Objective: Individual meta-analyses were conducted for six training methods as part of a U.S. Army basic research project. The objective was to identify evidence-based guidelines for the effectiveness of each training method, under different moderating conditions, for cognitive skill transfer in adult learning. Results and implications for two of these training methods, learner control (LC) and exploratory learning (EL), are discussed. LC provides learners with active control over training variables. EL requires learners to discover relationships and interactions between variables.

Background: There is mixed evidence on the effectiveness of both LC and EL learning methods on transfer relative to more guided training methods. Cognitive load theory (CLT) provides a basis for predicting that training strategies that manage intrinsic load of a task during training and minimize extraneous load will avail more resources that can be devoted to learning.

Method: Meta-analyses were conducted using a Hedges’s g analysis of effect sizes. Control conditions with little to no learner freedom were contrasted with treatment conditions manipulating more learner freedom.

Results: Overall more LC was no different from training with limited or no learner control, and more EL was less effective than limited or no exploration; however, each can be effective under certain conditions. Both strategies have been more effective for cognitive skill learning than for knowledge recall tasks. LC exhibited more benefit to very near transfer, whereas EL’s benefit was to far transfer.

Conclusion: Task type, transfer test, and transfer distance moderate the overall transfer cost of more learner freedom.

Application: The findings are applicable to the development of instructional design guidelines for the use of LC and EL in adult skill training.

Keywords: training strategies, transfer of training, cognitive load theory, exploratory learning, learner control, meta-analysis

INTRODUCTION

The term active learning has been used to refer to training methods designed to promote active learner engagement through more learner control over the learning process (e.g., what to process and how to organize) and/or opportunities to interactively explore the learning environment (e.g., Bell & Kozlowski, 2008; Means, Toyama, Murphy, Bakia, & Jones, 2009). These active learning methods often include additional training elements to support management of attention and cognitive effort with the aim of fostering skills for self-regulating learning (e.g., guidance methods—Bell & Kozlowski, 2008; error management training—Keith & Frese, 2008). Other researchers consider active learning as intentionally investing a significant level of cognitive effort to integrate new knowledge and skills into a coherent schema (e.g., Kalyuga, 2009; Mayer, 2004; Mayer & Moreno, 2003), regardless of whether the learner is behaviorally active in controlling the learning process (i.e., active learner—Mayer, 2004). Examples include self-explanation activities and constructing mental visualizations (cf. Kalyuga, 2009; see also Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013; Rodiger, 2013).

Does giving the learner a more active control role in the learning process (active learner) result in more active cognitive engagement with the learning content (active learning) and thereby more effective learning transfer? There is disagreement and mixed evidence on the advantages and disadvantages of learner controlled training methods (e.g., Clark, 2009; Corbalan, Kester, & van Merrienboer, 2011; Doolittle, 2010; Kirschner, Sweller, & Clark, 2006; Mayer, 2004; Smith, Ford, & Kozlowski, 1997). In the current paper we present results from separate meta-analyses of two different
active learner methods: learner control (LC) and exploratory learning (EL). Although these methods are related in that each allows the learner some degree of control over the learning process, LC and EL are considered separate training methods each with extensive research literatures including previous meta-analyses (e.g., for LC: Kraiger & Jerden, 2007; Parsons, 1991; Sitzmann et al., 2006; for EL: Keith & Frese, 2008).

The primary goal of the research was to use meta-analysis techniques as a tool to identify moderating factors where the effect size evidence suggests that a particular moderating variable may substantially differ in direction or size from the main effect, and can therefore suggest a benefit or cost to performance transfer under these conditions (e.g., Anello & Fleiss, 1995). LC and EL are typically associated with different aspects of the learning environment, and have different training method specific moderators.

LC methods provide learners with varying degrees of active decision making control over specific dimensions of a structured learning environment, and can range from control of a single training variable, such as the pace of training, to control over multiple aspects of the learning process (Kraiger & Jerden, 2007). Additional LC variables include branching or sequencing through the learning content (e.g., Tang, 2004), how much of a lesson to review (e.g., skip introductory lessons; e.g., Taylor, 2005), the amount to practice the content (e.g., Schnackenberg & Sullivan, 2000) or feedback to receive (e.g., Pridemore & Klein, 1991), and program-generated advice (e.g., suggestions for next task; e.g., Shyu, 1993).

EL methods involve active learner exploration in the task environment with the level and type of guidance as the primary modifying variable (Bell & Kozlowski, 2008). Although EL typically implies full LC in a relatively less structured training environment, it goes beyond LC in that it is designed to encourage active knowledge construction through a more inductive (i.e., discovery) learning process (Andrews, 1984; Bell & Kozlowski, 2008; Kirschner et al., 2006; McDaniel & Schlagler, 1990). This additional dimension differentiates EL and LC training methods; LC provides learners with options to adapt the learning content to their learning style, skill, or experience; EL requires learners to discover relationships and interactions between variables through exploring the learning content. Proponents emphasize a benefit of LC to learner motivation, level of active involvement (e.g., Corbalan et al., 2009; Schnackenberg & Sullivan, 2000), and trainee satisfaction with the learning environment (Fisher, Wasserman, & Orvis, 2010; Granger & Levine, 2009; Orvis et al., 2009), which should affect learning and transfer. EL proponents argue that it encourages metacognitive activity and self-regulation of learning skills required for developing adaptable complex skills (e.g., Bell & Kozlowski, 2008; Heimbeck, Frese, Sonnentag, & Keith, 2003; Ivancic & Hesketh, 2000; Keith & Frese, 2005).

For both training strategies, the experimental research includes control–treatment contrasts that compare programmatic instruction (i.e., no LC or no exploration) with a treatment condition that includes some degree of LC or EL. In addition, many experiments contrasted control–treatment conditions that allowed the learner more freedom to control training with conditions allowing less training freedom, for example comparisons of pace and branching versus pace alone for LC (e.g., Kraiger & Jerden, 2007; Orvis, Brusso, Wasserman, & Fisher, 2011) or comparisons of more instructor, or system, guidance for exploration versus learner guided exploration (e.g., Bell & Kozlowski, 2008).

In this paper our focus is on similarities and differences in the effectiveness of LC and EL under similar moderating factors. To describe these two active learner methods within a common framework, we employ the term “freedom” (e.g., Cronbach & Snow, 1977) as a general construct related to both LC training strategies that provide the learner with more freedom to control aspects of training and EL training strategies that provide the learner with more freedom to explore learning content, relative to more guided training. The learner freedom construct is a way to conceptualize the EL and LC active learner similarities; however, learner freedom has been operationalized in the two experimental literatures using very different manipulations of the active learner construct (degree of guidance for EL, degree of trainee
control for LC) with little, if any, overlap in the literatures (e.g., we found no studies that compare LC and EL). Although we focus, in this paper, primarily on moderators that are common to the two strategies, the differences in the primary training manipulations and range of training strategy specific moderators warranted separate meta-analyses of the distinct literatures.

**Active Learning and Cognitive Load Theory**

Cognitive load theory (CLT) provides a basis for predicting that training strategies that demand more cognitive effort during learning may benefit learning effectiveness if the additional cognitive effort is applied to active engagement in the learning task, but extract a cost if it is due to task complexity or extraneous features of the learning environment.

From the perspective of CLT the cognitive load imposed on working memory during learning is due to aspects of the learning task, the design of the learning environment and instructional methods, and individual differences (experience, ability, motivation) in learners (e.g., Kalyuga, 2009, 2011; Paas & van Gog, 2009; Sweller, 1988; van Merrienboer, Kester, & Paas, 2006). The complexity of the learning task (i.e., the number of task elements and the level of element interactivity) affects the level of working memory required for processing. As complexity increases, this *intrinsic load* can increase, requiring management through appropriate instructional strategies. The instructional environment and methods can impose additional cognitive load during training, for example, the control decisions and search requirements of active learners, that is extraneous to the task being learned (e.g., Kirschner et al., 2006; Tuovinen & Sweller, 1999). This *extraneous load* limits the resources available for active cognitive processing and schema construction that are *germane* to meaningful learning (Kalyuga, 2011; Sweller, 2010). Extraneous cognitive load can affect executive functions such as attention to self-monitoring and self-assessment for LC decisions while also engaging in the learning task (Kostons, van Gog, & Paas, 2010).

Consideration of the overall effect of the greater freedom availed by an active learner approach suggests that the effectiveness of EL and LC strategies should reflect a balance of the benefits of active learner participation, and the costs related to higher extraneous cognitive load involved when the learner must make instructional control decisions and explore a learning environment. This balance point is expected to be moderated by another set of variables including transfer type and measures. Prior literature suggests the direction of effects of some of these moderator variables with sufficient consistency that we can entertain directional hypotheses.

**Moderators of Active Learner Methods: Hypotheses**

The following hypotheses for the expected results of each meta-analysis on moderators common to both training strategies are based on evidence from the experimental literature and both the common unifying (e.g., cognitive load demands, active learner engagement) and differentiating (e.g., inductive learning requirements and level of guidance for EL, dimensions of control for LC) properties that may moderate the effects for the different moderating variables.

*Transfer measures.* Differences in the definition and measurement of transfer have implications for evaluating training effectiveness (e.g., Keith & Frese, 2008; Kraiger, Ford, & Salas, 1993). The type of learning measured by the *transfer test* is expected to modify the costs or benefits of active learner strategies. The Kraiger and Jerden (2007) meta-analysis found that procedural learning received a significant benefit from LC and declarative learning did not. Skill-based outcomes received a significant benefit from LC and cognitive outcomes did not. In addition, a number of studies report positive effects for LC in skill-based transfer tests but not for knowledge recall (Doolittle, 2010; Mayer & Chandler, 2001), suggesting that when LC is focused on integrated skill-based learning, preparation for knowledge retention tests may be limited, and hence harmed by LC. This general pattern is supported by the ambivalent and mixed evidence for the success of many active learning techniques in training a variety of mostly knowledge-based tasks (Dunlosky et al., 2013). A similar rationale applies for EL. EL's
emphasis on practicing a cognitive task (e.g., controlling a set of interrelated variables) improves task performance but not necessarily the ability to answer verbal knowledge questions, while providing explicit verbalizable instructions does improve ability to answer questions (Berry & Broadbent, 1984). Based on these findings we expect more learner freedom to benefit skill-based tests more than knowledge-based tests, where more freedom may hurt transfer performance (Hypothesis 1).

Transfer distance. The conceptual distance (identical, near, far) of the transfer task from the training task is expected to modify the costs or benefits of EL. Research evidence suggests that training methods that require more learner effort during training can yield higher performance during transfer (Schmidt & Bjork, 1992). Since active learner methods are designed to encourage self-regulation of learning skills, deeper processing of learning content, and strategies for finding new solutions, they are expected to benefit performance on far transfer tasks that require adapting learned skills to structurally distant tasks (Bell & Kozlowski, 2008; Keith & Frese, 2008). Based on this literature, we expect to see this transfer crossover effect for EL, that is, a cost for identical transfer, but a benefit emerging with greater transfer distance (Bell & Kozlowski, 2008; Hypothesis 2a). A similar crossover effect for LC is not apparent in the research literature and not expected here (Hypothesis 2b).

Training task. For EL the inductive learning process has been characterized as searching a problem space for the right strategy, rule, or procedure to apply, with the size of the search space a critical factor that increases cognitive load due to the increasing number of potentially interacting elements to be considered (Kirschner et al., 2006; Tuovinen & Sweller, 1999). Task environments that are primarily procedural such as learning to use digital systems and computer applications typically include visual features and intrinsic feedback that support and guide hypothesis testing and error diagnosis. Such tasks are consistent with minimal guidance approaches (e.g., Carroll, 1990) and error training approaches (Keith & Frese, 2008) in which EL methods have been shown to produce a transfer benefit. However, for more problem-solving tasks such as discovering rules from examples (e.g., McDaniel & Schlager, 1990), the inductive learning process can increase both intrinsic and extraneous load when there is only limited support for self-regulation. EL may therefore provide more transfer benefit to tasks that are more procedural rather than problem solving (Hypothesis 3a). Unlike EL, LC does not involve inductively learning task content and, to the extent it is helping to manage cognitive load rather than creating extraneous load due to control decision making requirements, LC should therefore benefit both procedural and problem-solving tasks (Hypothesis 3b).

Learner expertise. Within the framework of CLT, a variety of studies have observed an expertise effect, in that training strategies designed to reduce cognitive load are relatively more effective for “novice learners” than for more experienced learners (e.g., Pollock, Chandler, & Sweller, 2002; Rey & Buchwald, 2011; van Merrienboer et al., 2006). For the more skilled learner, fewer working memory resources are required for mastering the concepts, and hence the need for load reducing strategies is correspondingly reduced. In the current context, we can therefore hypothesize that the benefits of greater freedom, to control and to explore, will be more likely to emerge for the expert (Hypothesis 4).

LC of pace. Specific to LC, the moderating effects of training dimension(s) controlled included here are pace, branching, truncation of lessons, and truncation of feedback. Kraiger and Jerden’s (2007) meta-analysis reported a significant benefit for LC of pace. In addition, recent research on multimedia learning, although mixed, generally supports a benefit to transfer for LC of pace (Tabbers & de Koeijer, 2010). Based on these reported results, we expect a significant overall transfer benefit for LC of pace (Hypothesis 5).

METHOD

Effect Size Analysis

A conventional standardized effect size metric, Hedges’s g (Hedges & Olkin, 1985), is used here to evaluate the efficacy of a training intervention relative to a control method. A fixed effect model was utilized since it assumes variation across
studies only due to participant-level sampling error (Borenstein, Hedges, Higgins, & Rothstein, 2009), has greater statistical power, and is more likely to be sensitive to moderator differences (Lipsey & Wilson, 2001). From an exploratory meta-analysis perspective (e.g., Anello & Fleiss, 1995), the focus is on using the meta-analytic tools to identify contexts in which the treatment variable may be relatively more effective and contexts where effect size and direction may be contrary to the overall main effects. This argues for an emphasis on avoiding Type II errors and less emphasis on minimizing Type I errors. A detailed discussion of these trade-offs and how these and other factors informed our approach is available in Hutchins, Wickens, Carolan, and Cumming (2013). The Hedges’s $g$ data were analyzed in Comprehensive Meta Analysis Version 2.

**Search and Coding Strategy**

We searched the Defense Technical Information Center and the entire database services of EBSCO, Web of Science, Wiley Interscience, and Science Direct. Minimum inclusion criteria included adult populations representative of the Army population, a training strategy manipulation versus a control condition, and a measure of the transfer of training. The primary demographic was vocational and undergraduate students. Any generalization of results should therefore be limited to adult training. No date restrictions were imposed on the included studies. As in most meta-analyses, studies that were not published due to null or negative results (i.e., the file drawer problem; Rosenthal, 1979) and therefore not sampled may potentially introduce a source of bias in the results.

Due to an emphasis on investigating potential differences between learning as measured by posttraining, near transfer, and far transfer, transfer was defined to include any posttraining procedural, knowledge, immediate or delayed, or near or far transfer test, which was identical between the treatment and control condition. Pre- to posttraining test differences were used where reported for a study, otherwise only posttraining tests were used.

To ensure reliability in the moderators identified, an iterative process of member review, feedback, and consensus was applied until the team came to agreement on representative moderator variables. The coding process involved two reviewers (team members), familiar with the operational definitions created, independently coding each experiment for each moderator. A comprehensive coding scheme was developed to capture relevant qualitative method and moderator variables and quantitative “effects” data (see Wickens, Hutchins, Carolan, & Cumming, 2013, for additional methodological detail).

**Moderator Analysis**

Given the hypotheses identified, the emphasis here is on the moderating effects of the categorical variables that are common to both active learner methods. Where the moderating effects were significant and tending in different effect directions (as is the case here with factual knowledge and cognitive skill tests) a $Q$-test for heterogeneity (Hedges & Olkin, 1985) was conducted. Analogous to an analysis of variance, the $Q$-test partitions the variance into a portion that is explained by the moderator variable, $Q$-between ($Q_b$), and a residual $Q$-within ($Q_w$; Lipsey & Wilson, 2001). A significant $Q_b$ indicates a difference in effect sizes of the tested moderator levels which may account for some portion of the overall variance. A significant $Q_w$ implies significant additional variance, not accounted for by the tested moderator. Follow-on analyses were conducted to test for additional expected moderating effects (e.g., transfer crossover effect) on each level of the tested moderator (e.g., knowledge and cognitive skill tests).

Transfer test was coded as either a declarative knowledge test (multiple choice or recall) or a performance-based test (including paper and pencil tests that required problem solving or knowledge integration narrative). Transfer distance was coded as (a) identical to the training task, when the transfer test involved a task or problem identical to one used in training, or a declarative knowledge recall or recognition test, (b) near transfer when the transfer test was a task or problem different, but similar (analogical), to that used in training, or (c) far transfer, when transfer required applying learned skills to a new, structurally different, or more complex
task, or in a new performance environment (e.g., simulator to live, different user interface).

For task skills the experimental tasks were coded by the skills required to perform the task and then grouped for analysis by prevalent task/skill types. The largest groups were procedural tasks and problem-solving tasks. For learner experience, only studies that include experience as an experimental manipulation were included. In addition, for LC, training dimension(s) controlled were coded (nonmutually exclusively) as LC over branching, pace, truncation of lessons, or truncation of practice/feedback.

As noted in the introduction, overall effect sizes were based on treatment-control contrasts that compare both no learner freedom (no LC or exploration) with some degree of LC or EL, and experiments where the contrast involves conditions allowing the learner more freedom with conditions allowing less training freedom. For EL, training conditions were coded as no exploration, guided exploration, minimally guided exploration, or full (learner guided) exploration, resulting in six contrast levels, three comparing a no exploration with each of the guided exploration levels, and three contrasting the different levels of guided exploration. In the case of LC, the comparisons involved conditions with no LC and conditions with LC of more (e.g., pace and branching) versus fewer (e.g., pace alone) training dimensions (e.g., Kraiger & Jerden, 2007; Orvis et al., 2011). Detailed results of the EL and LC treatment-control contrast level effects were reported in Carolan, Hutchins, and Wickens (2012a, 2012b) and are not addressed here due to space limitations.

RESULTS

Results for each of the EL and LC common moderators are presented in the same tables and discussed together emphasizing the similarities and differences between moderating effects of the two approaches. The number of data points in each analysis is given by $k$. Tables 1, 2, and 3 present effect size and direction, standard error, and lower and upper confidence intervals for each effect size estimate. For Hedges’s $g$ the significant effects are identified by one, two, or three asterisks, indicating a probability value of less than .05, .01, or .001, respectively.

Statements of differences and significance with respect to moderator effects reflect differences between treatment and control groups, except where significance tests ($Q$ values) on mean differences between levels of a moderator variable are reported (Table 3).

Overall Effect

For LC the meta-analysis literature search and selection process yielded 40 experiments that provided sufficient data for 144 effects for the Hedges’s $g$ effect size analysis, including multiple subgroups, treatment comparisons, and outcome measures. For EL 31 research experiments with a total of 135 data points were identified for analysis.

The overall mean effect size for LC was close to zero ($g = 0.02$), indicating no overall average cost or benefit from LC. For EL the overall mean effect size was negative ($g = –0.15***$), indicating a small but significant overall benefit for more guided exploration. The 31 EL studies represented a heterogeneous data set with a significant $Q$ value, $p < .001$, and mean effects ranging from –1.83 to 0.73. Eight experiments favored more EL, 14 experiments favored less or no EL, and 9 experiments had nonsignificant overall effects. For the 45 LC studies, the $Q$ value was also significant, $p < .001$, with mean effects ranging from –1.24 to 0.98. In all, 10 experiments favored more LC, 10 experiments favored less or no LC, and 25 experiments had nonsignificant overall effects.

Transfer Tests

Tests of factual knowledge showed a consistent, although small, cost for more LC ($g = –.06*$), and a considerable cost for more exploration in EL ($g = –0.57***$). In contrast, consistent with the findings of Kraiger and Jerden (2007), for tests of skill performance, which involved more integrative cognitive skill-based learning, these costs for greater freedom (to control, to explore) were reversed, providing a benefit for LC ($g = 0.09***$) and greatly reduced for EL ($g = –0.08**$) supporting Hypothesis 1: More learner freedom will benefit skill-based tests but not knowledge-based tests.

The mean effect size difference between knowledge and skill tests was significant for
both LC and EL (Table 3). Given this significant mean effect size difference and the project emphasis on skill transfer, knowledge and skill subgroup analyses were conducted for several moderators.

**Transfer Distance**

For EL, consistent with the findings of Keith and Frese (2008), the costs of exploration were reduced from identical ($g = –0.43^{***}$) to near ($g = –0.13^{**}$), to far, where exploration showed a benefit ($g = 0.16^*$) exhibiting the expected transfer crossover effect (see Figure 1) supporting Hypothesis 2a. For LC, transfer was unaffected (and essentially zero) in the studies that examined transfer across distance (identical, near, far) supporting Hypothesis 2b: No transfer crossover effect was expected for LC. Separate transfer distance analysis, conducted on the cognitive skill tests, indicated a transfer benefit from more LC for training identical ($k = 35, g = 0.16^{**}$), whereas the near and far were not significant.

**Task Skills**

For EL the procedural tasks received a positive transfer effect ($g = 0.11^*$) for skill performance, indicating a relative benefit for more exploration (less guidance). However, for tasks that involved more problem-solving skills, transfer performance

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**TABLE 1:** Overall Mean and Moderator Effects

<table>
<thead>
<tr>
<th>Groups</th>
<th>Learner Control</th>
<th>Exploratory Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$k$</td>
<td>$g$</td>
</tr>
<tr>
<td>Overall</td>
<td>144</td>
<td>0.02</td>
</tr>
<tr>
<td>Test type</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge test</td>
<td>76</td>
<td>-0.06*</td>
</tr>
<tr>
<td>Performance test</td>
<td>68</td>
<td>0.09^{***}</td>
</tr>
<tr>
<td>Transfer distance</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training identical</td>
<td>97</td>
<td>-0.01</td>
</tr>
<tr>
<td>Near transfer</td>
<td>18</td>
<td>0.05</td>
</tr>
<tr>
<td>Far transfer</td>
<td>16</td>
<td>0.09</td>
</tr>
<tr>
<td>Task/skill type</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Problem solving</td>
<td>10</td>
<td>0.12^{**}</td>
</tr>
<tr>
<td>Procedural</td>
<td>16</td>
<td>0.24^{***}</td>
</tr>
<tr>
<td>Experience</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prior experience</td>
<td>4</td>
<td>0.43*</td>
</tr>
<tr>
<td>No experience</td>
<td>4</td>
<td>-0.004</td>
</tr>
</tbody>
</table>

*p < .05. **p < .01. ***p < .001.

**TABLE 2:** Learner Control Dimensions

<table>
<thead>
<tr>
<th>Groups</th>
<th>Learner Control (LC) dimensions</th>
<th>Effect Size Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Programmatic vs. LC of branching</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>Programmatic vs. LC of pace</td>
<td>22</td>
</tr>
<tr>
<td></td>
<td>Programmatic vs. LC of feedback/practice</td>
<td>14</td>
</tr>
<tr>
<td></td>
<td>Programmatic vs. LC of lesson truncation</td>
<td>8</td>
</tr>
</tbody>
</table>

**p < .01.**


TABLE 3: Summary of Hypotheses With Supporting Results

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>More Learner Control (LC)</th>
<th>More Exploratory Learning (EL)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hedges’s g</td>
<td>Cost/Benefit</td>
</tr>
<tr>
<td>Hypothesis 1: More learner freedom will benefit skill-based tests but not knowledge-based tests.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge test</td>
<td>–0.06*</td>
<td>Small transfer</td>
</tr>
<tr>
<td>Performance skill test</td>
<td>0.09***</td>
<td>Small transfer</td>
</tr>
<tr>
<td>Effect size difference between moderators</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypotheses 2a and 2b: Transfer crossover effect for EL but not LC.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training identical</td>
<td>–0.01</td>
<td>No difference</td>
</tr>
<tr>
<td>Near transfer</td>
<td>0.05</td>
<td>No difference</td>
</tr>
<tr>
<td>Far transfer</td>
<td>0.09</td>
<td>No difference</td>
</tr>
<tr>
<td>Effect size difference between moderators</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypotheses 3a and 3b: EL will benefit procedural but not problem-solving tasks. LC should benefit both.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Procedural tasks</td>
<td>0.24***</td>
<td>Moderate transfer benefit</td>
</tr>
<tr>
<td>Problem-solving tasks</td>
<td>0.12**</td>
<td>Small transfer benefit</td>
</tr>
<tr>
<td>Effect size difference between moderators</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypothesis 4: EL and LC will benefit trainees with prior experience, but not novices.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low experience</td>
<td>–0.004</td>
<td>No difference</td>
</tr>
<tr>
<td>Prior experience</td>
<td>0.43*</td>
<td>Moderate transfer benefit</td>
</tr>
<tr>
<td>Effect size difference between moderators</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypothesis 5: LC of pace will benefit transfer performance.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LC of pace—overall</td>
<td>0.15**</td>
<td>Small transfer benefit</td>
</tr>
<tr>
<td>LC of pace—knowledge tests</td>
<td>0.14*</td>
<td>Small transfer benefit</td>
</tr>
<tr>
<td>LC of pace—cognitive skill tests</td>
<td>0.15*</td>
<td>Small transfer benefit</td>
</tr>
</tbody>
</table>

*p < .05. **p < .01. ***p < .001.
(g = –0.28***)) indicated an overall benefit for more guided training. These results support Hypothesis 3a, that EL will benefit procedural but not problem-solving tasks. However, for LC, procedural (g = 0.24***) and problem solving (g = 0.12***) subgroups benefitted similarly on transfer performance when the learner controlled more training elements (supporting Hypothesis 3b, that LC should benefit both procedural and problem-solving tasks).

Transfer distance for each task/skill type. Follow-on analysis of transfer distance (training identical, near, far) by task/skill type (procedural, problem solving) was conducted to further evaluate the transfer crossover hypothesis for the individual task/skill types. Figure 1 presents the joint effect of distance and skill type revealed from EL studies. The figure illustrates both the diminishing cost of more freedom to explore with increasing distance, and the overall greater benefit for exploration in procedural tasks (dashed line) than in problem-solving tasks (solid line). Most important, the figure signals the strong crossover effect for procedural tasks, whereas in contrast, problem-solving tasks consistently show a cost to exploration at all levels of transfer (albeit diminishing to nonsignificant at far transfer).

For LC cognitive skills received a benefit at the training identical level from more LC (albeit with few data points) for both problem-solving tasks (k = 1, g = 0.35*) and procedural tasks (k = 11, g = 0.47***), albeit with few data points, and nonsignificant results for near and far transfer. Contrary to EL, cognitive skills therefore appear to receive a significant benefit from the greater freedom availed by LC at the level of training identical rather than at far transfer.

Experience

Learner experience. There was only one EL experiment that compared experience levels (Tuovinen & Sweller, 1999) and it found the expected EL cost for low experience learners and benefit for individuals with prior experience. For LC, two experiments contributed to the analysis (Shyu & Brown, 1995; Taylor, 2005). For participants with prior experience there was a significant benefit for more LC but no relative benefit for individuals with limited task experience. These results are both consistent with an “expertise effect” that EL and LC will benefit trainees with prior experience, but not novices (Hypothesis 4).

Learner Control Dimensions

Analysis of contrasts between individual LC training dimensions and a no LC control indicate a significant transfer benefit from LC of pace (supporting Hypothesis 5), but a significant relative cost to transfer from LC of the amount of feedback or practice. Separate
As expected (Hypothesis 1: More learner freedom will benefit skill-based tests but not knowledge-based tests) and consistent with Kraiger and Jerden (2007), more LC benefits skill-based transfer measures but imparts a relative cost to knowledge tests. For EL both
cognitive skills and knowledge tests suffered with less guidance (more freedom), but the costs to knowledge tests were much larger. Two factors may be influencing these results. First, LC findings are consistent with previous reviews, suggesting strategies that focus on active schema development to support transfer performance may not benefit declarative knowledge recall tests (e.g., Doolittle, 2010; Mayer & Chandler, 2001). Similarly, for EL, when the emphasis is on performing a task or learning a skill, more freedom (less guidance) allows learners to minimize attention to factual, verbalizable information and focus on discovering and practicing procedures; without guidance, in the form of explicit verbalizable instructions, they may not perform well on knowledge recall tasks (Berry & Broadbent, 1984).

Second, more LC freedom during factual knowledge oriented lessons may increase cognitive load due to search activity/decisions in the content environment with the potential for missing, skipping, or not actively engaging information relevant to posttraining knowledge tests, whereas for cognitive-skill-oriented tasks there is typically more intrinsic feedback to guide self-regulation. The finding that LC of lesson truncation benefits cognitive skills but yields substantial cost for knowledge learning (Table 2) provides additional support for this hypothesis.

Consistent with Hypothesis 5, LC of pace was one of only two moderators (prior experience was the other) showing benefits from more LC to both factual knowledge and cognitive skill transfer. LC of pace may provide learners a tool to self-regulate attention and effort based on their own abilities and experience and the complexity of the learning task (e.g., Mayer & Chandler, 2001; Tabbers, Martens, & van Merrienboer, 2004), thereby reducing cognitive load and potentially increasing the amount of knowledge acquired.

Although the moderator analysis indicates significant differences in the overall effectiveness for knowledge and performance test subgroups, the results indicate a heterogeneous set of effect sizes. For cognitive skill tests 8 of 18 EL experiments with significant effect sizes favored more EL; the other 10 favored the less or no EL condition. Two LC skill test experiments...
significantly favored the less or no LC condition (Taylor, 2005; Tovar & Coldevin, 1992).

Procedural Versus Problem-Solving Tasks

As anticipated (Hypotheses 3a and 3b: EL will benefit procedural but not problem-solving tasks; LC should benefit both) for both LC and EL more learner freedom provided a transfer benefit for more procedural tasks (e.g., computer applications, digital skills) and, for LC, also problem-solving (e.g., math and science) tasks. However, for EL the effect was in the opposite direction for tasks requiring more problem-solving-skills (e.g., learning rules from examples), with transfer benefitting from less freedom, more guidance. One explanation is that procedural task environments may provide more intrinsic feedback to support self-regulation and guide exploration, allowing for more learner management of cognitive load. Many of these tasks were designed within minimal guidance (Trudel & Payne, 1995; Van Oostendorp & De Mul, 1999) or error management approaches (e.g., Keith & Frese, 2005; Lazar & Norcio, 2003) that include strategies that emphasize and support active engagement and have previously demonstrated a positive effect for EL (Keith & Frese, 2008). In contrast, the problem-solving tasks required more inductive learning (McDaniel & Schlager, 1990) and/or complex variable interactions (e.g., Ahmad, 2006) with presumably less support for managing the search space and consequently increasing task complexity and cognitive load. However, as the small effect sizes suggest, not all studies with digital procedural learning tasks found a transfer benefit for more exploration (e.g., Debowski, Wood, & Bandura, 2001; Dyer, Singh, & Clark, 2005; Yorke, 2005). And there were problem-solving studies that received more benefit from the more exploratory conditions (e.g., Guthrie, 1967; McDaniel & Schlager, 1990; Wood, Kakebeeke, Debowski, & Frese, 2000).

LC benefited both task/skill types equally since it does not essentially change the nature of the learning task (i.e., no inductive learning component) and, when it is effective, serves to manage intrinsic cognitive load based on the learner’s abilities and learning process.

Transfer Distance

As expected (Hypotheses 2a and 2b: Transfer crossover effect for EL but not LC) LC and EL strategies differed in the type of transfer benefit they provided for cognitive skills. Overall, EL exhibited the expected transfer crossover effect with training identical transfer receiving a significant benefit from less freedom, near transfer receiving a smaller benefit, and far transfer receiving a significant benefit from more freedom in exploration (Figure 1). However, this transfer crossover effect for EL was realized for skill-based tests but not knowledge tests and for procedural tasks but not problem-solving tasks, suggesting that the benefits of EL to far transfer require support/guidance for self-regulation skills and cognitive load management. For LC, rather than a crossover effect, the significant benefit for problem-solving skills was for training identical transfer (0.35**). That is, LC exhibited more benefit to very near transfer whereas the beneficial effect of EL was felt on far transfer, suggesting that LC and EL may operate by different mechanisms for benefitting transfer performance. For EL a proposed benefit is the emphasis during training on finding procedures and strategies for generating rules and solutions. For LC, when successful, greater control freedom appears to affect performance by allowing the learner to manage cognitive load during training thereby increasing the opportunity for learning, which is realized in very near transfer.

Learner Experience

The moderating effects of experience on both active learner strategies benefitting cognitive skill learning were as expected (Hypothesis 4: EL and LC will benefit trainees with prior experience, but not novices) and consistent with predictions of CLT. Experienced learners with existing domain schemas should have more working memory available to effectively utilize more freedom in LC or EL. Although the results are based on only one (EL) or two (LC) experiments, both methods displayed the expected
expertise effect (e.g., Pollock et al., 2002; Rey & Buchwald, 2011; van Merrienboer et al., 2006). That is high experienced learners were more tolerant of the added cognitive load imposed by more learner freedom during training.

**SUMMARY**

The objective of the research effort was to conduct meta-analyses to identify evidence for the effectiveness of different training methods, under different moderating conditions, for cognitive skill transfer in adult learning. In this paper we presented findings from two of these meta-analyses, EL and LC, focusing primarily on the common moderators identified for all training methods and in a format that allowed for qualitative comparison of the commonalities and differences between the two methods. The data did reveal some commonalities in the direction of effects of common moderator variables:

1. For both training strategies more learner freedom provided relatively more transfer benefit (LC) or less cost (EL) when the transfer tests were performance skill tests as opposed to knowledge tests.
2. For both training strategies more learner freedom provided relatively more transfer benefit (LC) to procedural tasks (compared to problem-solving tasks) or turned a cost into a benefit (EL).
3. For both training strategies more learner freedom produced a benefit (LC) or eliminated a cost (EL) for learners with prior task experience.

For transfer distance, the results suggest that more learner freedom led to differences in transfer effectiveness for the two strategies. The more distant transfer tests received more benefit from EL than the near or identical tests, but for LC the overall effects were not significantly different across transfer distance, and for performance tests only, training identical transfer received a benefit from more LC.

Although the individual meta-analyses of the two active learner training methods allowed for conceptual comparisons between the two methods, they did not, of course, allow for a direct statistical comparison between the effect size findings for EL and LC under these common moderating variables.

**Implications for Training**

Based on the meta-analysis results presented here, training situations where using an EL approach may provide some benefit include: task-based environments focused more on procedural skills such as learning to use computer-based and other digital applications, domain experienced learners, and adapting learned skills to new tasks or environments. Some degree of LC, especially pace, may be effective for tasks that involve developing cognitive skills, with perhaps more LC for more domain experienced learners.

**Implications for Research**

Results suggest a number of areas where additional research evidence would inform the use of active learner methods to support adult learning and transfer performance. Some examples include research investigating (a) comparisons of the effectiveness of EL methods for different types of skills within a complex task domain, (b) strategies for integrating LC and EL components to promote more effective near and far transfer, and (c) strategies for adapting EL and LC guidance based on experience levels and abilities.

**Limitations**

As with any meta-analysis, there are a number of inherent limitations, including internal validity, unintentional exclusion of studies, and limited control over potentially confounding moderator variables. Due to the exploratory nature of the current meta-analyses, there was less emphasis on estimate precision than would have been afforded with random or mixed effects models, and the investigation of moderator combinations is open to potential interactions between moderating variables.

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**KEY POINTS**

- Overall, more freedom in learner control and exploratory learning strategies has been, respectively, no different or less effective than training with limited or no learner control; however both strategies can be effective under certain conditions.
- Both strategies have been more effective for cognitive skill learning than for knowledge learning tasks.
- Exploratory learning was more effective when tasks were more procedural than problem solving.
- Learner control and exploratory learning differ in the type of transfer benefit with learner control exhibiting more benefit to very near transfer and exploratory learning far transfer.
- The costs and benefits of both strategies were consistent with cognitive load theory learner task experience predictions.

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Thomas F. Carolan is a senior scientist and program manager with Alion Science and Technology, where he works on research and development efforts related to human performance measurement and training effectiveness. He earned a PhD in psychology from the University of Connecticut.

Shaun D. Hutchins is a senior human factors engineer at Alion Science and Technology in Boulder, Colorado. He is also a PhD candidate in the School of Education at Colorado State University. He earned his MA in experimental psychology with a minor in experimental statistics at New Mexico State University and his BA in psychology from the University of Maine at Farmington.

Christopher D. Wickens is a senior scientist at Alion Science and Technology Corporation, Micro Analysis and Design Operation, in Boulder, Colorado, and professor emeritus at the University of Illinois at Urbana-Champaign. He earned his PhD in psychology from the University of Michigan in 1974.

John M. Cumming, PhD, is a graduate of the Research Methodology program within the School of Education at Colorado State University. He earned his MA in educational psychology, emphasizing in research and evaluation methodology, from the University of Colorado at Denver and his BA in psychology from the Metropolitan State College of Denver.

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