The Science of Workplace Instruction: Learning and Development Applied to Work

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The Science of Workplace Instruction: Learning and Development Applied to Work

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Keywords

training and development, learning, instruction, training effectiveness, instructional principles

Abstract

Learning is the engagement in mental processes resulting in the acquisition and retention of knowledge, skills, and/or affect over time and applied when needed. Building on this definition, we integrate the science of training and the science of learning to propose a new science of workplace instruction, linking the design of instructional events to instructional outcomes such as transfer and job performance through the mediating effects of learner events and learning outcomes. We propose three foundational elements: the learner, instructional principles, and training delivery (methods and media). Understanding and applying instructional principles are the primary methods for enhancing training effectiveness; thus, we detail 15 empirically supported principles. We then discuss the erroneous pursuit of aptitude-by-treatment interactions under the guise of learner styles and age-specific instruction. Finally, we offer suggestions for future research that draw on the foundation of instructional principles to optimize self-directed learning and learning in synthetic learning environments.

INTRODUCTION

Workplace training is a systematic approach to learning and development to improve individual, team, and organizational effectiveness. Industrial and organizational (I-O) psychologists have played various roles relevant to improving the quality and effectiveness of training, including research on learning and transfer, development of training evaluation measures, enhancement of methods for training design and delivery, and the positioning of the training function within organizations. Research has focused on theoretical perspectives of what is meant by learning (Kraiger et al. 1993) and transfer (Baldwin & Ford 1988) as well as investigating factors that affect learning and the transfer of training to the job (Ford & Kraiger 1995).

Training research as a reflection of existing training practices and a stimulus for innovation has undergone three major cycles in the past century (Bell et al. 2017). First, between approximately 1920 and 1950, research tested and developed theories of learning and skill acquisition. Second, research between approximately 1950 and 1980 focused on training methods and institutionalizing training events within a larger organizational context, e.g., development of methods for needs assessment to determine training needs and evaluation practices to demonstrate training impact (Kraiger & Ford 2007). As such, the research at that time was described as "nonempirical, nontheoretical, poorly written, and dull" as well as "fadish (sic) to an extreme" (Campbell 1971). With regard to the third cycle, researchers went both narrower and broader in focus: The application of cognitive science to understand changes in the learner (e.g., Ford & Kraiger 1995, Kraiger et al. 1993) and broader systems perspectives to understand organizational influences on training effectiveness (e.g., Colquitt et al. 2000) fueled several decades of interest and activity. At the individual level, Kraiger et al. (1993) clarified that learning occurs not only when trainees can do something they were not able to do before, but also when there are changes in affective and cognitive states as well. This significantly impacted how training researchers have evaluated training (Aguinis & Kraiger 2009, Salas et al. 2012). At a systems level, Colquitt et al. (2000) and others tested models of training effectiveness identifying how individual and system-level influences affect the extent to which knowledge and skills are learned, retained, and transferred to appropriate situations. Salas & Cannon-Bowers (2001) dubbed the term the science of training, characterizing it as an "exciting and dynamic field," and challenged the field to find new ways to influence practice via theory and best practice–oriented research.

Twenty years after that declaration—anecdotally and based on observations of manuscripts we (the authors) review, conferences we attend, as well as the content of scientific and practitioner journals—there has been a diminishing interest in learning and development within I-O psychology. At the same time, basic research on learning in cognitive science and educational psychology continue to evolve (e.g., Cotton 1976, Glaser & Bassok 1989) and have expanded rapidly over the past twenty years (e.g., Mayer 2019). Although training research has benefited greatly from individual (learning) and organizational (systems) perspectives, training as an applied science is in danger of drifting from both its roots in learning theory and its potential for impacting the building up of human capital in organizations.

Just as there was value in clarifying what is learned (Kraiger et al. 1993), there is value today in focusing on how we learn and applying this knowledge to optimize learning. The purpose of this article is to direct attention to how individuals learn in order to organize what we know and need to know about maximizing training effectiveness. We link the science of learning to the science of training to identify and more fully understand the factors affecting learning outcomes. In particular, the science of workplace instruction is the application of evidence-based principles that have been found to help individuals learn knowledge, skills, and attitudes that impact job performance and organizational effectiveness. We extend the "science of instruction" found in educational contexts (e.g., Mayer 2011a, 2019) to the workplace to account for the complexities introduced by different training content (e.g., greater focus on skills and task completion) and greater variability in learning contexts (e.g., easy versus difficult sales clients).

The article is organized into three parts. In the first section, we provide a framework of possible areas of inquiry with respect to learning and training. In the second section, we describe the core elements of the science of workplace instruction, emphasizing instructional principles, as mechanisms for improving training practice and stimulating training research. In the third section, we explore the advancement of the science of workplace instruction by examining the intersection of instructional principles with training delivery and discussing two emerging trends in training—self-directed learning and synthetic learning environments.

A TRAINING SYSTEMS FRAMEWORK

To understand how effective instruction promotes learning in participants, we first must be clear on what we mean by learning. Ford (2021) recently presented and compared many popular definitions of learning from both the cognitive science and training domains. There were three common characteristics across most definitions: (*a*) change in knowledge, skill, and/or affect; (*b*) relative permanency of the change; and (*c*) that it is inferred from observed changes in the learner. These core characteristics highlight that learning in an organizational context must be at some level intentional and lasting.

So, what is learning? One helpful definition is from Quinn (2018), who defined learning as the retention (of knowledge, skills, and affect) over time until needed and transferred to appropriate situations. The elaboration in parentheses is ours and reflects the views of educational scholars (e.g., Anderson et al. 2001) and the current authors (see also Kraiger 2002, Kraiger et al. 1993) that learning is multidimensional. Building from this, we define learning as engagement in mental processes—learning events—that result in the acquisition and retention of knowledge, skills, and/or affect over time and until needed, along with the capacity to identify conditions of performance and respond appropriately. More colloquially, learning is an increased capacity to do the right thing at the right time.

Instructional Outcomes

Figure 1 presents an organizing framework to guide our discussion of training system components relevant to learning. Instructional (or training) outcomes are observable and measurable criteria that occur as a result of learning. These outcomes are the foci of most training reviews over the past 50 years. Prior reviews have concentrated on whether, when, and why training transfers to the job (Ford et al. 2018), individual performance improves (Aguinis & Kraiger 2009, Salas et al. 2012), and organizational effectiveness increases (Aguinis & Kraiger 2009). The main question addressed in these reviews is whether (or which) instructional events lead to instructional outcomes of value to learners or the organization.

System Components

The lower half of **Figure 1** shows dynamic changes in the learner as a result of instructional events. Learning events and learning outcomes mediate the relationship between instructional events and instructional outcomes but receive only sporadic attention from training researchers.

Learning outcomes. Learning outcomes are constructs that change as a result of learning events. Kraiger et al. (1993) examined learning taxonomies from educational and cognitive science

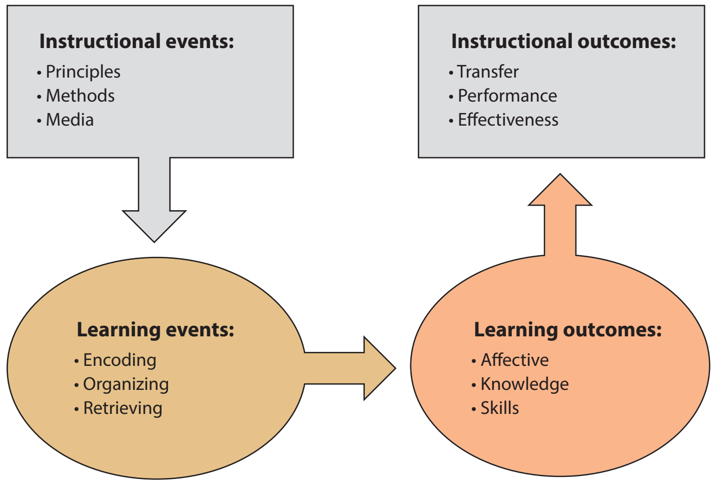

Figure 1

Organizing framework linking instructional events and learning events to learner outcomes and instructional outcomes.

disciplines (e.g., Bloom 1994) and developed a conceptually based classification scheme of learning outcomes that included three major learning outcome categories: cognitive, skill-based, and affective. Cognitive learning outcomes included verbal knowledge, knowledge organization, and cognitive strategies. Skill-based outcomes included issues of compilation and automaticity. Affective outcomes included issues of attitude change and motivational shifts in terms of mastery goals, self-efficacy, and goal direction. Although not addressed in this article, training evaluation is the practice of assessing the achievement of learning outcomes (Kraiger 2002) and using that data to drive decisions that improve the learner and the training system (Surface & Kraiger 2018).

Instructional events. **Figure 1** distinguishes between instructional events and learning events but links the two. Instructional events are observable and typically initiated by the organization to trigger learning events within individuals. These events include training strategies to build individual capabilities from novice to expert, develop team members to enhance team effectiveness by developing team knowledge and skills, and facilitate the progression of leadership excellence. There are a variety of other forms of instruction that take place outside of formal training, such as informal field-based learning (Wolfson et al. 2018), self-directed learning (Clardy 2000), mentoring (Kraiger et al. 2019), and coaching (Griffiths & Campbell 2009). We focus primarily on formal instructional events but recognize that the same components of instructional events that drive learning in formal, structured environments will be effective in these less structured environments as well.

Learning events. Learning events refer to individual actions of encoding, organizing, and retrieving new content presented from instructional events. Learning is what we do when presented situations and content that are outside our current states of affect, knowledge, and skill capacities. Learning can be incidental but largely results from instructional events. Multiple theories of learning center on the processes by which learners capture environmental stimuli, act upon it, then store it in ways that make it accessible for later application. Mayer's (2008) cognitive theory of multimedia learning describes how learners actively coordinate and monitor selecting relevant words and images from a multimedia message, building connections among them to create coherent personally meaningful models, and then integrating those models with prior knowledge to facilitate storage and recall. More generally, learning from instruction requires cognitive processes of encoding, organizing, and retrieving, as well as the importance of building connections in an active, intentional way among these processes.

Encoding is the process by which learners select content into working memory. We are constantly encoding and making conscious and unconscious decisions of what to attend to and what to let pass. Organizing occurs during consolidation and is the process by which learners build personally meaningful representations of training content. Examples include building task sequences—the steps necessary to generate a budget report online—and if-then responses—such as "if my direct report gets defensive when I am giving feedback, then I respond by ___." Finally, retrieval is the act of successfully recalling and applying acquired knowledge, skill, and affect when needed. Retrieval also helps strengthen the connections in memory around what has been learned.

Advancing Training Research and Practice

The science of training has largely focused on how effective training is and the individual and organizational factors that predict or moderate training effectiveness (see **Figure 1**, upper right). The science of learning focuses principally on the upper left corner: What are the most effective instructional events given what we know about how people learn? The proposed science of workplace instruction considers this framework as a whole—linking instructional events to meaningful outcomes through an understanding of learning events in people and desired learning outcomes of organizations.

To advance the science of workplace instruction and reinvigorate training research, we need a better understanding of how instructional events affect outcomes through learning events. To advance training practice, we need greater guidance on implementing instructional events in ways that affect learning events, improve learning outcomes, and lead to lasting positive instructional outcomes.

How Effective Instruction Works

Referring to educational contexts, Herb Simon stated "Learning results from what the student does and thinks and only from what the student does and thinks. The teacher can advance learning only by influencing what the student does to learn" (quoted in Ambrose et al. 2010). This statement highlights the appropriate focus on what a learner does to learn and how to build effective workplace instruction to better facilitate the process of learning.

In general, effective workplace instruction facilitates encoding by improving learner engagement, directing attention to key material, and drawing connections between new content and what the learners already know or need to know to perform their jobs. It facilitates organization by providing an overarching structure to the content, providing sufficient time for organization and consolidation to occur, and helping learners understand connections between content elements and between those elements and the work context. Retrieval processes occur during and after training. In particular, effective instruction facilitates retention and retrieval by having learners practice retrieval during learning, ensuring that the content is well ingrained (overlearning), incorporating physical, functional, psychological, and social fidelity between training and performance environments, and preparing learners to generalize or adapt newly acquired knowledge or skills to novel contexts. In the next section, we describe steps toward building a science of workplace instruction around instructional events and learning events.

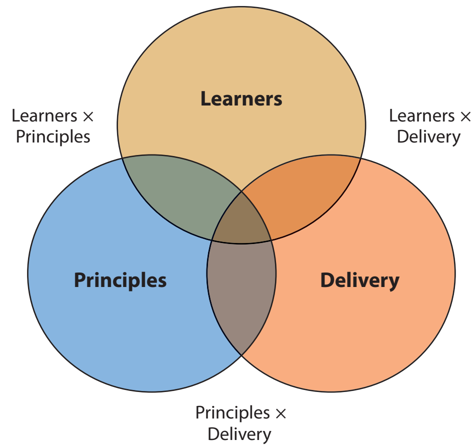

Figure 2

Primary elements of the science of workplace instruction: learners, instructional principles, and delivery.

ELEMENTS OF THE SCIENCE OF WORKPLACE INSTRUCTION

Figure 2 shows the three primary elements of the science of workplace instruction: the learner, instructional principles, and instructional delivery. As the goal of instruction is to facilitate change in the learner, research and practice should be considered from this perspective. In this section, we clarify the role of the learner, present core instructional principles for workplace instruction, and differentiate delivery methods and media from principles. This discussion sets the standard for understanding the intersections among learners, principles, and delivery—intersections we believe should be at the forefront of future training research.

The Learner

Learning occurs when individuals retain new knowledge, skills, and affect over time and apply these changes to appropriate situations. Learners are directly referenced as a foundational element of the science of workplace instruction in **Figure 2** and are implicit in **Figure 1** within learning events (how change occurs) and learning outcomes (what change looks like). Because the science of workplace instruction builds on both the science of learning and the science of training, it is instructive to understand how individuals—and the concept of individual variability—are treated in these paradigms.

With its roots in experimental psychology, the science of learning progresses by ignoring or controlling for individual differences. Individual variability contributes to within-cell variability, such that main effects for, say, an instructional principle can be assumed to generalize across learners. In other words, empirically supported instructional principles are effective for most learners. With its roots in applied psychology, the science of training seeks to identify individual difference variables, e.g., motivation to learn or goal orientation, that are predictors or moderators of the learning during training or transfer after it. This paradigm leads to empirically supported conclusions about the relative importance of these individual factors but provides little guidance as to how to use this knowledge to build better training.

To the extent that knowledge of individual variability matters in applied contexts, it must trigger the design of interventions to reduce pretraining variability among learners. For example, the effects of how training is framed can influence trainee attitudes (e.g., Hicks & Klimoski 1987) by maintaining the status quo in learners who already have positive attitudes about training and improving attitudes (e.g., motivation-to-learn) in trainees with initially lower attitudinal levels (e.g., Cox & Beier 2009).

By designating the learner as a primary element in the science of workplace instruction, we not only establish the learner is the point of instruction but also highlight the importance of examining how variability among learners (during learner events) interacts with instructional principles and methods. Although there will be variance in cognitive ability, job knowledge, and trainee motivation, the science of learning reveals that learning events are relatively intransient across learners and are facilitated by the same set of empirically supported instructional principles.

Instructional Principles

The science of workplace instruction is the application of evidence-based principles that have been found to help individuals learn knowledge, skills, and attitudes related to job performance and organizational effectiveness. Instructional principles are empirically supported propositions that guide the design and delivery of effective training. Instructional principles can affect both instructional events (how training is structured and designed) and learning events (how learners interact with material) and lead to learning particular outcomes. The search for generalizable principles of learning has a long history in psychology, for example Thorndike & Woodworth (1901) advocated for the use of identical elements to improve transfer of learning. I-O psychologists and instructional psychologists were instrumental in developing foundational instructional principles in the 1950s and 1960s, typically in the quest to improve efficiency in and transfer of military training. These principles included recommendations for increasing task difficulty (e.g., Briggs & Naylor 1962), stimulus variability (e.g., Ellis 1965), and distributed practice (e.g., Briggs & Naylor 1962). More recently, the identification and validation of instructional principles have been conducted primarily by cognitive scientists and educational psychologists with the intent of improving formal education (e.g., Dunlosky et al. 2013, Halpern et al. 2007, Mayer 2008, National Research Council 2012), with minimal attention to workplace training (but see Plott et al. 2014).

Not all empirically supported principles are useful for the science of workplace instruction. A useful principle must be actionable, resulting in instructional design or learning events that result in knowledge/acquisition and retention. Statements (offered as principles) such as "prior knowledge can help or hinder learning" may be true but are not prescriptive. Other principles may be too narrowly focused on primary or secondary education. Because we believe instructional principles are the bedrock of effective workplace instruction, we provide a brief summary of those that are both actionable and the most relevant to adult learners and workplace training. We return to these principles later in the article when we talk about their relationship to learners and training design.

Core instructional principles. **Table 1** shows five core instructional principles, each with two to three specific principles or instructional strategies. A core principle is an empirically supported approach to facilitating learning that can be accomplished in multiple ways, including the specific principles nested under each. To conserve space, those principles are defined in the table along with examples and citations to key explanatory texts and/or reviews providing empirical evidence on effectiveness.

For each specific principle or instructional strategy, **Table 1** provides the following: a definition, one or more examples (with citations when helpful), references of primary sources for more in-depth understanding, and one or more key findings. A definitive review of each principle or strategy is beyond the scope of this review. However, the table directs researchers or training

Table 1 Empirically supported instructional principles

Principles	Characteristics	Examples	Sources	Key findings
1. Organize content				
a. Coherence	Ensure there is a well-connected representation of the essential ideas to be learned.	Delete interesting but nonessential facts. Design course materials such that main points are prominent and easy to discern.	Halpern et al. 2007, Moreno 2006	Mayer & Fiorella (2014) found a median effect size of 0.86 across 23 studies for concise presentation of material.
b. Contiguity	Present knowledge, principles, and ideas that are closely associated in space and time.	Explain a learning event close in time to when it is depicted. Place onscreen text near corresponding graphics (e.g., illustrations placed next to the paragraph describing it) and put words from the paragraph in the illustration.	Halpern et al. 2007, Mayer 2019	A meta-analysis of 29 studies showed a mean $d = 0.80$ for effects of contiguity, with a similar effect for spatial and temporal contiguity (Ginns 2006). Mayer & Fiorella (2014) found a median effect size of 1.10 across 22 studies.
c. Advanced organizer	Present introductory (pretraining) material that provides the learner with a structure, schema, or example of what is to be covered in training.	Short pretraining video demonstrating behavior to be trained. Cues in the form of outlines, diagrams, and concept maps. Mnemonics.	Mayer 1979, Moore et al. 2017	Preiss & Gayle (2006) reported a mean $d = 0.46$ ($K = 20$, $N = 1{,}937$) for providing advanced organizers. Stone (1983) reported a mean $d = 0.66$ ($K = 112$), with larger effect sizes for written or illustrated advanced organizers and with advanced organizers that bridge with material to be learned.
2. Optimize sequencing of material				
a. Scaffolding	Provide learner assistance in the early phases of instruction to help focus attention; start with the simple aspects of the task and then build in task complexity.	Expert advice and support that fades over time. Design into the plan of instruction appropriate support mechanisms by anticipating learner needs.	Metcalfe & Kornell 2005, Reiser 2004	Meta-analytic results showed a large (60%) benefit for scaffolding ($TR = 1.58$, $g = 0.46$) (Plott et al. 2014). Another meta-analysis revealed mean effects of $g = 0.46$, 0.54, and 0.63 for concept, principles, and application outcomes, respectively (Belland et al. 2015).

(*Continued*)

Table 1 ***(Continued)***

Principles	Characteristics	Examples	Sources	Key findings
b. Adaptive difficulty	Allocate the optimal time for mastery and increase the level of task difficulty over the time of the instruction based on mastery of earlier phases.	Trainee performance below expectations leads to reducing task difficulty, whereas performance above expectations leads to increasing task difficulty.	McDermott et al. 2013, Metzler-Baddeley & Baddeley 2009	Meta-analytic results show that increasing difficulty adaptively for the learner led to greater learning ($TR = 1.36$, $K = 21$, $g = 0.75$, $K = 7$) than fixed increasing in difficulty and constant difficulty control conditions (Wickens et al. 2013). In a meta-analysis of simulation-based medical training, variation in task difficulty or complexity produced a mean $d = 0.68$ ($K = 20$) (Cook et al. 2013).
c. Interleaving	Implement a practice schedule that mixes different kinds of problems or training content.	Alternating practicing long shots and short shots at the driving range. Having customer service representatives alternate practice with technical and interpersonal problems	Bjork & Bjork 1992, Dunlosky et al. 2013	A meta-analysis revealed an overall significant effect $g = 0.42$ ($K = 59{,}238$ effect sizes) for interleaving (Brunmair & Richter 2019).
3. Engage learner in own learning				
a. Generative effects	Help learners integrate and elaborate on new knowledge by making personal connections between the new knowledge and the existing knowledge base of the learner.	After lecture, prompt learners to generate an original example or apply the concept to a real-world situation (Gingerich et al. 2014). Have learners explain or demonstrate a concept to others.	Fiorella & Mayer 2016, Gingerich et al. 2014	A meta-analysis showed an overall significant effect ($g = 0.55$, $K = 69$, $N = 5{,}917$) for prompting or directing learners to self-explain content (Bisra et al. 2018). Each of eight unique generative learning strategies yielded median effect sizes of $d = 0.40$ or higher across studies (Fiorella & Mayer 2016).
b. Prompts/ metacognition	Facilitate the self-regulation of learning by the learner through questioning of learning strategies.	Have learners provide self-explanations that connect the material to what they already know.	Azevedo & Cromley 2004, Kruger & Dunning 1999	"The benefits on learning of meta-cognitive prompts in *younger learners* is consistent (across) a large number of . . . studies" (Kraiger et al. 2020, p. 49).
c. Retrieval (aka the testing effect)	Have learners recall information that is now consolidated in long-term memory.	Frequent repeated testing on concepts while in training.	Dunlosky et al. 2013, Roediger & Karpicke 2006	Retrieval practice has been found to be a powerful mnemonic enhancer producing large gains in long-term retention relative to repeated studying (Roediger & Butler 2011). In a review of 120 studies, testing effects have been demonstrated across a large range of practice-test formats and material (Dunlosky et al. 2013).

(*Continued*)

Table 1 ***(Continued)***

Principles	Characteristics	Examples	Sources	Key findings
4. Conduct effective practice				
a. Variability of practice	Ensure learners have opportunities to apply skills across different tasks, people, and job-relevant situations.	Change the software programs used to address the same task, or change the functions available for use. Randomly assign tasks to be learned.	Shea & Wulf 2005, Wulf & Shea 2002	"There is strong evidence that such variability of practice is important for achieving transfer of learning—both for relatively simple tasks . . . and highly complex real-life tasks" (Kirschner & Van Merriënboer 2008). For a meta-analysis of simulation-based medical training, clinical variation produced a mean $d = 0.20$ ($K = 16$) (Cook et al. 2013).
b. Spaced practice	The implementation of a training or practice schedule in which learning events are spread over time as opposed to setting schedules with practice sessions close in time.	Medical residents are given one day of training to learn four procedures—2 h per procedure—or given 2 h of training each week for four weeks (Moulton et al. 2006).	Dunlosky et al. 2013, Moulton et al. 2006	A meta-analysis revealed an overall mean weighted effect size of 0.46 ($K = 112$) for effectiveness of spaced practice (Donovan & Radosevich 1999). For a meta-analysis of simulation-based medical training, distributed practice produced a mean $d = 0.66$ ($K = 6$) (Cook et al. 2013).
c. Identical elements	Have learners produce responses within an accurate representation of the operational system, equipment, and environmental context.	Job-relevant tasks with events unfolding in a realistic manner. Place learner in situations that incorporate what it feels like (time pressures, challenges) when completing the task on the job. Mirror the collaborative nature for tasks on the job.	Baldwin & Ford 1988, Marlow et al. 2017	Issenberg et al. (2005) reviewed 109 published studies in medical journals and found it "clear that high-fidelity medical simulations facilitate learning among trainees when used under conditions . . .[that include]. . . curriculum integration . . . and simulator validity" (p. 24). In a meta-analysis of simulation-based nursing education, high- and moderate-fidelity simulations resulted in greater learning than did low-fidelity simulations (Kim et al. 2016).

(*Continued*)

Table 1 (*Continued*)

Principles	Characteristics	Examples	Sources	Key findings
5. Develop past initial mastery				
a. Knowledge of results	Whether a response is correct or incorrect [knowledge of results (KR)]; what the correct response is [knowledge of correct response (KCR)].	A learner is only able to go forward in a language app if they provide the correct answer.	Shute 2008, Van der Kleij et al. 2015	In a meta-analysis of computer-based instruction (Van der Kleij et al. 2015), KR produced an effect size of 0.05 and KCR produced an effect size of 0.33.
b. Feedback and feedforward	Information communicated to the learner that is intended to modify his or her thinking or behavior for the purpose of improving learning (Shute 2008).	Identify and possibly correct inaccurate skills, misconceptions (errors of commission), and missing information (errors of omission).	Kluger & DeNisi 1996, Shute 2008	In a meta-analysis of 53 studies of computer-based instruction, elaborative feedback produced an effect size of 0.49 (Van der Kleij et al. 2015). van de Ridder et al. (2015) conducted a meta-review of 22 meta-analyses and 24 narrative reviews on feedback. She concluded the following: "The main effect of the provision of feedback is that feedback is effective and improves performance such as in safety-related performance, work productivity, judgement abilities, learners' goal-setting abilities, and clinicians' and physicians' performance. The impact of feedback is often small to moderate" (p. 664).
c. Overlearning	Continued practice on a task after some criterion of mastery on that task has been achieved.	Repeated practice. Refresher training.	Driskell et al. 1992, Wang et al. 2013	A meta-analysis showed a mean $d = 0.63$ ($K = 88$), with stronger effects for cognitive than physical tasks. Furthermore, the greater the overlearning, the stronger the effect (Driskell et al. 1992).

Variables: d, the difference between a treatment and comparison group in standard units; g, Hedges' effect size estimate; K, number of studies or number of effect sizes if larger; N, total number of participants across studies; TR, ratio of the performance of the treatment group to the control group (e.g., $TR = 1.4$ means treatment group performed 40% higher on the outcome measure).

professionals who want to learn more about each one. Examining the table is beneficial, as the remainder of the article references many of these specific principles and strategies.

The Key Findings column of **Table 1** warrants clarification. When there are meta-analytic findings of studies relevant to workplace instruction, we provide a summary effect size. When there are no meta-analyses but there are widely recognized narrative reviews (e.g., the testing effect), we provide a summary statement. When there is no narrative review (e.g., prompts/meta-cognition), we provide a recent quote summarizing the extant research. These findings are provided to assure the reader that these are empirically supported principles. The summaries also provide some evidence of the level of effectiveness for each principle/strategy. In providing this, we admit to oversimplifying what are sometimes complex research questions. For example, although Belland et al. (2015) report moderately large effect sizes for scaffolding, they also cite prior meta-analyses in which the mean effect sizes (*d*) range from 0.02 for multimedia instruction to 0.96 for dynamic assessment.

To illustrate the relevance of these principles to effective workplace instruction, we briefly discuss the five core principles. One key to effective instruction is to organize content in ways that are meaningful and helpful to learners. Adult learners function best when they are presented with clear objectives and see a connection to current or future work (Noe & Colquitt 2002). Learning events are organized logically, and extraneous details that waste cognitive resources are reduced (Mayer 2008). For example, graphics that illustrate key concepts should be placed in close proximity to the concept, and explanations for an event should be provided as soon as the event occurs, not days after.

A second key is to optimize the sequencing of training content. Effective training presents content relevant to the learner's level of expertise, ensuring that learners master requisite knowledge before attempting complex skills, providing learning support for more difficult content, ordering learning tasks in increasing difficulty, and, when appropriate, decomposing and learning complex tasks or skills before combining them. For example, early in language training, foreign words might be paired with visual cues, but the cues are removed as learners develop their vocabulary. Interestingly, although part-whole training has been a long recommended instructional principle, meta-analyses suggest that part-training either produces negative effects or only produces positive effects under fairly narrow conditions (e.g., Fontana et al. 2015, Wickens et al. 2013). This is in part due to the inability of learners to practice time-sharing skills in managing task subcomponents (Wickens et al. 2013). On the basis of this evidence, we did not include this popular principle in **Table 1**.

By extension, the more that the instruction actively engages learners in the learning event, the better the outcomes. Engagement means more than interest and takes the form of the learner responding to and acting on training content by restating, generating answers or explanations, consciously monitoring, and evaluating progress toward learning goals. The benefits of encouraging deliberate practice are irrefutable (although claims of the number of hours to become an expert are questionable). In an exemplar study, Gingerich et al. (2014) examined two groups: One group of students was prompted to generate their own personal examples of a concept defined by the instructor, whereas the other group was given the examples by the instructor. The study showed that the personal example group retained the information more from the prompts, which helped them integrate the new concept with their existing knowledge base, thus making it easier to retain and access when needed.

Effective practice leads to the acquisition of new knowledge or skills by requiring attention, rehearsal, and repetition in the learner (Campitelli & Gobet 2011). However, not all practice conditions are equal, and learning and retention are improved to the extent learners (*a*) encounter practice conditions similar to performance conditions, (*b*) are exposed to problems or conditions that vary trial to trial, and (*c*) encounter practice trials that are distributed over time. In a classic study involving British postal workers, Baddeley & Longman (1978) compared the speed of acquisition and retention of learning to the type of new postal codes for workers depending on whether trainees practiced for several hours a day or had their practice distributed over longer intervals. As is now commonly found in such studies, postal workers who practiced all at once required fewer hours of training to reach the desired criterion, but the workers who spaced their practice retained their new skills longer.

Finally, as any parent discovers with a baby's first words or first steps, initial mastery does not ensure fluid subsequent performance, such that instruction is necessary to facilitate development past initial mastery. Continued repetition leads to overlearning, but greater mastery also results from reinforcement that declarative knowledge, mental models, and skills are correct, as well as constructive feedback of how to refine further knowledge or skills. Common examples of overlearning come from public speaking or acting. It has been estimated that TED Talk presenters practice on average 70 h for a 15-min talk, ensuring that they will remember their points even if they feel stressed in the moment.

Delivery

Delivery represents the processes by which instructional events are designed and shared to facilitate learning events. Delivery consists primarily of instructional methods and training media.

Methods. Instructional methods refer to theoretically sound approaches to structuring learning events. Examples of instructional methods include behavioral modeling training, error-management training, adaptive guidance training, and intelligent tutoring systems. Theoretically sound is a key attribute of a method, in part because it differentiates a broad, systemic approach to instruction from the use of tools or submethods such as PowerPoint. A theory-driven instructional method is more likely to be effective because it is built on sound theory of human behavior. One instructional method is not inherently better than another, but any method is likely to result in achieving learning outcomes when it is theoretically sound, is suitable for the intended learning outcomes (e.g., hands-on skills versus mental models), and incorporates evidence-based instructional principles.

Media. Training media or channels refer to the materials and physical means that are used to convey content to learners. Examples of media are job aids, workbooks, classroom lectures, podcasts and webinars, technology-distributed instruction (TDI) (e.g., online learning), and technology-enabled instructional systems (e.g., virtual reality and serious games). Media are not explicitly called out because effective instructional methods are equally effective regardless of channel. This point was made forcibly more than 25 years ago by educational psychologist Richard Clark (1994), who argued that "media will never influence learning" (p. 21). Clark's argument is that any empirical evidence of the superiority of one medium over another is due to the inclusion of attributes of instructional design in one but not the other; when design principles are held constant, media should be equally effective. This is illustrated in a meta-analysis by Sitzmann et al. (2006), who found that across all studies, web-based instruction was more effective than classroom instruction on the acquisition of declarative knowledge. However, when they controlled for the presence or absence of training attributes (e.g., feedback and practice), the effectiveness of both methods was equivalent.

The effectiveness of methods should be invariant over forms of media. As we discuss below, effectiveness can be enhanced not by changing the medium (e.g., incorporating virtual reality) but by successfully incorporating instructional design principles into the training.

Intersection of Learners and Methods

Building from these three foundational elements, the science of workplace instruction can advance training practice and guide future training research through the areas of intersection in **Figure 2**: learners and delivery, instructional principles and delivery, and learners and instructional principles. In the case of the latter two areas, training researchers are uniquely positioned to contribute to the science of workplace instruction by investigating the interactive nature of principles and methods and principles and learners in the context of rich organizational cultures and a wide range of learners with different needs. In the case of the former area, progress will occur more rapidly when training researchers and professionals reject a long-standing tradition in training orthodoxy to group participants on some individual difference variable and offer different training methods for each group. As we show below, this practice is not supported by empirical research and runs opposite of our assertion (and meta-analytic findings) that effective training works for all.

Aptitude-treatment interactions. The study and promotion of aptitude-treatment interactions (ATIs) have been called for in several different domains in psychology and education, including training research (Aguinis & Kraiger 2009, Salas & Cannon-Bowers 2001). This has occurred despite the early insistence of Cronbach & Snow (1977) that ATIs are complex and difficult to demonstrate reliably and that no particular ATI effect is sufficiently understood to stand as the basis for instructional practice. Cronbach (1975) admitted, "Snow and I have been thwarted by the inconsistent findings coming from roughly similar inquiries. Successive studies employing the same treatment variable find different outcome-on-aptitude slopes" (p. 119).

Although the methodological and statistical challenges in validating ATIs—if they exist—are beyond the scope of this article, in the educational domain there is now more than 50 years of research that has struggled to find replicable, substantive, and theoretically meaningful ATIs (e.g., Bracht 1970, Preacher & Sterba 2019). In training research, Kowollik et al. (2010) conducted a meta-analysis to test a popular ATI hypothesis that lower general mental ability (GMA) learners benefit from greater training structure: Across 51 studies, Kowollik et al. found that although there was evidence for small interactions, there was not consistent support for the commonly purported disordinal ATIs across outcome criteria. They concluded that the small instructional gains from designing a GMA-structure ATI approach would not outweigh implementation costs and that ATIs imported from educational psychology are somewhat of a "received doctrine" (Kowollik et al. 2010) in the training literature. In short, training research and training practice are better served by linking instructional principles to training delivery for all learners and not by chasing ATI effects. The disruptive effects of chasing ATIs can be seen in two lines of research: learning styles and age-specific learning.

Learning styles. Tailoring instruction to match individual learning styles is a long-standing instructional practice not empirically supported by research. The approach assumes individuals have innate, measurable learning styles. The meshing hypothesis states that if learners are provided instruction in their preferred modality (e.g., visual versus kinesthetic versus auditory), they will learn better than if given a different modality (Pashler et al. 2008). However, there is no consensus as to what constitutes a learning style; one review reported more than 50 distinct learning style theories (Cofield et al. 2004).

Pashler et al. (2008) conducted an extensive review of the learning styles research applying strict screening criteria to the inclusion of studies. They were unable to find any evidence using their study criteria supporting the learning styles hypothesis and found several reputable studies providing evidence that contradicted the effect. Thus, Pashler et al. concluded that although there is ample evidence that when asked, individuals will state a preference for one learning modality over another, there is little evidence that catering to these preferences leads to superior learning outcomes. Pashler et al. did not report the number of studies they reviewed or overall effect size; however, Aslaksen & Lorås (2018) recently conducted a meta-analysis of the same literature and found "still no replicable statistical evidence for enhanced learning outcome by aligning instruction to modality-specific learning styles" (p. 1).

Empirical support for styles instruction is undoubtedly hampered by several methodological issues, including low statistical power for detecting moderation. Nonetheless, the promise of the ultimate customization of learning to individuals is not supported empirically and runs counter to our proposition that well-designed instruction works for all learners. In the words of Pashler et al. (2008), "it is undeniable that the instruction that is optimal for a given [learner] will often need to be guided by the aptitude, prior knowledge, and cultural assumptions that [the learner] brings to a learning task. However, assuming that people are enormously heterogeneous in their instructional needs may draw attention away from the body of basic and applied research on learning that provides a foundation of principles and practices that can upgrade everybody's learning" (p. 117).

Age-specific learning. A second ATI application is the design of age-specific instruction. This practice stems from research confirming age-related differences in cognitive skills such as processing speed (Kraiger 2017, Wolfson et al. 2014) as well as meta-analytic evidence that adults on average learn less and take longer to complete training compared to younger learners (Kubeck et al. 1996). Advocates of age-specific training call for unique training interventions that account for known age-related deficits of older learners (e.g., Mead & Fisk 1998, Truxillo et al. 2015). For example, training design could remove practice variability to support older adults with slower cognitive processing speeds.

In contrast, age-inclusive training proposes that empirically based instructional principles should be beneficial to all age groups (Van Gerven et al. 2006, Wolfson et al. 2014). There may be treatment by age interactions, but of a different form. Because older adults may need more learning support, it may be the case that well-designed training works for all but especially for older learners. This includes the use of instructional principles (discussed above) as well as fundamental submethods such as clear learning objectives, job-relevant exercises, instructional aids to organize encoding and recall, and timely feedback (Kraiger 2017). Many studies in fact demonstrate that implementing validated instructional principles significantly improves outcomes in learners of all ages (e.g., Kornell et al. 2010, van Gerven et al. 2006, Wolfson & Kraiger 2014). Well-designed training works for all.

ADVANCING THE SCIENCE OF WORKPLACE INSTRUCTION

At the outset of this article, we noted a diminishing interest in training research; we are also aware that the learning and development industry continues to change—perhaps not always with a solid foundation in empirically supported principles and methods (Rynes et al. 2007). We contend that training research can be reinvigorated and training practice advanced by applying the framework shown in **Figure 1** and understanding how theoretically based instructional methods incorporating empirically supported principles facilitate effective learner events, leading to targeted, multidimensional learning outcomes that ultimately result in positive changes at the learner, job, and organizational levels.

A specific and important research need is to examine how to optimize learning in work contexts through a focus on instructional principles. We recommend three areas for further research. First, research should focus on how to optimize theoretically based training methods by incorporating relevant instructional principles. Second, given the move to self-directed learning, research should determine direct ways to support learners through known instructional principles. Third, the rapid adaptation of technology-enhanced instructional methods can be supported through the integration of instructional design with these synthetic environments.

Intersection of Instructional Principles and Training Methods

At the outset of their review, Salas et al. (2012) asserted "(*a*) properly designed training works, and (*b*) the way training is designed, delivered and implemented can greatly influence its effectiveness" (p. 74). Meta-analytic evidence confirms the first assertion, but there is important work to be done to understand precisely how training design and implementation affect the achievement of training objectives in organizational contexts. Specifically, meta-analyses reveal the effectiveness of many training methods, including behavioral modeling (Taylor et al. 2005) and error-based framing (Keith & Frese 2008). However, meta-analyses such as these typically report large heterogeneity in effects across studies, suggesting the possibility of study-level moderators. For example, crew resource management training is a specific training method that is informed by several theories of shared cognition and root causes of errors (Salas et al. 1999). O'Connor et al. (2008) conducted a meta-analysis on crew resource management training and found overall positive effects on attitudes, knowledge, and behaviors but noted "substantial variation in effect sizes across these studies" (p. 361). Similarly, cross-cultural training encompasses a variety of training practices that are grounded in theories of social learning and culture shock, as well as the dynamics of adjustment (Littrell et al. 2006). In their meta-analysis of cross-cultural training, Morris & Robie (2001) found significant main effects for training on performance and adjustment. However, effect size variance attributed to statistical artifacts was small, again suggesting the possibility of substantive factors moderating study outcomes. Observing this study-to-study variability in the effectiveness of cross-cultural training, Littrell et al. speculated that this variability could have been due to variance in training rigor. Similarly, Mattingly & Kraiger (2019) conducted a meta-analysis of emotional intelligence training. They reported a significant main effect for training, but substantial heterogeneity across studies. Using regression analysis, they found that variance in training properties including practice and feedback explained significant variance in training outcomes.

One implication is that although theory-based training works, its effectiveness is likely moderated by characteristics of effective instruction that are generalizable across all forms of training (Noe & Colquitt 2002). (This is not to discount other moderators of training effectiveness but to stress that variation in effects due to design characteristics has been understudied and likely underrecognized.) Researchers have begun to explore the intersection of training methods and instructional principles through meta-analysis by coding for the absence of principles in source studies, as Mattingly & Kraiger (2019) demonstrate. Several meta-analyses provide direct evidence for the moderating effects of design characteristics generally and instructional principles specifically on relationships between methods and learning outcomes. For example, Taylor et al. (2005) found that behavioral modeling training (method) is more effective with spaced versus massed practice (instructional principle). Kalinoski et al. (2013) also reported that distributed practice led to stronger effects for diversity training on cognitive and affective outcomes compared to massed practice. Finally, Keith & Frese (2008) reported that the clarity of task feedback moderated the effectiveness of the error-based training methods. Collectively, these reviews show that empirically supported training methods are more effective when accompanied by the use of sound instructional principles and training design.

Latham & Saari's (1979) classic study of behavioral modeling illustrates nicely the benefits of pairing empirically supported instructional principles with theoretically sound training methods. Drawing on social learning theory, they found strong evidence for the effectiveness of behavioral modeling on knowledge, skill, and transfer outcomes. The study demonstrated the value of social reinforcement to enhance motivation and use of demonstration and practice to aid retention and reproduction. However, a closer examination reveals how multiple time-tested instructional principles facilitated encoding, organization, and retrieval processes. Consistent with the principle of distributed practice, Latham & Saari spaced their 18 h of instruction over nine 2-h sessions. Consistent with the principle of practice variability, the training presented nine different practice scenarios based on a prior job analysis. The generative effect was implemented by asking trainees to recreate actual situations that had happened to them and role-play that event. After each instructional session, learners were given a performance aid listing the key behaviors and instructed to practice the skills learned immediately with an employee, illustrating practice effects (Dunlosky et al. 2013) and opportunity to perform (Ford et al. 1992). Theory-based training interventions are effective, but they work better when they incorporate sound instructional principles.

Because workplace training interventions and instructional principles have been proposed and tested in different disciplines, less is known about the intersection of the two. From a research perspective, the greatest progress will come not from designing new methods or from testing additional instructional principles, but from examining how best to integrate instructional principles into effective training methods. For example, how important are identical elements for the effectiveness of error management training? Does the length of spacing matter for behavioral modeling training? What are the best ways to implement generative learning into adaptive guidance platforms? In the science of workplace instruction, questions such as these can be pursued within the rich context of providing job-relevant training within organizational contexts.

Enhancing Self-Directed Learning

Self-directed learning refers to "learners' active and volitional approach to conceptualize, design, conduct, and evaluate a learning project" (Noe et al. 2014, p. 249). Organizations increasingly are encouraging employees to stay on top of their career by identifying learning needs and managing their own discrete learning events. In this way, incumbents can reduce the potential for skill obsolescence or gain new skills for other more sustainable types of jobs within the organization. Properly executed, self-directed learning can increase learning efficiency and enhance individual performance. Organizations may also save costs by shifting the responsibility for learning to members of their workforce.

As with various forms of formal training, there is cumulative evidence that self-directed learning is effective. One variation of self-directed learning is informal learning. Informal learning typically occurs on the job and without organizational oversight, for example, when learners ask a coworker for help or search the Internet for job-relevant information. A recent meta-analysis showed positive effects for informal learning behaviors on outcomes such as knowledge/skill acquisition and job performance (Cerasoli et al. 2018).

The problem. With self-directed learning, the learner assumes greater control in the planning, scheduling, and executing of learning events than during formal training. Accordingly, the effectiveness of self-directed learning is limited by how well learners manage these events. Effective self-management requires two broad skill sets—the monitoring of learning processes and outcomes and the regulation of the affective, cognitive, and behavioral processes that promote learning (Sitzmann & Ely 2011). Evidence suggests learners are challenged in both respects.

Monitoring and regulating are implicit in the construct of learner control—how the training system allows learners to make decisions that alter the learning environment (Landers & Reddock 2017). Landers & Reddock proposed a nine-dimensional framework of objective learner control consisting of instructional control (skipping content, supplementing content, and managing the sequence, pace, practice, and guidance control of content), style control (control of aesthetic training characteristics), and scheduling control (time and location control). Their meta-analysis showed that these dimensions of instructional control generally had small but positive effects on skill outcomes. However, for training reactions and knowledge outcomes, effects were smaller and inconsistent across specific dimensions (e.g., practice control versus supplement control). Although these findings show some support for providing learner control, the researchers cautioned that multiple dimensions were so frequently confounded within single studies that it may be misleading to conclude that any one dimension is effective.

The limitations of learner control revealed by research can be explained by the predictable errors trainees make in regulating their learning behaviors. Bjork et al. (2013) reviewed research in educational psychology on learner self-regulatory behavior and concluded the following: "Although individual differences occur in effective strategy use, with some students using effective strategies that contribute to their achievement, many students not only use relatively ineffective strategies (e.g., rereading), but believe that they are relatively effective" (p. 423). Specifically, learners generally (*a*) mistakenly believe that blocked or massed practice is more effective than spacing, (*b*) erroneously believe that rereading content is more effective for learning than being tested on it, (*c*) fail to overlearn to enable mastery, and (*d*) are overconfident in their mastery or poor judges of whether they have retained newly learned content. Furthermore, the use of ineffective self-regulatory behaviors can be difficult to extinguish. For example, in Kornell & Bjork's (2008) study, students rated their learning as superior using massed study practices even when they were given feedback that they perform better using spacing. Bjork et al. suggested that this may be a metacognitive illusion because massed practice is perceived to be easier than spacing.

The sum effect of these judgments and biases is that providing instructional control may undermine learning due to suboptimal decisions during the learning event (Kraiger & Jerden 2007). Thus, the problem is that learners are being given more responsibility for guiding their own learning, whereas research demonstrates that they are flawed executors of the necessary skills to do so.

Research to enhance self-directed learning. The science of workplace instruction allows us to view the problem of suboptimal self-directed learning from the broader perspective of workplace training. For example, prior training research has shown positive effects for accountability on instructional outcomes, but there is no research on how it affects learning events. Accountability refers to the perceived need to justify one's action to an audience with sanction or reward power (Frink & Klimoski 1998). Accountability manipulations or perceptions of trainee accountability have been shown to positively impact learning during training (DeMatteo et al. 1997) and transfer (Saks & Belcourt 2006). But there is little research on how accountability affects learning. DeMatteo et al. found a stronger effect for an accountability manipulation before training rather than after training—but before transfer was measured. They also reported that increased accountability resulted in greater notetaking by participants during training. Thus, it appears that holding learners accountable may increase their engagement during learning events and their efforts to encode or organize information. However, this needs to be established empirically. Additionally, it would be useful to investigate the extent to which specific instructional principles interact with increased accountability. For example, cognitive prompts are brief queries inserted into training for purposes of encouraging meta-cognitive, elaboration, or active processing (Kraiger et al. 2020). Cognitive prompts have a demonstrated impact on learning outcomes (Sitzmann et al. 2009). Would prompts that remind learners of the need to justify their actions increase accountability and promote improving encoding and organizing processes? Is the need to apply training content to the job sufficient to create accountability, or does there need to be a threat of post-training evaluation? What are effective prompts that increase perceived accountability but do not distract from the learning task?

The necessity of providing job-related learning and development leads to other solutions for organizations. Kraiger & Jerden (2007) speculated that many learners either expect or prefer that the learning and development enterprise structure their training experiences—determining what should be learned when. They further distinguished between objective and perceived learner control, with the former managed by the training system and the latter by personal perception. Landers & Reddock (2017) found that objective control is related to learning outcomes and perceived control is related to training reactions. Together, these propositions create opportunities to mitigate negative effects of learner control by minimizing what aspects of training the trainees can affect. To improve training, multiple instructional principles could be added to the system and learners given guidance as to which principles are activated and how they are operationalized. For example, trainees could be given freedom to choose the timing or space between learning trials and specific transfer tasks from within a broader population of potential, varied tasks. In these ways, training could be structured to enhance perceived control and agency, but with sufficient design features "baked in" to support learning. Using scaffolding, as learners progress, the system would provide more choice in designing learning and transfer trials. Tactics to support learner decision making have been common for a long time in technology-enhanced environments such as intelligent tutoring systems (Ma et al. 2014). They are also consistent with adaptive guidance training (Bell & Kozlowski 2002), which has been found to have a positive effect on trainees' study and practice, self-regulation, knowledge acquisition, and performance. Determining the optimal balance of objective and perceived control, as well as how that balance is affected by individual, job-related, and organizational factors, is an important applied research problem.

Another research area worth pursuing is the investigation of optimal instructional principles to guide self-directed learning as a function of the developmental stage of the learner. Kanfer & Ackerman (1989) demonstrate how in early stages of skill acquisition, learners must devote greater attentional resources to a task, and learning events require less attention as skills are compiled and automatized. Thus, it stands to reason that instructional principles that facilitate attentional control (e.g., coherence and contiguity) would be more effective early in self-directed learning events, and principles that demand less attention (e.g., metacognition and practice variability) would be more effective later. Although these effects have not been closely studied in the self-directed learning literature, we know from studies of formal instruction that the utility of some principles has been dependent on the stage of learner acquisition. As one example, the principle of part-whole training holds that part-task instruction has greater utility early in skill acquisition, but whole-task instruction is more useful at later stages (Plott et al. 2014). Similarly, research on the development of motor skills shows that constant, blocked practice schedules are beneficial early in training to enable the acquisition of basic skills, but more variable practice is more beneficial later to promote fine-tuning and generalization (e.g., Lai et al. 2000). Because much of this is basic research on discrete knowledge or skills, additional research is needed to determine the extent to which such effects generalize to self-directed workplace learning.

Research in educational contexts confirms that students frequently endorse and practice ineffective study methods (Dunlosky et al. 2013). To support self-directed learning in organizational contexts, it would be beneficial to know what instructional principles adult learners routinely use to monitor and guide their learning. We also need to better understand how effective each instructional principle is with respect to self-directed learning and how to help learners adopt the most effective strategies. Given our tendency to overestimate our own abilities (Kruger & Dunning 1999), we may be prone to resist efforts to improve our capacity to learn. Thus, research will need to explore ways to overcome these tendencies so as to best guide individuals during self-directed learning.

Enhancing Synthetic Learning Environments

Synthetic learning environments refer to technology-enabled training media that augment, create, and/or manage learning events in a world characterized by both realistic context and embedded instruction (Cannon-Bowers & Bowers 2010). Common examples are simulations (e.g., Hays et al. 1992), serious games (Susi et al. 2007), and virtual reality (Howard & Marshall 2019). There is considerable overlap in the definitions and operationalizations of these three forms of media, as all involve the creation of technology-enabled interactive and artificial environments that facilitate the development of job-related knowledge, skills, and affect. Serious games stand somewhat apart, because although they also employ a synthetic environment for purposes of training or education, they add elements associated with most forms of games such as immersion, conflict/challenge, rules/goals, and human interaction (Bedwell et al. 2012).

Meta-analytic evidence supports the effectiveness of both simulations and virtual reality. Many of these investigations are specific to an industry, job, or function. For work simulators, there is evidence of building skills in contexts such as medical education (Issenberg et al. 2005) and flying (Hays et al. 1992). Meta-analytic evidence for the effectiveness of virtual reality training includes areas of laparoscopic surgery (Alaker et al. 2016) and social skills (Howard & Gutworth 2020). However, the level of effectiveness of synthetic learning environments may depend on the type of learning tasks. A recent meta-analysis found support for virtual and augmented reality training for physical tasks, but null effects for cognitive tasks (Kaplan et al. 2020). Additionally, the efficacy of serious games remains in question. Mixed or null effects have been typically reported for large-scale reviews of serious games in both education contexts (Lamb et al. 2018) and training and education when the comparison group had similar activity levels as the test group (Sitzmann 2011). Despite several decades of empirical research on games for training purposes, even these results should be viewed with caution, as there is a relatively small percentage of rigorous investigations (e.g., Clark 2007).

The problem. Synthetic learning environments are increasingly popular in industry and education (e.g., Gasparevic 2018) and are being driven largely by the availability of ubiquitous, device-enabled, high-bandwidth distribution channels. Capability is only increasing as 5G becomes more prevalent. As others have noted (e.g., Bedwell et al. 2012, Gunter et al. 2006), advancements are being implemented by software providers without evidence that the platforms facilitate learning (e.g., Mayer 2011b). Thus, the risk here is that we are building and propagating high-speed, data-rich instructional tools that do not take advantage of what is known about how people learn (the science of learning) or how to best facilitate learning (the science of instruction). Just as we have advocated for greater integration of instructional principles into theoretically supported training methods, we see the value in understanding which instructional principles best lend themselves to synthetic learning environments and how these principles can be incorporated.

Research to enhance synthetic learning environments. In the short run, there is a need for theory-based papers that marry scientific principles with technology-based training (e.g., Gunter et al. 2006; Mayer 2008, 2019). However, such work needs to appear in forums that are available to developers who in turn see value in implementing scientifically sound instruction. In the long run, research is needed to understand optimal conditions for implementing instructional principles in various forms of TDI.

As have others before us (Clark 1994, 2007; Mayer 2011b; Sitzmann et al. 2006), we contend that the medium is much less important than sound instructional design—incorporating empirically based instructional principles improves learning regardless of the medium. That said, we also believe that some principles can be more easily and more effectively implemented in synthetic learning environments. For example, the instructional principle of identical elements states that transfer is enhanced to the extent to which the stimuli and responses during learning events are identical to those in the actual work environment (Saks & Belcourt 2006). As one example of this, Libin et al. (2010) trained customer support staff in healthcare settings by showing them realistic videos of scenarios in which they are confronted with actual patient problems and must make real-time decisions and then see the consequences of their actions. Practice variability can be easily implemented by varying the situations and problems that trainees must confront, and in more sophisticated software, generative learning can be supported by enabling learners to author their own scenarios from problems previously faced.

With baseline knowledge of the effectiveness of each instructional principle (see **Table 1**) and sound theories underlying synthetic learning environments as instructional events (e.g., Howard & Marshall 2019, Landers et al. 2019), researchers can select and test the principles that are expected to be more effective in these contexts. Thus, referring to **Figure 2**, we expect some instructional principles to be differentially relevant for facilitating learning when enacted in certain synthetic learning environments. There may well be ordinal interactions of some principles with different environments. For example, although generative learning is generally effective in all contexts, it may be more effective in virtual reality training where learners may be more used to exploratory behavior.

CONCLUDING COMMENTS

The past three decades has seen tremendous growth in theory and research on learning and development in organizations. The development and testing of models of training systems embedded in organizational contexts have demonstrated both the overall impact of training and role of individual and organizational factors as antecedents and moderators of that effectiveness. From this we understand that instructional events lead to instructional outcomes. Less clear are the ways in which learning events and outcomes mediate that relationship. To reinvigorate training research, we proposed the learner, instructional principles, and training delivery as the elements of the science of workplace instruction. By delineating the critical role of instructional principles in workplace training and by exploring the intersections of those principles with learners and emerging training technologies, we hope to inform the next decade of research on workplace instruction.

SUMMARY POINTS

1. The science of workplace instruction postulates that instructional events managed by the organization lead to learning events and learning outcomes within individuals which are manifested as instructional outcomes at the organizational level.
2. The science of workplace instruction postulates that learning is facilitated by active processing of the learner and sound application of instructional principles and delivery.

3. Five core instructional principles have empirical support and can be applied in multiple ways to facilitate learning.
4. The most effective instructional methods are rooted in sound theories of human behavior and incorporate evidence-based instructional principles.
5. The relative impact of different training media or channels is substantially less important than the use of theory-based methods and empirically supported instructional principles.
6. There is little to no evidence to support matching instruction to individual learning styles; effective instruction results from the use of theory-based methods and empirically supported instructional principles.
7. There is little to evidence to support varying instruction based on learner age; effective instruction results from the use of theory-based methods and empirically supported instructional principles.

FUTURE ISSUES

1. Include information on the incorporation of instructional principles in training research reports even if not the primary focus of the study or training.
2. Examine the moderating influence of instructional principles on training effectiveness in meta-analyses of training methods and training effectiveness.
3. Determine the value of including specific empirically supported instructional principles when combined with effective, theoretically based training methods.
4. Investigate the impact of the organizational context on learners' disinclination to effectively monitor and regulate their own learning, as demonstrated in educational contexts.
5. Specify and test the effectiveness of instructional principles that are most likely to optimize learning in synthetic learning environments.

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