the client and fifty time values. This provided an adequate amount of data for making the predictions. However, in some cases, a work sample or situational assessment task may result in obtaining only one score for the entire task during each administration. And the actual standard time needed to complete the task may take several minutes or even a few hours. In such cases, the evaluator obviously will not be able to collect as many data points as in the research example. However, it is recommended that the task be administered as many times as possible since this will help ensure better accuracy in prediction. In most cases, at least ten pieces of data or time values should be obtained for a task before attempting to use the best-20% method.

Clearly, the best-20% method offers a number of advantages over other methods previously described. Its ease of use makes it attractive for application in vocational evaluation settings. And obviously, the research indicating its accuracy is also a strong reason for using this method. However, like the other methods described, it too has its limitations.

First, as was suggested previously, some evaluation tasks will not lend themselves to this method. This is true with regard to many situational assessment tasks, job-site evaluations, or work sample tasks which require extended periods of time to complete with only one time value provided at the end of each administration. For example, if a client is assigned to a janitorial task which requires approximately three hours for the average examinee to complete, practical considerations limit the number of times the task can be readministered. And unless an adequate number of time values are obtained, clearly the best-20% value will have little reliability.

Another possible drawback to this approach was suggested by Blakemore and Coker (1982). They indicated that while this approach appeared to offer accurate predictions in comparison to traditional learning curve formulas, more research is needed to support their findings since relatively little work has been done in this area. They specifically indicated more research is needed to further test the overall reliability and accuracy of this method, as well as whether or not the 20% factor is the best possible value. Further research might indicate that a different percentage factor might offer a more accurate basis for prediction.

Despite these drawbacks, the best-20% method has much to offer in terms of accuracy and ease of use, particularly in comparison to current static prediction methods. As Blakemeore and Coker (1982) indicated, "the best-20% method can certainly reduce the amount of prediction error when compared to the use of the traditional static performance measure of work sample performance" (p. 33).

METHOD NUMBER 5

It should be apparent from reviewing each of the methods discussed thus far that learning curves hold much potential for use in vocational evaluation. In addition, learning curve formulas and the best-20% method offer proven techniques for ensuring accuracy in these predictions. However, both approaches also require that a relativley large amount of data be collected on client performance. The more data collected, the better predictive accuracy is enhanced. However, collecting the data is often time consuming and attempting to manually analyze it can be an overwhelming task for evaluators with limited mathematical training. This process is also prone to error. Thus, there is clearly an important tradeoff. These problems are even more pronounced when evaluators attempt to use sophisticated learning curve equations as described in method number 3. As a result, to date, the use of learning curves has been limited by practical considerations.

One way to overcome these obstacles is to use relatively inexpensive yet powerful microcomputer technology to not only assist the evaluator in collecting the data but also in making the mathematical computations that are involved in applying the learning curve formulas. The "Performance Analyzer and Enhancer" is a computer software program designed to meet just these needs. It runs on a relatively low cost 64K Commodore microcomputer. The primary functions of the Performance Analyzer and Enhancer are to:

1. Collect data relating to the amount of time it takes an individual to perform a repetitive task.

2. Analyze the data collected.

3. Calculate learning curves and make predictions about the level of performance the individual can be expected to achieve with additional learning and experience.

4. Increase or enhance the individual's level of performance by providing feedback following each repetition of the task, to the examinee.

A photo of the Performance Analyzer and Enhancer configuration for a work sample in Appendix B.

During administration of a work sample task, the microcomputer is basically linked to a remote switch which is attached to the work sample and thereby automatically indicates when the work sample or task has been completed by the client. The time needed for the client to complete the task is recorded by means of the switch which automatically starts and stops the timer. One of the primary advantages of this system is that the switching can be hooked up in a variety of different ways so that the software and the computer itself can be used with a variety of different kinds of existing work samples or job samples, particularly those that are repetitive in nature and involve psychomotor tasks.

The Performance Analyzer and Enhancer is a versatile software program which is designed to collect substantial amounts of data on client performance and plot learning curves which can be used for predictive purposes. Three different learning curves may be plotted based on each of the three equations. In addition, the best-20% method may also be calculated. Users may choose to plot curves using all four methods since some variation can be expected. Once this variation is established, it can be taken into account when making decisions about the most optimal performance level expected and the least optimal perrformance level expected. In addition, calculating all four methods also helps offset the fact that one technique or equation may be more appropriate and more accurate than other techniques, for a given task. In most cases, the end result of this effort is that a printout similar to the one shown in Appendix C is provided.

Clearly, this type of information is very useful to evaluators and clients in terms of gaining a more accurate picture of improvements in a client's performance as a result of learning. And the predictive use of the data is equally important. Further, the Performance Analyzer and Enhancer, as a computer based system, is able to overcome many of the problems associated with the other methods described in this section, chief of which are the time needed to compute the learning curves and analyze the data if a manual system is used.

It should be noted that the Performance Analyzer and Enhancer has a number of other uses beyond those related to learning curve applications. It can be used in work adjustment programs to enhance client performance by providing clients with visual and auditory feedback while they work. Clients may observe a video monitor showing colorful graphics designed to display their performance and compare it to some desired goal. Thus the Performance Analyzer and Enhancer represents more than simply a feasible solution to the need to use learning curves in vocational evalaution.

Finally, it must be noted that the Performance Analyzer and Enhancer is still in the experimental stage. Initial field tests indicate much promise for this software; however, additional testing and research will be conducted throughout 1985 and possibly into 1986. It is not expected that this tool will be available for widespread commercial use in facility programs until each phase of the testing has been completed.

SUMMARY

Learning curves have long held much potential for use in vocational evaluation. However, to date, their use has been limited because of three important factors: (1) vocational evaluation personnel have had relatively little training in the use of learning curves, particularly with regard to the application of learning curve equations; (2) manually collecting and computing the data that makes up most learning curves is a time-consuming process for evaluators who are already constrained for time in many cases; and (3) perhaps evaluators, educators, and to some extent referral sources are guilty of complacency in continuing to accept the predictive validity of current static approaches to assessment despite the glaring paucity of research or other information supporting this notion of "presumptive validity."

Yet, despite its value, it should be equally apparent that learning curve technology is not without its limitations. The use of learning curve equations can be a complicated, time consuming process unless microcomputer technology is used. Current efforts to integrate microcomputer technology into this process hold much promise but much work still needs to be done in this area before a viable system is available on a widespread basis. One possible alternative to this approach is the best-20% method. It provides a practical and easy-to-use approach to learning curve analysis. Yet, even here, additional research is needed to validate this approach. And while the simplest approach, involving little more than administering a task several times and plotting changes in performance, is useful in gaining more understanding of client capabilities than current static procedures offer, the problems of objectively determining when "peak performance" has been achieved, time needed for several administrations and related problems come to the forefront once again.

Thus, it is clear that learning curves are not a panacea. Use of any of the five methods described in this research utilization report will undoubtedly add valuable information to one's understanding of a client's capabilities when prediction is a significant goal of the evaluation. It must be recognized, however, that there are boundaries to these predictions. Use of even the most sophisticated learning curve equations, based on hundreds of trials, still does not allow the evaluator to make absolute predictions about "ultimate" performance capability. There is a limit to the predictive capacity of learning curves and depending on the approach used, number of trials available etc., this limit can be reached fairly quickly. One cannot provide a client with a few trials and then predict into the infinite future what absolute performance level is possible. Predictions must be tempered by the reality of the evaluation setting itself and limitations of the technology. Thus, while it is possible to predict with relative accuracy how a client will perform on the fiftieth trial based on only ten trials, evaluators must recognize that as predictions extend further into the future, their reliability and accuracy can become increasingly doubtful. With this in mind, it should be apparent that learning curves offer much in terms of complementing many existing existing vocational evluation practices. They should not, however, be viewed as a substitution or replacement for existing practices.

This monograph has presented a rationale for the integration of learning curve technology into current vocational evaluation practice. Five different approaches to learning curve utilization have also been described. They range in complexity from Tillman's simple notion of constantly readministering a task and plotting performance until "peak performance" is achieved, to sophisticated learning curve equations and the use of the microcomputer-based Performance Analyzer and Enhancer.

Each of these techniques, while having significant limitations, also has much to offer current vocational evaluation practice. However, learning curve technology should be viewed as a complement to current vocational evaluation practices. It provides an additional means for better understanding client capabilities and limitations. Continued research and field-testing, along with an increased emphasis among educators in providing training in learning curve technology to professional evaluation personnel, will perhaps lead to a wider use of learning curves in vocational evluation programs as well as further refinement and improvement of many of the methods and techniques presented in this monograph.

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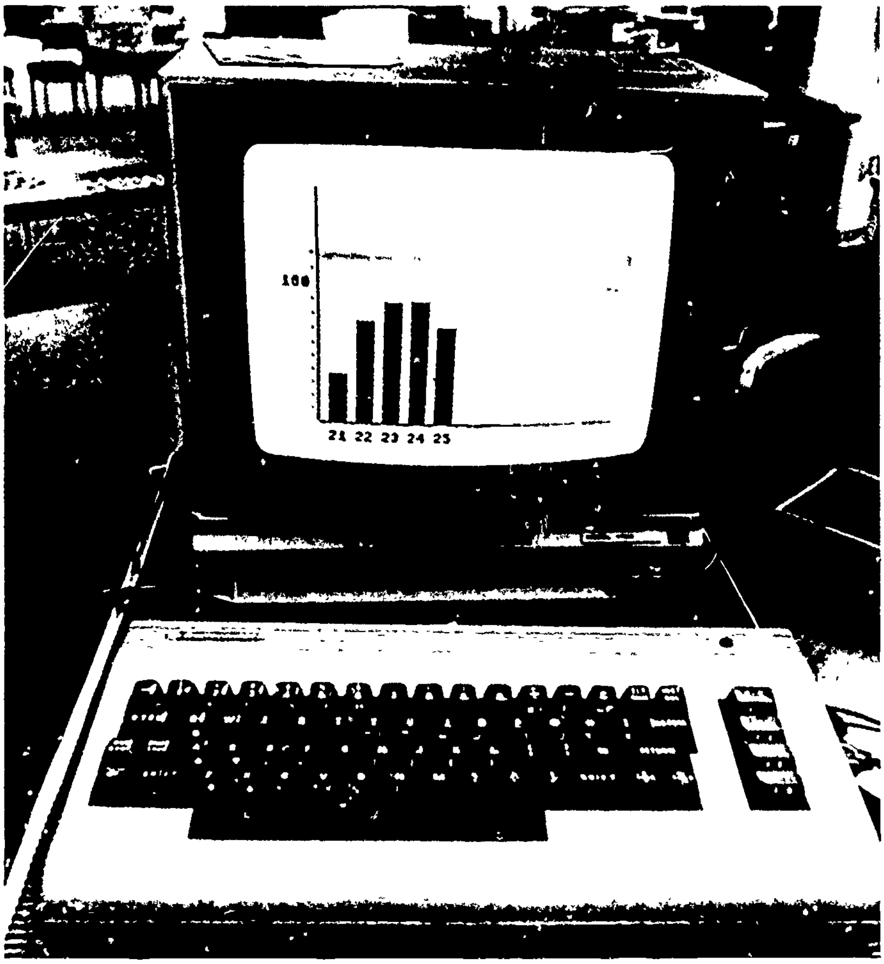
APPENDIX A

Table to be Used When Calculating the
Hyperbolic Learning Curve Equation (Y = (LX)/(X - A))

	Values Used in the Calculation						
	X	Y	X2	Y2	XY	XY2	X2Y
	0						
	1						
	2						
	3						
	4						
	5						
	6						
	7						
	8						
	9						
	10						
	11						
	12						
	13						
	14						
	15						
	16						
	17						
	18						
	19						
	20						
	21						
	22						
	23						
	24						
	25						
Total							

APPENDIX B



PERFORMANCE ANALYZER AND ENHANCER

APPENDIX C

NAME: DAN
DATE: 3/7/84   SESSION NUMBER: 1
TIME: 8 AM
TASK: MAIL SORT

NUMBER OF PIECES/ASSEMBLY: 25
PIECES/ASSEMBLIES PER TRIAL: 1
NUMBER OF TRIALS: 25
PREVIOUS TRIALS COMPLETED: 0

NORMATIVE BASE LINE

TIME HOURS: 0
MINUTES: 1
SECONDS: 0
PER 1 PIECES/ASSEMBLIES

STANDARD TIME FOR ONE TRIAL: 60 SECONDS
STANDARD TIME FOR ONE PIECE/ASSEMBLY: 60 SECONDS

PERFORMANCE

MEAN TIME PER TRIAL: 169.87 SECONDS
MEAN TIME PER PIECE/ASSEMBLY: 169.87 SECONDS
STANDARD DEVIATION: 72.38 SECONDS
MEAN PERCENT OF STANDARD: 35.32 %

QUALITY

INCORRECT ASSEMBLIES: 0
CORRECT MEAN TIME PER TRIAL: 169.87 SECONDS
CORRECT MEAN TIME PER PIECE/ASSEMBLY: 169.87 SECONDS
CORRECT MEAN PERCENT OF STANDARD: 35.32 %

SUMMARY

TOTAL TIME: 4246.86 SECONDS
FASTEST TRIAL: 88.08 SECONDS
SLOWEST TRIAL: 327.01 SECONDS
MEAN OF THE FASTEST 20% OFTHE TRIALS: 100.25 SECONDS

BAR GRAPH

TRIALS	TIME	%	0 · 50 · 100 · 150 · 160	COMMENT
1	283.81	21		
2	311.91	19		AB
3	310.91	19		CDE
4	227.87	26		F
5	327	18		GH
6	201.95	29		I
7	179.95	33		J
8	178.5	33		
9	88.07	68		
10	120.93	49		
11	158.1	37		
12	100.68	59		K
13	121.75	49		
14	110.88	54		
15	120.68	49		
16	142.43	42		L
17	102.4	58		
18	100.78	59		
19	219.43	27		M
20	157.63	38		N
21	177.23	33		
22	141.55	42		
23	109.33	54		
24	137.87	43		
25	115.1	52		

NAME DAN
DATE: 3/7/84 SESSION NUMBER: 2
TIME: 1 PM
TASK: MAIL SORT

NUMBER OF PIECES/ASSEMBLY: 25
PIECES/ASSEMBLIES PER TRIAL: 1
NUMBER OF TRIALS: 25
PREVIOUS TRIALS COMPLETED: 25

NORMATIVE BASE LINE

TIME HOURS: 0
MINUTES: 1
SECONDS: 0
PER 1 PIECES/ASSEMBLIES

STANDARD TIME FOR ONE TRIAL: 60 SECONDS
STANDARD TIME FOR ONE PIECE/ASSEMBLY: 60 SECONDS

PERFORMANCE

MEAN TIME PER TRIAL: 95.63 SECONDS
MEAN TIME PER PIECE/ASSEMBLY: 95.63 SECONDS
STANDARD DEVIATION: 15.37 SECONDS
MEAN PERCENT OF STANDARD: 62.74 %

QUALITY

INCORRECT ASSEMBLIES: 1.06
CORRECT MEAN TIME PER TRIAL: 99.68 SECONDS
CORRECT MEAN TIME PER PIECE/ASSEMBLY: 99.68 SECONDS
CORRECT MEAN PERCENT OF STANDARD: 60.18 %

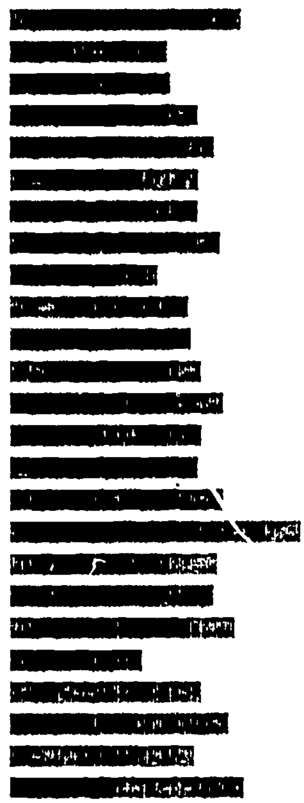
SUMMARY

TOTAL TIME: 2390.75 SECONDS
FASTEST TRIAL 63.75 SECONDS
SLOWEST TRIAL: 137.66 SECONDS
MEAN OF THE FASTEST 20% OFTHE TRIALS: 77.56 SECONDS

DAN 2

BAR GRAPH

TRIALS	TIME	%	0 50 100 150 160	COMMENT
1	79.72	75		A
2	117	51		B
3	114.03	52		
4	97.75	61		C
5	90.06	66		
6	97.28	61		D
7	96.9	61		
8	87.12	68		
9	123.93	48		
10	102.43	58		E
11	100.1	59		
12	96.18	62		
13	86.82	69		
14	95.87	62		
15	98.25	61		F
16	86.72	69		
17	63.75	94		
18	89	67		
19	90.65	66		
20	82.09	73		G
21	137.65	43		
22	96.25	62		H
23	83.84	71		
24	98.81	60		
25	78.4	76		I



NAME: DAN
DATE: J/7/84 SESSION NUMBER: 3
TIME: 3 PM
TASK: MAIL SORT

NUMBER OF PIECES/ASSEMBLY: 25
PIECES/ASSEMBLIES PER TRIAL: 1
NUMBER OF TRIALS: 25
PREVIOUS TRIALS COMPLETED: 50

NORMATIVE BASE LINE

TIME HOURS: 0
MINUTES: 1
SECONDS: 0
PER 1 PIECES/ASSEMBLIES

STANDARD TIME FOR ONE TRIAL: 60 SECONDS
STANDARD TIME FOR ONE PIECE/ASSEMBLY: 60 SECONDS

PERFORMANCE

MEAN TIME PER TRIAL: 94.29 SECONDS
MEAN TIME PER PIECE/ASSEMBLY: 94.29 SECONDS
STANDARD DEVIATION: 21.92 SECONDS
MEAN PERCENT OF STANDARD: 63.62 %

QUALITY

INCORRECT ASSEMBLIES: 0
CORRECT MEAN TIME PER TRIAL: 94.29 SECONDS
CORRECT MEAN TIME PER PIECE/ASSEMBLY: 94.29 SECONDS
CORRECT MEAN PERCENT OF STANDARD: 63.62 %

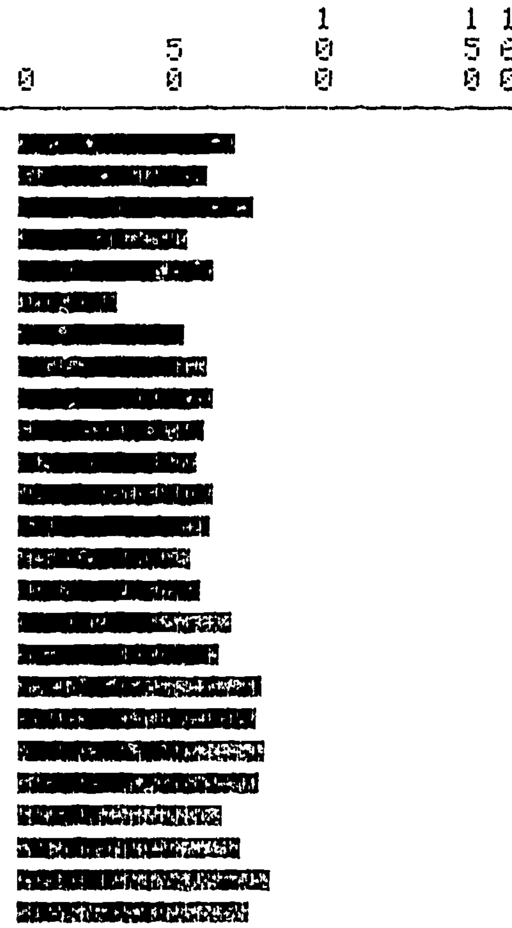
SUMMARY

TOTAL TIME: 2357.46 SECONDS
FASTEST TRIAL: 72.8 SECONDS
SLOWEST TRIAL: 184.69 SECONDS
MEAN OF THE FASTEST 20% OFTHE TRIALS: 75.29 SECONDS

DAN 3

BAR GRAPH

TRIALS	TIME	%	COMMENT
1	85.62	70	
2	97.18	61	
3	78.07	76	
4	108.4	55	
5	94.68	63	
6	184.68	32	
7	111.05	54	
8	97.62	61	A
9	94.4	63	
10	98.75	60	
11	103	58	
12	95.05	63	
13	95.9	62	
14	106	56	
15	100.18	59	B
16	85.93	69	CD
17	91.97	65	
18	75.53	79	
19	77.82	77	
20	74.12	80	
21	76.18	78	E
22	90.05	66	
23	82.68	72	
24	72.8	82	
25	73.65	75	F



NAME DAN
DATE: 3/8/84 SESSION NUMBER: 4
TIME: 10 AM
TASK: MAIL SORT

NUMBER OF PIECES/ASSEMBLY: 25
PIECES/ASSEMBLIES PER TRIAL: 1
NUMBER OF TRIALS: 25
PREVIOUS TRIALS COMPLETED: 75

NORMATIVE BASE LINE

TIME HOURS: 0
MINUTES: 1
SECONDS: 0
PER 1 PIECES/ASSEMBLIES

STANDARD TIME FOR ONE TRIAL: 60 SECONDS
STANDARD TIME FOR ONE PIECE/ASSEMBLY: 60 SECONDS

PERFORMANCE

MEAN TIME PER TRIAL: 74.34 SECONDS
MEAN TIME PER PIECE/ASSEMBLY: 74.34 SECONDS
STANDARD DEVIATION: 9.23 SECONDS
MEAN PERCENT OF STANDARD: 80.7 %

QUALITY

INCORRECT ASSEMBLIES: 0
CORRECT MEAN TIME PER TRIAL: 74.34 SECONDS
CORRECT MEAN TIME PER PIECE/ASSEMBLY: 74.34 SECONDS
CORRECT MEAN PERCENT OF STANDARD: 80.7 %

SUMMARY

TOTAL TIME: 1858.62 SECONDS
FASTEST TRIAL: 50.38 SECONDS
SLOWEST TRIAL: 98.63 SECONDS
MEAN OF THE FASTEST 20% OFTHE TRIALS: 63.44 SECONDS

53 BEST COPY AVAILABLE

BAR GRAPH

TRIALS	TIME	%	0 50 100 150 160	COMMENT
1	75.05	79		
2	70.47	85		
3	53.37	112		
4	71.47	83		
5	78.37	76		
6	72.9	82		
7	76.53	78		
8	80.9	74		
9	92.1	65		
10	70.2	85		
11	78.12	76		
12	98.62	60		
13	78.43	76		
14	74.59	80		
15	89.31	67		
16	71.81	83		
17	72.09	83		
18	73.93	81		
19	64.06	93		
20	71.7	83		
21	62.4	96		
22	67.18	89		
23	71.09	84		
24	72.4	82		
25	71.37	84