The Influence of Task Characteristic and Training Approach on Task Compilation

Nikou Sabzevar and Theodor Freiheit
Department of Mechanical and Manufacturing Engineering
University of Calgary, Calgary, Alberta, T2N 1N4 Canada

Abstract

Human capital is an important asset and training offers an opportunity to upgrade worker skills and significantly influence the workforce’s delivery of products or services. Different task characteristics such as complexity, cognition, difficulty, motivation, and fatigue may influence individual task outcomes and affect the training methods applied. Historic success may result in applying training methods without consideration to recent changes to markets, product characteristics, technologies, or workforce skills. This paper explores the effect of task characteristics on the efficacy of training methods. Tasks are classified in two dimensions having complexity and cognition characteristics. An experiment investigates the relationship between training methods and task oriented characteristics. A statistical analysis of process time and error occurrence determined that training method, task type, and task difficulty perception are significant factors. Overall, on-the-job training modes were generally observed to perform best, but the written training performed equally well for cognitive tasks and may be better for complex tasks.

Keywords
Task Performance, Training Methods, Cognitive Tasks, Complex Tasks

1 Introduction

Competition from economic globalization requires organizations to continuously improve the performance of their workforce, and training offers workers the opportunity to upgrade their skills [1, 2]. The workforce can influence factors important to customers such as product or service delivery time, cost, and quality. Reducing error occurrence is one step companies can take to stay competitive. Workforce training provides workers with critical information to perform their roles with minimum error. In rapidly changing business environments, companies must push their workers to learn new tasks as effectively and quickly as possible in order to achieve success [3].

This study is motivated by reconfigurable manufacturing’s need to minimize ramp-up time following a system re-configuration [4]. In this context, ramping-up reconfigured systems requires a focus on the training of closed skills, that is, training cognitive and psychomotor tasks to conduct the processes required of the new manufacturing configuration [5, 6]. While ramp-up also requires more general open skills such as error diagnosis and debugging or interpersonal skills, these skills are reinforced during each reconfiguration and are arguably applied after an understanding of the new tasks is obtained from closed skill training. Thus, the training of closed skills most affects ramp-up efficiency and necessitates identifying the most appropriate training approaches that lead to skill compilation [7].

It is not the training methods per se that are at question, but rather using uniform training approaches for all situations, as employee capabilities and their perceptions may create less effective training situations. For example, Sitzmann et al. [8], in a meta-analytic comparison of web-based and classroom instruction, found differences in the effectiveness of teaching declarative knowledge, but not for procedural knowledge. Grossman and Salas [9] summarize the important inputs that influence training transfer from research to date into trainee characteristics, work environment, and training design, which converge into learning and retention outcomes. Trainees vary in motivation, self-efficacy, and cognitive ability, but task performance outcomes are also affected by mental and physical exhaus-
tion, uncomfortable working conditions, or lack of attention to the task or to details within the task. Work environments also complicate task performance with, for example, environmental noise or supervisor or peer support. While training design refers to the learning methods used to facilitate outcomes, e.g., behavioral modeling, or self-paced individual study strategies [10], it should also align those strategies to the type of task being trained.

External factors have long been recognized as important to task performance, but task type may also strongly affect the efficacy of training methods. Modis [3] emphasized that training should be designed and frequently modified in accordance to the characteristics of tasks. While it is generally assumed that simple tasks need shorter and less rigorous training programs [11], some tasks are more complex [12] or cognitive [6], and workers may believe that these tasks are harder to learn, take longer to understand, and lead to more errors. Fitz-Enz [13] stated it is crucial to consider task complexity, as workers perform a wide variety of simple and complex tasks. Ford et al. [14] suggest different training methods should be used for tasks of different complexity levels, but did not indicate what training method is most appropriate. Topi et al. [15] found task complexity strongly influences database query performance, but did not manipulate training method. Arthur et al. [6], in a meta-analysis of training design, stated that practitioners have little control over the skills that must be trained for a task, having more latitude on the training delivery method, but very little research has been directly aimed at assessing delivery. His meta-analysis found that both psycho-motor and cognitive skill or task characteristics have a medium to large relative effect on behavior training outcomes, and most training delivery reviewed (e.g., lecture, audiovisual, discussion) has a medium-small to medium-large effect size. In most cases, no training method was indicated as superior due to lack of statistical separation.

In summary, considering the training approach in conjunction with more general aspects of task type is limited in earlier work. Task type characteristics and training approach should be clearly defined and their most effective combination determined to enhance training compilation and transfer. This research is limited to training compilation outcomes. This paper is organized as follows. In the Section 2, the objective of this study is defined and factors influential to the objective are explained. In Section 3, an experiment is designed to explore task type and training modes. Section 4 analyzes and discusses the results. Section 5 presents a brief summary and the general conclusions.

2 Objective and Experimental Factors
The objective of this study is to investigate effective training methods for tasks of different complexity and cognition requirements that will facilitate skill compilation. This paper presents the results of the study design reported in [16]. The effectiveness of a training method is evaluated by the performance time and the number of errors that occur during task performance. For this objective, the two main factors controlled in a design of experiment are task type and training method. Trainee characteristics such as cognitive ability will not be considered as it is presumed that the workforce is what it is, and while attitudinal targets could be considered important training outcomes, they are outside of the context of reconfiguration ramp-up and will not be addressed in this study. Work environment was addressed by the test task design as explained in [16]. Therefore, the other factors that may influence error occurrence will be treated as noise in the statistical analysis.

Task type refers to characteristics that are either intrinsic to a task or are subjective to the task performer. Characteristics such as task complexity and cognition are intrinsic to the task and are called task oriented characteristics. There are standard criteria that can define task complexity and cognition, and in general, an agreement can be collectively obtained that certain tasks are more complex or cognitive than others even though workers and managers may have individually subjective opinions as to what degree. Task characteristics such as its perceived difficulty, worker interest in the task, or the degree to which worker fatigue affects the task are called subject oriented characteristics, as different people will have different opinions about these characteristics.

This study concentrates on task oriented characteristics and classifies tasks into two dimensions of complexity and cognition. The complexity of a task, which ranges on a continuum from simple to complex, changes as a result of information availability and the interaction of parts or processes, etc., to indicate a task’s level of variety (distinction) and dependency (connections) between aspects of the task. The cognition of a task, which ranges on a continuum from manual to cognitive, indicates whether processes need more thinking and background knowledge, or are merely physical interactions with the task. A purely manual task would have all cognitive functions embedded in the task procedure such that task performance and outcomes are limited to physical interactions with the task; no thinking is required. In contrast, a cognitive task cannot separate out thinking from the task, e.g., decision making is a fundamental requirement for completion of the task. In this study, four tasks were developed covering the classes of: Complex-Cognitive, Simple-Cognitive, Simple-Manual, and Complex-Manual.
In the literature [17], training methods are categorized into the following groups: (a) inflexible modes, including classroom instruction, lectures, or video sessions; (b) self-paced methods, such as personalized system; (c) job methods, where processes are learned by doing, such as on-the-job training; and (d) specialized methods, such as coaching and mentoring. Among training methods, written instruction (self-paced), pictorial illustration (self-paced), and on-the-job training were selected for this study. Their selection was based on their appeal to different learning styles, the different modes for which the same information could be presented, a limited training time and budget, and lack of experienced trainers. Moreover, they are the most commonly used methods and have been widely applied for different purposes [18-20].

3 Experimental Design and Task Selection
A designed experiment was employed to evaluate the influence of training method on error occurrence related to task complexity and cognition. The main experimental factors are task characteristics, having three levels, and training mode, having four levels, and the outcome measures are the number of errors that occurred while performing the task and the time to complete the task. Other potential sources of variation to the outcome measure include the test subjects’ perceived level of difficulty for the task, sex, English language ability, and expertise. These factors were not of interest to this research, but could affect the results, and were blocked variables in the experimental analysis. Other external sources of variation were addressed by standardization of the training processes, randomization of tasks, a limited repeated measures approach, and repeating a given task set for two different test subjects. The experimental design and details on task selection employed for this study are fully described in [16].

The task type factor requires four tasks that will nominally embody each of the four complexity and cognition classes. In selecting tasks for this experiment, it is important to choose representative tasks that exhibit higher extremes in the complexity and cognition dimensions, and thus more than fifty task candidates were screened to determine which task would embody each task classification. Criteria like safety and the compatibility with the training methods was critical to the limitations of constructing and implementing the experiment. The four tasks in this study are applying the Analytical Hierarchy Process (AHP), making a mosaic, assembling a lamp, and making a box from sheet metal. AHP has both complex and cognitive traits, mosaic making has only cognitive characteristics, lamp assembly has neither complex nor cognitive characteristics, and box making has only complex characteristics.

3.1 Test Subjects and Data Collection
Forty volunteers were recruited from a university campus and paid an honorarium for their time. All volunteers were students 18 to 35 years old in an engineering discipline. The first four participants were eliminated from the data analysis to minimize the effect of the trainer’s learning curve in performing this experiment. The demographics of the remaining 36 test subjects are summarized in Table 1.

<table>
<thead>
<tr>
<th>English Capability</th>
<th>Educational Major</th>
<th>Educational Level</th>
<th>Sex</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowest (1)</td>
<td>Geomatics</td>
<td>Graduate</td>
<td>Male 26</td>
</tr>
<tr>
<td>Intermediate (2)</td>
<td>Mechanical</td>
<td>Graduate</td>
<td>Male 24</td>
</tr>
<tr>
<td>High (3)</td>
<td>Electrical</td>
<td>Undergraduate</td>
<td>Female 12</td>
</tr>
<tr>
<td>Native (4)</td>
<td>Bioengineering</td>
<td></td>
<td>Female 10</td>
</tr>
</tbody>
</table>

The test subjects were asked to perform a set of tasks using an assigned training method. A self-paced instruction manual corresponding to each task was given to those assigned to the written and pictorial training methods. The pictorial training method used a set of pictures, a combination of tables, an engineering drawing, or an assembly installation drawing to conduct the task. Subjects assigned to on-the-job training (OJT) were mentored by the researcher who trained and answered questions. The OJT method included performing the tasks once in the presence of the researcher and then the subject performed the task on their own. All subjects took similar and equivalent training sessions. Each test subject was asked to rate their perception of the difficulty of each task on a five level Likert scale at the completion of the test.

The task performance outcome measures were the time to task completion (process time) and the aggregated sum of errors observed for each participant weighted by an estimate of the probability of occurrence of that particular error. Errors were generally categorized into related or unrelated errors. Related errors are attributed to the capability of the training methods, while unrelated errors are associated with external factors such as participants’ lack of attention or environmental noise. Potential errors were determined by studying each task, with the total number of poten-
tial errors corresponding to each error type for each task displayed in Table 2. Related errors are of most interest since the objective is to determine the effect of training method on task performance, but since an error in performing a task is still an error regardless of the cause, the total of related and unrelated errors will also be analyzed. Note that, unsurprisingly, cognitive tasks have a higher potential for unrelated errors. While the test was conducted with each test subject working independently, it was observed that a few participants talked to each other about the tasks during subject recruitment, which may have affected the number of errors observed.

The aggregated sum of the errors observed for each participant was determined by weighting each error by an estimate of the probability of its occurrence, and the range of error occurrence across the various test subjects was normalized for each task because each task varies in the number of errors that can occur and not all errors are equivalent. Errors that occur more frequently should have more weight in the analysis, as an error that occurs more frequently is presumed to be associated with a larger deficiency in the training mode. The probability of error occurrence, assumed to follow a binomial distribution, is estimated by dividing the sum of the occurrences of that error by the number of test subjects, e.g. 36:

\[
W_i = \binom{n}{k} p_i^k (1 - p_i)^{n-k} = \frac{1}{1} p_i (1 - p_i)^0 = p_i
\]

\[
p_i = \frac{\sum_{j=1}^{36} I_{ij}}{36}
\]

where \( W_i \) is the error weight of the \( i^{th} \) error for a given task, \( n \) is the number of times a test subject performed the task (once), \( k \) is one if the error occurred (zero if not), and \( I_{ij} \) is the indicator variable for whether the \( i^{th} \) error occurred for the \( j^{th} \) test subject for a given task. Note that when an error doesn’t occur it is not counted, and there is no need to give it a weight.

### 4 Data Analysis

A statistical analysis of the normalized process time and the binomially weighted, normalized measures of error occurrence was undertaken in order to identify the most effective training methods that minimize the error for tasks of different complexity and cognition. The test subject’s perception of task difficulty was taken into account in the analysis. It was determined that other sources of variation, namely test subject sex, ability in the English language, and their background experience as represented by their major, were not statistically significant and therefore were not blocked in the experimental analysis. Note that in the ANOVA analyses, the variance from repeated measures is captured and accounted for in the ‘Test Subject ID’ variable.

#### 4.1 Perception of Task Difficulty

The difficulty ratings and the average task completion time is summarized in Table 3. The perception of task difficulty is correlated to error occurrence, Figure 1(a). Since the difficulty rating was given after task performance, it is not surprising that higher difficulty ratings are associated with more errors. Most of the difficulty ratings (84%) were between one and three. Since no criteria was given to help subjects distinguish the relative difficulty, and since few data points were given at four or five, for better statistical tractability, ratings of three and higher were aggregated into one difficulty code, distributing roughly 38%, 26% and 35% to the D1, D2, and D3 categories, respectively. Figure 1(b) shows how this categorization distinguishes between less and more difficult tasks and its affect on the variability of error occurrence. Difficulty perception will be included in all subsequent analysis of variance (ANOVA) as a categorical, nested co-variant, as the perceived level of task difficulty is a subject oriented characteristic independent of the task complexity-cognition model.

#### 4.2 Task Type-Training Method Process Time Analysis

Process time is a measure of initial skill acquisition and compilation into procedural knowledge [7]. This measure of the integration of discrete skill steps can be quantified by time to task completion, where faster performance indi-
The completion time for each of the four tasks was normalized to between zero and one to account for variability in content between tasks. Minitab’s™ general linear model (GLM) ANOVA was then used to analyze the significance of the parameters. The test subjects were treated as random categorical variables to account for the correlation of test subject performance within their repeated measures of the different tasks. The perceived difficulty of tasks was controlled by treating difficulty as a nested random variable within test subject ID. Table 4 shows the ANOVA output for process time. Figure 2 shows the interaction plots between task types and training methods.

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Easy -1</td>
<td>4</td>
<td>6</td>
<td>36</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>14</td>
<td>0</td>
<td>13</td>
</tr>
<tr>
<td>3</td>
<td>10</td>
<td>13</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Difficult -5</td>
<td>8</td>
<td>2</td>
<td>1.00</td>
<td>2.44</td>
</tr>
<tr>
<td>Avg. Difficulty Rating</td>
<td>3.06</td>
<td>2.42</td>
<td>1.00</td>
<td>2.44</td>
</tr>
<tr>
<td>Avg. Completion Time (min.)</td>
<td>56.3</td>
<td>33.0</td>
<td>6.6</td>
<td>60.1</td>
</tr>
</tbody>
</table>

Figure 1 Variance in the Perception of Difficulty (all tasks and training modes)

Cognitive tasks had significantly less process time than manual tasks (p<0.05), while simple tasks are almost significant in taking less time than complex tasks (p=0.16). The OTJ training method resulted in significantly less process time than pictorial and writing training (p<0.01), which were statistically equivalent. Significant differences in the interactions according to Tukey’s test included complex-cognitive tasks take less time than complex-manual (p<0.001) and are almost significantly less than complex-manual (p=0.13). Complex-cognitive tasks take statistically equivalent time as simple-manual tasks. Simple-cognitive and simple-manual tasks take significantly less time than simple-manual (p<0.02). Almost all significant differences in process time related to task type and training method were for OTJ, with both simple-OTJ taking less time than complex task training with pictorial and written methods, and cognitive-OTJ taking less time than cognitive and manual tasks trained with pictorial and written methods (p<0.1). Generalizing from Figure 2, OTJ appears to provide better initial skill acquisition and compilation as represented by process time, followed by pictorial, then written training methods.

4.3 Task Type-Training Method Error Analysis

As shown in Table 3, the mean time to complete the complex tasks was approximately the same, and the averaged perceived difficulty of the complex-cognitive task was about 25% higher than the complex manual task. The simple cognitive task took about half the time on average as the complex task, and was perceived to be about as difficult as the complex-manual task. Unfortunately, the task selected to represent the simple-manual classification was too
simple, having an average completion time of $\frac{1}{5}$th that of the simple-cognitive task, and was rated easy by all test subjects.

A postori, an ideal simple-manual task would have taken about 30 minutes on average to complete and have received a perceived difficulty rating average of about 1.9. The overly simple nature of the lamp assembly task creates problems with the statistical analysis, as the predominance of zero errors observed while performing this task doesn’t provide sufficient statistical separation between training modes. However, the data set is sufficient to evaluate the variation in errors for cognition in complex tasks and the variation in complexity in cognitive tasks as a function of training modes. In the subsequent analysis, the error occurrence observations (and the influence of its training modes) for the lamp task are ignored.

4.4 Variance of Cognition in Complex Tasks
The complex tasks were extracted from the data set to evaluate the effect of variation in cognition for complex tasks. The general linear model ANOVA was again used to analyze the significance of the parameters per the process time.
While the difference between training modes for complex tasks was not significant, written training has indications that it could be superior to on-the-job training (p-value = 0.23) for related errors if this trend held with a larger sample size. The difference between both on-the-job and pictorial training, and pictorial and written training, was not significant at a p-value of about 0.70. For total errors, on-the-job training also has indications that it could be superior to pictorial training (p-value = 0.20) if its trend also held up with a larger sample size. While interactions between training mode and the cognitive dimension were not significant, there is a trend that on-the-job training may result in fewer total errors for manual tasks (p-value = 0.56 with pictorial training). In summary, one cannot definitively conclude that a superior training mode for cognitive dimension of complex tasks exists, but there may be a trend where written training produces lower related errors, and on-the-job training produces lower total errors.

### 4.5 Variance of Complexity in Cognitive Tasks

The cognitive tasks were extracted from the data set to evaluate the effect of variation in complexity for cognitive tasks. Table 6 shows the statistical output for the GLM for both the aggregated, binomially weighted normalized related and total errors. For the cognitive task, test subject perception of task difficulty is significant for both related and total errors. In Figure 4, the difference between training modes is significant at less than 10% confidence, as is the difference between complex and simple tasks. Both on-the-job and written training modes result in fewer errors than the pictorial training mode. The complex task also had fewer errors following training (p-value = 0.006). The interaction between training modes and the complexity dimension was not significant.
The difference between training modes for cognitive tasks was significant for related errors to a p-value of 0.1 between on-the-job and pictorial training modes, and 0.06 between the written and pictorial training modes, and was not significant between on-the-job and written training modes. According to Tukey’s test, written and on-the-job training modes are equivalent and both are better than pictorial training. For total errors, only on-the-job training is significantly better than pictorial training (p-value = 0.01), but on-the-job training has indications that it could be superior to written training (p-value = 0.27) if its trend held with a larger sample size. The difference between the pictorial and written training, while not significant (p-value 0.45), implies that the on-the-job training is better than the written training, which is better than the pictorial training for total errors. In summary, one can definitively conclude that on-the-job training is superior for the complexity dimension of cognitive tasks, but is equivalent to written training for related errors, and that there may be a trend where written training produces an intermediate number of total errors, while pictorial training produces the most total errors.

### Table 6: GLM ANOVA - Complexity Variation in Cognitive Tasks

<table>
<thead>
<tr>
<th>Model</th>
<th>Related Errors</th>
<th>Total Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variance Source</strong></td>
<td>Seq SS</td>
<td>Adj SS</td>
</tr>
<tr>
<td>Test Subject ID</td>
<td>2.39</td>
<td>2.16</td>
</tr>
<tr>
<td>Difficulty(ID)</td>
<td>1.53</td>
<td>1.75</td>
</tr>
<tr>
<td>Training</td>
<td>0.47</td>
<td>0.47</td>
</tr>
<tr>
<td>Complexity</td>
<td>0.62</td>
<td>0.58</td>
</tr>
<tr>
<td>Training * Complexity</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Error</td>
<td>0.86</td>
<td>0.86</td>
</tr>
<tr>
<td>Total</td>
<td>71</td>
<td>5.87</td>
</tr>
<tr>
<td>Linear Model Fit</td>
<td>R-Sq(adj) = 35.2%</td>
<td>R-Sq(adj) = 41.4%</td>
</tr>
</tbody>
</table>

The difference between training modes for cognitive tasks was significant for related errors to a p-value of 0.1 between on-the-job and pictorial training modes, and 0.06 between the written and pictorial training modes, and was not significant between on-the-job and written training modes. According to Tukey’s test, written and on-the-job training modes are equivalent and both are better than pictorial training. For total errors, only on-the-job training is significantly better than pictorial training (p-value = 0.01), but on-the-job training has indications that it could be superior to written training (p-value = 0.27) if its trend held with a larger sample size. The difference between the pictorial and written training, while not significant (p-value 0.45), implies that the on-the-job training is better than the written training, which is better than the pictorial training for total errors. In summary, one can definitively conclude that on-the-job training is superior for the complexity dimension of cognitive tasks, but is equivalent to written training for related errors, and that there may be a trend where written training produces an intermediate number of total errors, while pictorial training produces the most total errors.

### Figure 4: Main Effects Plot of Complexity Variation

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#### 4.6 Discussion

In this study, skill compilation and error occurrence are indicators of task performance and productivity [21]. When managers understand which training mode is most effective, they can realize cost-savings and better worker motivation. According to our results, when a manager selects OJT to train the workers, skill compilation is highest. The next best method is pictorial, followed by the written training, as the cognitive load is higher to decode a written message than a pictorial representation of instructions. However, while the pictorial mode may lead to better skill compilation, it does not necessary translate into higher task performance quality. On the other hand, to reduce error occurrence in complex tasks, OJT leads to lower unrelated errors because the presence of a trainer makes the trainee more focused. However, trainees make more related errors than those trained by the pictorial or written mode since they must rely on their memory to complete the task. More errors were also observed in manual tasks, and we believe this is due to a lack of task repetition in the training, wherein there is a failure to develop muscle memory. Moreover, representing cognitive task by pictorial methods properly is difficult, potentially resulting in more errors.
Lower related and total errors were observed for the complex-cognitive task regardless of the training mode, both for the cognitive task in the complex dimension and the complex task in the cognitive dimension. This was statistically significant at an aggregated level, but not at the training mode level. The closest it came to being significant on a training mode level was for related errors in the cognitive-manual dimension of complex tasks (p-values on the order of 0.13 to 0.38). Two reasons may explain this observation. First, the test subjects, as students, were drawn from a population whose current life orientation is cognitively focused in a complex discipline (engineering). Two-thirds were graduate students involved in engineering research, many foreign students, and as Driskell et al. [21] stated, cognitive task are significantly related to academic performance. This may have influenced their attention to detail, values toward cognitive work being more important than manual work, or generally provided more competence (through practice) in performing complex-cognitive tasks. Second, more concentration may be applied to complex-cognitive tasks than complex-manual or simple-cognitive tasks, resulting in more focus and fewer errors. This is somewhat supported by the higher weighted, normalized difference between total and related errors (the unrelated errors) that occurred for the complex-cognitive task (0.044) over the simple-cognitive task (~0), indicating an occasional disruption of focus.

Managers should select OJT and written training methods as equivalently suitable for cognitive tasks as demonstrated by the results. Moreover, trainees tend to make more errors in simple tasks due to lack of focus, which may be resolved by repetition. Consequently, the trend that the written training mode produces lower related errors may result from trainees referring back to the written instructions as they perform the task, but pictorial training may be more suitable for skill compilation. Additionally, the trend that OJT produces lower errors in general, and lower errors in complex-cognitive tasks specifically, may result from an open-ended dialog between the trainer and trainee that permits clarification and emphasis of training requirements. Although OJT provides an open ended interaction between the trainer and trainee, it should always be accompanied with a complementary training mode that can be referred to as job aids after the trainer leaves. This complementary mode should be selected depending on task characteristics. This is supported by the trend that the written mode produces lower related errors may result from the ability of the trainee to refer back to the written instructions as they perform the task. Therefore, on-the-job training should always be accompanied with well written training documentation. Poor performance of the pictorial training mode was observed in general, which may again be related to the nature of the test subjects. Pictorial training may appeal more to and perform better with less educated workers, and the trend of using on-the-job training followed by supplying well developed pictorial documentation for reference is hypothesized as performing best for a less educated worker demographic.

5 Conclusion

This research was initiated due to the need to improve the productivity and performance of workers in different industries. Effective training is of particular importance to modern production systems, e.g. reconfigurable manufacturing systems, where quick product change-over and short ramp-up is desired. A statistical separation in performance has been confirmed when classifying tasks into the cognitive/complex dimensions. A goal of this study was to demonstrate that training design should consider other factors for improved efficiency. It was determined that training mode, task type, and difficulty perception influence or are a factor to error occurrence. Other factors not significant in this test include sex, educational background, and English ability.

Overall, on-the-job training generally performed best, but written training performed equally well for cognitive tasks and may be better for complex tasks. For best performance, it appears that on-the-job training should always be accompanied with well written job aids that can be referred to after the trainer leaves. Note that the cost and time of training were not considered in this study, and if factored in, might change the conclusions about the relative value of different training methods.

In future work, it is recommended that a better simple-manual task be determined and the test be repeated with a larger sample size to confirm or refute the trends identified. A broader cross-section of test subjects that reflect worker demographics should also be recruited, both to test the observations beyond the limited demographics present in this study, as well as to test the hypothesis that pictorial training modes may be better for lesser educated workers and possibly simpler task types. Other areas recommended for future work include examining the effect of stress, exhaustion, and uncomfortable working situations on training modes, an area of interest to military or training in times of crisis, and the influence of different training modes on the experience curve effect, an area also of interest for short product ramp-up.
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