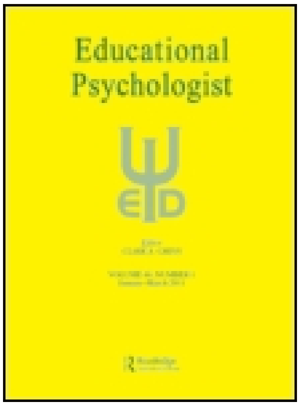

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The Import of Knowledge Export: Connecting Findings and Theories of Transfer of Learning

Samuel B. Day [a] & Robert L. Goldstone [b]

[a] Department of Psychology, Susquehanna University

[b] Department of Psychology, Indiana University

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The Import of Knowledge Export: Connecting Findings and Theories of Transfer of Learning

Samuel B. Day
Department of Psychology
Susquehanna University

Robert L. Goldstone
Department of Psychology
Indiana University

After more than 100 years of interest and study, knowledge transfer remains among the most challenging, contentious, and important issues for both psychology and education. In this article, we review and discuss many of the more important ideas and findings from the existing research and attempt to bridge this body of work with the exciting new research directions suggested by the following articles.

Like many of the people reading this article, we find mathematics intrinsically interesting. However, even if most students shared in our appreciation of the inherent elegance of mathematical explanation, it is unlikely that this would justify the immense amount of educational time spent on the topic. The goal of learning mathematics is to prepare students to use it in the real world, or even more broadly, to employ rigorous, formal thought processes to their everyday life. In various ways, the same can be said for any educational topic—from physics to history to biology to literature, education is fundamentally about acquiring knowledge to be used outside of the classroom. It is therefore especially troubling that a considerable corpus of research finds systematic failures in people's ability to apply their relevant knowledge in new situations. Because of both the difficulty and the importance of transfer, aspects that bear on the very foundation of education, an enormous amount of research has been conducted on knowledge transfer. The topic remains both frustrating and contentious; however, with some researchers going so far as to argue that meaningful transfer seldom if ever actually occurs (e.g., Detterman, 1993).

We had two primary goals in writing this article. First, as a lead-in to this special issue, we have attempted to provide a review of the (sometimes daunting) existing literature on knowledge transfer. Of course, such a review will never be close to complete. However, we have tried as much as possible to include a broad sampling of some of the more important and influential findings and ideas and to organize these along themes that are renewed by the current set of articles. When combined with the other articles in this issue, our hope is to provide the reader with a solid understanding of the "state of the art" in transfer research. Our second goal for this article was to join with the other authors in presenting our own proposal for a productive way of advancing research in this area—namely, a discussion of the role of perceptual processes and perceptual representations in knowledge transfer.

FINDINGS FROM THE TRADITIONAL APPROACH TO TRANSFER

The traditional approach to knowledge transfer has its roots in ideas from the early 20th century. In particular, Thorndike's (1924; Thorndike & Woodworth, 1901) seminal ideas regarding the importance of overlapping features, or "identical elements," between the learning and transfer situations remain an important aspect of current psychological theories. However, contemporary views of transfer have been very much shaped by the computational metaphor of cognition that emerged during the "cognitive revolution" of the 1960s (see Gardner, 1987), and much of the psychological research on transfer has become tightly linked with symbolic cognitive approaches, particularly with theories

Correspondence should be addressed to Samuel B. Day, Department of Psychology, Susquehanna University, 514 University Avenue, Selinsgrove, PA 17870. E-mail: days@susqu.edu

of analogical reasoning (e.g., Gentner, 1983; Hummel & Holyoak, 1997, 2003). It is therefore worth spending some time reviewing some of the assumptions of these approaches.

According to traditional cognitive approaches, knowledge is represented in terms of systems of discrete symbols, each of which corresponds to a meaningful concept (see Markman, 1999). To meaningfully represent a situation, these mental symbols are combined according to a structured syntax that defines the relationships between the constituent concepts. As an example of the critical role that relations play in knowledge representation, the situation described by the sentence "John loves Mary" reflects a different set of relationships than the situation described by "Mary loves John," although both are made up of the same three constituent symbols (*John*, *Mary*, and *loves*). This capacity to productively reconfigure the same set of symbols into many distinct structures is one of the primary benefits of the symbolic approach, and it provides a very straightforward way of capturing the power of the human cognitive system (Fodor & Pylyshyn, 1988).

These assumptions, that concepts are represented in a way that is psychologically discrete and allows for flexible recombination, have important consequences for cognition. Most important for our purposes, they imply that the *structure* of a situation may be understood and processed independently of the particular objects and features that are involved. For example, consider the following situation: *John loves Mary, but Mary loves David, causing John to be jealous of David*. The symbolic approach allows us to easily generate new situations involving a completely new cast of characters while maintaining the same underlying system of relationships—for example, *Susan loves Mark, but Mark loves Gretchen, causing Susan to be jealous of Gretchen*. Furthermore, this approach allows for the possibility of understanding the system of relations independent of *any* specific characters, that is, holding an abstract representation of a "love triangle."

According to traditional cognitive approaches, it is this capacity to represent systems of relations independently of the objects and features that they bind together, which underlies our ability to reason analogically (see Gentner, 1983). An analogy is simply a match between the systems of relations in two represented situations (their "deep structure"), regardless of any differences in the objects and features they involve (their "surface features"). An individual's recognition of this similarity relies on a mapping process, in which structurally based correspondences between the situations are identified (e.g., in the aforementioned examples, John and Susan would correspond to each other as a result of their shared role of "jealous unrequited lover"). This mapping process may then support *analogical inference*, the generation of some new potential knowledge on the basis of these structural commonalities. For example, when confronted with a situation in which Nick loves Melanie but Melanie loves Greg, one might use prior knowledge to reasonably conclude that Nick will be jealous of Greg.

Traditional approaches to knowledge transfer fundamentally rely on this symbolic conception of analogical processing. For example, a student may learn a formula for mathematical permutations in the context of a problem involving pizza toppings (e.g., Ross, 1984), and subsequently encounter a new permutations problem that describes the assignment of people to teams. To effectively make use of the information from the first problem, the student must recognize the structural commonalities between the two cases, despite their overt surface differences, and use his or her understanding of the correspondences to correctly assign values to the variables in the formula. Although there is some variation in the theoretical approaches taken by different researchers (e.g., Gentner, 1983; Hummel & Holyoak, 2003; Keane, Ledgeway, & Duff, 1994), psychologists have widely adopted the view that transfer is the recruitment of previously known, structured symbolic representations in the service of understanding and making inferences about new, structurally similar cases.

Surface Similarity

Over the last several decades, the traditional view of transfer has been a fertile source of research and has greatly expanded our understanding of the conditions under which transfer is likely (and unlikely) to occur. By far the most robust finding involves the influence of the concrete surface similarities between cases. Although psychologists view structural similarity as the critical component in meaningful, productive knowledge transfer, research has repeatedly shown that it is the surface commonalities between cases that are more often the driving force in determining whether transfer actually occurs (e.g., Anderson, Farrell, & Sauers, 1984; Holyoak & Koh, 1987; Reed, 1987; Ross, 1987; Salomon & Perkins, 1989; Singley & Anderson, 1989). When a new case differs in its surface characteristics from a previously learned analogous case, spontaneous transfer is typically quite poor (e.g., Gick & Holyoak, 1980, 1983; Simon & Hayes, 1976; Weisberg, DiCamillo, & Phillips, 1978).

In general, the greatest cognitive difficulty seems to be in simply noticing that a new case is structurally similar to a previously known one. For instance, Gentner, Ratterman, and Forbus (1993) found that although structural commonalities predicted the degree to which participants found an analogy to be "apt" or inferentially sound, these abstract similarities were very unlikely to produce reminding on their own. In contrast, surface commonalities between two cases led to frequent remindings, even though participants explicitly recognized their limited benefit.

Probably the best known (and most cited and replicated) example of this type of recognition failure is the work of Gick and Holyoak (1980, 1983), based on Duncker's (1945) classic "radiation problem." In that problem, individuals are told about a patient with an inoperable tumor in his stomach. There is a kind of ray that could be used to treat the patient, but at intensities sufficient to destroy the tumor, a great deal of healthy tissue would also be destroyed. At lower intensities, the ray would be harmless to healthy tissue but would not affect the tumor. Individuals are asked to propose a solution that could destroy the tumor while also leaving healthy tissue intact. The intended solution involves a convergence approach, in which several low intensity rays are administered from different locations but converge at the site of the tumor, creating a greater aggregate intensity there. Participants have a very difficult time solving this problem independently. Furthermore, preceding the problem with a relevant analogous example—for instance, a story about soldiers simultaneously converging on a fortress—did little to improve performance (Gick & Holyoak, 1980, 1983). However, when the demands for spontaneous reminding were removed from the task by giving participants an explicit cue to consider the relevance of a previously learned situation (e.g., "the story you read earlier might be relevant in solving this problem"), transfer rates were dramatically higher (also see Catrambone & Holyoak, 1989; Reed, Dempster & Ettinger, 1985).

In the absence of such hints, however, recognition failures can be surprisingly robust. In one striking example, Anolli, Antonietti, Crisafulli, and Cantoia (2001) interrupted participants during their attempts to solve Duncker's radiation problem, asked them to answer a relevant question about the previously seen, analogous problem, and then allowed them to continue working on the test problem. Despite this seemingly extreme manipulation, successful transfer occurred only rarely (5–10% of the time) and was no better than a control condition in which no analogous prior problem had been given.

As previously discussed, in the symbolic view of analogical processing, reminding is only the first step in achieving transfer. To make accurate inferences between the cases, after reminding occurs individuals must perform a mapping between the two representations to determine structural correspondences. There is evidence that surface similarity can have an important influence during this phase as well. High surface similarity between entities in the same role (e.g., entities that would be represented by the same variable in a mathematical formula) tends to facilitate transfer, even when reminding is not a factor (Ross, 1987, 1989). This can be contrasted with cases of "cross-mapping," in which two situations share similar entities, but these entities play *different* roles within their respective systems. For example, after studying a problem in which various cars are assigned to mechanics, an individual may be asked to solve a new problem in which mechanics are assigned to cars. Under these conditions, the concrete commonalities between the situations may improve reminding (Ross, 1989), but the added difficulty required in *ignoring* the surface similarities between entities during the mapping process (because *cars* in the study problem does not correspond to *cars* in the transfer problem) generally leads to poorer overall performance than when cross-mapping does not occur (Gentner & Toupin, 1986; Ross, 1987, 1989).

In general, however, more attention has been given to the role of surface content on reminding than on mapping, and, in fact, these kinds of effects may be seen as an example of the broader influence of encoding specificity (Tulving & Thomson, 1973) on memory and knowledge application. Indeed, Barnett and Ceci (2002) have developed a fairly comprehensive taxonomy of the many ways in which learning and transfer situations may differ from one another. These included factors such as physical context, temporal context, functional context, social context and modality, in addition to the content of the materials themselves. The authors suggested several areas for future research to fill gaps in our knowledge about the effects and interactions between these factors, but also noted many existing studies in which differences along these dimensions negatively influenced transfer. For instance, Spencer and Weisberg (1986, again using a version of Duncker's radiation problem) found that even small changes in the context of the learning and testing episodes (one was described as an experiment, the other as a classroom exercise) eliminated all evidence of transfer, even though the physical context (the classroom) remained constant and the delay between tasks was only a few minutes.

Likewise, there is evidence that the similarity between the kinds of cognitive processing used during learning and testing may influence the likelihood of transfer. For instance, researchers have examined people's ability to solve brief insight puzzles, such as, "A man in the U.S. married 20 different women in the same town. All of them are still living and he has never divorced one of them, yet he has broken no law. Can you explain?" Surprisingly, providing participants with highly relevant information immediately prior to the test phase (e.g., reading the sentence "A minister marries several people each week.") has no impact on their ability to correctly solve the problems (Perfetto, Bransford, & Franks, 1983). However, when this prior information is presented in a way that mirrors the likely "confusion-resolution" processing involved in the test puzzles—such as, "You can marry several people each week . . . if you are minister"—transfer rates increase considerably (Adams et al., 1988; Lockhart, Lamon, & Gick, 1988).

The literature thus provides a strong and consistent picture of the role of similarity in transfer. Structural similarity represents the actual basis for meaningful knowledge transfer, and people are aware of, and sensitive to, this fact (e.g., Gentner et al., 1993). In practice, however, contextual similarity between the situations themselves seems to play a much larger role in determining whether transfer will actually occur.

Discerning Deep Structure

The role of surface similarity in transfer represents a very serious issue for educators. Educational curricula contain an enormous number of concepts that students are expected to master, each of which reflects (directly or indirectly) some knowledge or skill that is presumed to be of value outside of the classroom. The literature on similarity and transfer suggests that students may often fail to recognize the relevance of these ideas when they are confronted with analogous situations in the real world, particularly when the specific concrete details of those situations do not closely match those presented by teachers. However, the sheer breadth and volume of the material to be learned, combined with limited class time, means that this will typically not be the case. Teachers will never be able to anticipate and address most of the contexts in which important concepts could be applicable. Furthermore, even if this were possible, research suggests that students would encounter difficulties simply because of changes to the learning context itself: Information learned in the classroom is often unlikely to be accessed and applied outside of the classroom (e.g., Spencer & Weisberg, 1986). Findings such as these seem to call into question the entire enterprise of formal education.

However, the research discussed earlier also points to some reasons for hope. Researchers found that when information was encoded in a way that made it more accessible during the test phase—for instance, by matching the kinds of cognitive processes that were likely to be engaged (Adams et al., 1988; Lockhart et al., 1988)—transfer was much more likely to occur. More broadly, there has been a considerable amount of research looking at the ways in which specific aspects of the mental representations that learners initially form may help (or hinder) their ability to generalize their knowledge in new contexts.

Most frequently, these efforts have involved seeking ways to emphasize the structural aspects of the learned representations while deemphasizing contextual features that are irrelevant to that structure. Sometimes this has been accomplished very directly. For instance, after giving children a story to read, Ann Brown and her colleagues (A. L. Brown, Kane, & Echols, 1986) asked them a few questions emphasizing relevant aspects of its underlying goal structure, such as the protagonist, the goal, and the obstacle to be overcome. Under these conditions, children were more than 3 times as likely to spontaneously suggest the relevant strategy when solving a new problem. The researchers also found that the children who had emphasized these structural aspects of the story on their own, without the leading questions, were similarly quite likely to transfer the solution (also see Gick & Holyoak, 1983).

Another straightforward way to emphasize structural features during learning is through explicit labeling. For example, Catrambone (1996, 1998) found that labeling the subgoals involved in a complex mathematical procedure helped students accurately understand the important structural aspects of a new problem, and thereby transfer the solution more effectively. This result held even when the label was not inherently meaningful. Labeling has proven particularly effective in research with younger children (e.g., Kotovsky & Gentner, 1996; Loewenstein & Gentner, 2005). For instance, preschool-aged children were better able to recognize and take advantage of structural commonalities between two physical models when the spatial locations of one of the models were meaningfully labeled (e.g., *in*, *on*, *under*; Loewenstein & Gentner, 2005). For adults as well, labels that emphasize structural relations can promote transfer to new situations that are structurally similar (Son, Doumas, & Goldstone, 2010).

Perhaps the most obvious way of deemphasizing the superficial, context-specific aspects of a situation is by simply reducing their presence in the training materials. Evidence suggests that this can also be an effective strategy. For instance, the "seductive details" effect (e.g., Garner, Gillingham, & White, 1989) occurs in situations where interesting but structurally irrelevant information distracts learners from the important concepts to be acquired. Harp and Mayer (1997) found that recall and transfer from a scientific passage dropped precipitously when interesting but tangential text or illustrations were included (also see Garner, Brown, Sanders, & Menke, 1992; Garner et al., 1989; Harp & Mayer, 1998; Hidi & Baird, 1988; Wade, 1992). Similarly, Mayer, Griffith, Jurkowitz, and Rothman (2008) reported studies in which interesting extraneous information significantly impaired transfer while leaving retention largely intact. Based on these results, the authors argued that even if the added extraneous material is engaging, the net benefit for learning may be negative due to interference with the deep cognitive processing necessary for the construction of generalizable knowledge structures.

The presence of completely extraneous information seems to represent a clear impediment to learning and transfer. A potentially more insidious issue, however, involves contextual content that is inherently relevant to the training materials. For instance, an instructor may present the concept of *positive feedback systems* through a specific contextualized example, such as the effects of polar melting on global warming. In this case, the concrete details of the situation—the sun, the ice, the reflected light—may still interfere with a learner's ability to transfer their knowledge to new contexts, even though they promote comprehension of the example. Researchers have had some success in facilitating mapping and transfer between situations by simply reducing the "richness" of the content in the training materials (e.g., Clement, Mawby, & Giles, 1994; DeLoache, 1995; Goldstone, Medin, & Gentner, 1991; Goldstone & Sakamoto, 2003; Markman & Gentner, 1993; Rattermann & Gentner, 1998). For example, Goldstone and Sakamoto (2003) taught participants about the principle of *competitive specialization* in the context of ants foraging for food. When a computer simulation of the system portrayed these ants as dots rather than realistic drawings, participants were better able to transfer their knowledge to a new, superficially dissimilar instantiation of the same principle. Clement and colleagues (1994) found a similar pattern with text materials that used domain-general or domain-specific words. For instance, a domain-general version of one of the scenarios described a political candidate who *stole* ideas and *incorporated* them into his speeches; in the domain-specific version, the candidate was described as *plagiarizing* ideas and *typing* them into his speeches, terms which are much more specific in their applicability. Participants in these studies were far more likely to recognize and retrieve structurally similar cases when their relationships were described in more domain-general rather than domain-specific terms.

In work with young children, DeLoache (e.g., 1991, 1995; DeLoache & Burns, 1994) has consistently found evidence that salient concrete details in a learning experience can impair knowledge transfer, even between situations that are seemingly very similar. In one of her standard experimental paradigms, children watch a miniature item being hidden in a small model of a room (e.g., a miniature toy might be hidden under a miniature bed) and are then asked to find the matching item in the corresponding location of a matching full-sized room (a real toy under a real bed). Younger children have a surprisingly difficult time with this task. However, their success or failure can be influenced by the subjective concreteness of the learning case. For instance, they are more successful when the initial model is a two-dimensional image rather than a three-dimensional scaled model. Similarly, it was found that children were better able to transfer their knowledge from a scaled model when it was seen behind a plexiglass window, but transfer was impaired when they were allowed to interact and play with the scaled items prior to using the model to find the corresponding items in the full-sized room. DeLoache argued that these effects reflect the difficulty of representing something both as a physical object and as a symbol for something else and that this issue is exacerbated when the concrete physicality of the object is emphasized.

As some of these examples demonstrate, the notion of concreteness is not necessarily equivalent to the objective "quantity" of perceptual features. Perhaps the broadest and most applicable way of construing concreteness is in terms of the amount of information that a representation conveys to a particular individual (e.g., Kaminski & Sloutsky, 2011). For instance, a simple line drawing of a cat would contain less information than a photograph of a cat, and would therefore be a less concrete representation. Important to note, this conception of concreteness can reflect more than just the information inherent to the materials themselves. For instance, a picture of one's *own* cat could be considered even more concrete, in that it evokes a great deal of previously existing knowledge. Along these lines, Kaminski, Sloutsky, and Heckler (2008) taught students about the *modulo* 3 operation, using either symbols representing a familiar, well-structured context (e.g., line drawings of measuring cups) or more generic symbols without any relevant preexisting associations. The generic symbols led to much greater transfer to a new context, whereas performance by the concrete training group did not differ from chance. Similarly, Son and Goldstone (2009) reported that participants' ability to transfer the principles of signal detection theory was impaired when the protagonist of the scenario was a well-known fictional television character rather than an anonymous doctor. Activation of specific, preexisting knowledge appears to have negative consequences for transfer similar to the hindrance for transfer caused by overt contextual detail.

There is therefore a broad range of evidence that reducing the concrete content of a learning experience can aid in an individual's ability to apply their knowledge to new, dissimilar situations. Taken to its natural conclusion, this pattern suggests that the ideal learning materials would be those that eliminate such information altogether. For instance, mathematical ideas could be taught entirely in terms of numbers, variables, and formulae, or a principle such as "positive feedback loop" could be conveyed in terms of abstract relationships and processes (e.g., "A system in which changes to a variable result in additional changes to that variable in the same direction"). However, evidence suggests that this is generally an ineffective approach. Although completely abstract materials can present information in a way that is both efficient and maximally general, it seems to do so at the expense of comprehensibility (e.g., Bruner, 1966; Carraher, Carraher, & Schliemann, 1987; see Nathan, 2012, for a related argument).

In one clear example of the issues associated with complete abstraction, researchers (LeFevre & Dixon, 1986) provided participants with both explicit written instructions for a task and a worked example. For some participants, however, these two sources of instruction were in conflict and reflected entirely different tasks that would lead to different correct responses. Under these conditions, more than 90% of the participants ignored the verbal instructions and instead followed the example of the worked concrete problem. Work by Ross (1987) suggests a similar phenomenon. In his study, participants learned about a particular mathematical procedure in the context of a specific, concrete example. During a later test, individuals were provided with the correct formula needed to solve a new analogous problem. Nevertheless, performance was significantly affected by the details of the example that had been seen earlier (also see Anderson et al., 1984). A similar pattern has been observed in perceptual classification tasks. Even when people know a simple, clear-cut rule for a classification, performance is better on frequently presented, compared to rare, examples (Allen & Brooks, 1991).

A recent study by McNeil and her colleagues (McNeil, Uttal, Jarvin, & Sternberg, 2009) captures the complexity of the issue of concreteness in learning. Students in that study were less successful in solving word problems about money when the task involved interaction with actual physical bills and coins than when it did not. However, the concreteness of the physical money seemed to convey some important advantages as well. Analysis of students' work showed that those who used the perceptually rich money were less likely to make conceptual errors (i.e., they were more likely to attempt the correct mathematical operations), suggesting that the concreteness helped them to comprehend the overall structure of scenarios. Similarly, in a recent study exploring the tradeoffs between contextually grounded versus abstract (equation-based) representations, Koedinger, Alibali, and Nathan (2008) found that for simple problems, grounded word problems were solved better, but for complex problems, equations were solved more accurately. In both of these studies, the real-world contextualization provides useful checks and constraints that prevent certain kinds of mistakes, but this same contextualization can interfere with transfer to new, complex situations.

Combining Concreteness and Abstraction

The research on concreteness in learning and transfer presents researchers with some confounding issues. On one hand, presenting information via concrete examples may lead to mental representations that are overly "bound" to a particular context and may interfere with a person's ability both to recognize new situations where their knowledge could be relevant and to apply their knowledge in an appropriate way. On the other hand, efforts to circumvent these problems by presenting information abstractly, with minimal specific context, may seriously impair the learner's ability to accurately represent the information at all. Educators may, reasonably, feel faced with the unappealing task of choosing between comprehensibility and applicability.

Of course, these extremes do not represent the only possibilities, and researchers have given serious attention to finding ways to leverage the benefits of both concreteness and abstraction. For instance, Goldstone and Son (2005) conducted a study in which a previously unfamiliar scientific principle (competitive specialization) was taught through two interactive computer simulations, each of which could be either relatively concrete or relatively idealized. They found that participants showed superior performance on learning and transfer after interacting with one concrete and one idealized version of the simulation, relative to participants who had interacted with two simulations of the same type. This advantage was especially pronounced under conditions of "concreteness fading," in which a concrete simulation was followed by one that was less perceptually rich. Scheiter, Gerjets, and Shuh (2010) replicated and extended this finding. In their study, a computer simulation demonstrated a continuous morphing between very concrete and more abstract visual representations. For example, an initial display of realistically rendered trees became progressively less detailed, until they were ultimately transformed into small green squares, which were then combined into larger contiguous groupings that made the relative proportions of different types of trees very salient. This approach (which simultaneously used both rich and idealized representations and facilitated cognitive mapping between the two types) led to reliable gains in transfer.

One of the most investigated—and apparently most effective—ways of overcoming the limitations of specific concrete examples is by comparing multiple dissimilar cases. This approach can allow a learner to encode the content in terms of meaningful, comprehensible situations, but then to distill the structurally relevant information on the basis of commonalities across the examples. In particular, there is evidence that the act of mapping the correspondences between two situations (i.e., identifying which entities play the same respective roles) can serve to highlight the structural content. For example, Loewenstein, Thompson, and Gentner (2003) conducted research with management (MBA) students enrolled in a course on negotiation. Some of the students compared two specific cases involving a "contingency contract," a useful but sometimes counterintuitive negotiation technique. Other students received the same two cases but read and analyzed them sequentially, without any explicit comparison. Later, all students took part in a face-to-face bargaining exercise in which the use of a contingency contract represented the optimal approach. Students who had compared cases were nearly 3 times as likely to apply this principle to the new case as those who had analyzed the cases separately. In fact, the latter group performed no better on the transfer task than those who had received no training on the contingency principle at all. Results from many other studies across a variety of contexts are consistent with the idea that comparison and mapping between dissimilar cases facilitates structural processing (e.g., Catrambone & Holyoak, 1989; Christie & Gentner, 2010; Cummins, 1992; Gentner, Loewenstein, Thompson, & Forbus, 2009; Gick & Holyoak, 1983; Richland & McDonough, 2010). In one example from a real-world educational setting, Richland and McDonough (2010) found that explicitly cuing the meaningful commonalities between two math problems—for example, by visually presenting both examples at once and gesturing between corresponding aspects of them—improved students' ability to transfer to new cross-mapped cases.

Research on this approach has typically involved explicit, directed comparison between cases, but there is also evidence that multiple examples may provide a benefit under less directed conditions as well. Quilici and Mayer (2002) taught students about statistical tests (*t* test, chi-square, correlation) by sequentially presenting a set of examples that systematically varied surface and structural properties. Specifically, students read examples describing *t* tests in three different concrete contexts, followed by examples of chi-square tests in the *same* three contexts, followed by the same for correlation problems. Although participants in this study were not explicitly asked to map between the cases, the structure of the problem presentation invited at least informal comparison. Consistent with this, transfer rates were reliably higher relative to other study structures.

Ross and Kennedy (1990) also examined the effects of nondirected comparison. Specifically, when participants in their study used a previous example to solve a new problem (as a result of spontaneous reminding), they then showed superior performance on *subsequent* problems of that type. This is consistent with the idea that the initial reminding and application involved a comparison and mapping process that helped to create a stronger structural representation. The authors suggest that this kind of "unsupervised" comparison reflects a natural and realistic way in which generalizable knowledge could develop in the real world, particularly given that in many domains, surface, and structural characteristics tend to be correlated (e.g., Gentner, 1989; Lewis & Anderson, 1985; Mayer, 1981). Finally, as discussed earlier, research has found that explicit labeling can be beneficial in highlighting structural commonalities between situations (e.g., Catrambone, 1998). Some researchers have argued that these labels are effective because they invite spontaneous comparison (e.g., Kotovsky & Gentner, 1996; Namy & Gentner, 2002), and there is some recent evidence to support this interpretation (Son et al., 2010).

Despite a growing body of evidence for the benefits of comparison, however, the results are not uniformly positive. For example, Reed (1989) found that comparing two algebra problems did not improve performance on new problems. Catrambone and Holyoak (1989) found that although comparison helped transfer in the short term, these benefits disappeared after short delays or changes in context (although longer term transfer could be facilitated through more intensive, experimenter-directed comparisons). In one recent study (Mayer, DeLeeuw, & Ayres, 2007), exposure to multiple cases was actually found to impair transfer. Participants in that study learned about the design and function of hydraulic brake systems, and some of those participants also saw descriptions of other types of brake systems (air and caliper brakes). The researchers found that those who had learned about multiple systems performed worse on tests of both retention and transfer than those who had only learned about one. One possible explanation for this disadvantage is that the transfer questions in this study all involved inferences about hydraulic brakes themselves, not inferences based on any structural commonalities across the different systems. If true, this suggests that the benefits of generalizability associated with comparison may sometimes come at the expense of more specific kinds of knowledge.

Overall, however, research suggests that the comparison of multiple cases represents a particularly promising avenue for developing generalizable representations from concrete examples. There are still important questions about the optimal ways of organizing these comparisons, however, and much less evidence exists regarding the kinds of cases that should be compared. On one hand, a case could be made that comparing situations with very dissimilar surface features should lead to the best generalization. If comparison serves to highlight commonalities between cases while deemphasizing differences, comparing situations that share irrelevant features could result in those features being retained in a learner's mental representation (the idea of "conservative generalization"; Medin & Ross, 1989; Ross & Kennedy, 1990). This, in turn, could limit generalizability to new, dissimilar cases. Some research is consistent with this conclusion (e.g., Day, Goldstone, & Hills, 2010; Goldstone & Sakamoto, 2003; Halpern, Hansen, & Riefer, 1990; Rittle-Johnson & Star, 2009). For example, Halpern and colleagues (Halpern et al., 1990) asked students to read scientific passages that included either "near" (superficially similar) or "far" (superficially dissimilar) analogies. The passages including far analogies led to superior retention, inference, and transfer than those featuring superficially similar comparisons, which showed no benefit at all.

On the other hand, there are also good reasons to suggest that the comparison of more similar cases might be beneficial, particularly early in the learning process. As discussed earlier, the process of mapping two representations to find structural correspondences is facilitated when entities in similar roles are concretely similar. The less similar two situations are overall, the less likely it becomes that corresponding entities will share overt surface similarities, and thus the process of mapping itself becomes both more cognitively demanding and more prone to error (see Gentner, Loewenstein, & Hung, 2007). Together with the considerable evidence that cognitive demands represent a general impediment to learning (see Sweller, 1999), this suggests that there may be circumstances in which the comparison of concretely similar cases would lead to better transfer, and there is some evidence to support this idea. For instance, Kotovsky and Gentner (1996) found that although young children initially had a very difficult time recognizing and responding on the basis of structural similarities between perceptually dissimilar stimuli, they became reliably better at this task when they had first observed the structural commonality between overtly similar stimuli, a phenomenon termed "progressive alignment" (also see Genter et al., 2007; Loewenstein & Gentner, 2001).

Thus, there is some evidence for each of these two competing ideas—that transfer will benefit most from the comparison of similar and of dissimilar cases. One possible way to reconcile these findings is by suggesting that different kinds of learners may benefit from different kinds of comparisons. In the absence of other constraints, comparisons of dissimilar situations should be best, because they can serve to highlight only those features that are relevant to the broadest possible set of applicable cases. Of course, learning and cognition are inevitably subject to (often serious) constraints. When an individual's working memory capacity is more restricted, because of limited background knowledge, individual differences in ability, or both, the comparison of concretely similar cases may be preferable. In fact, some recent findings are consistent with this idea (Day et al., 2010; Rittle-Johnson, Star, & Durkin, 2009). If this reconciliation is correct, then a general recommendation for promoting transfer would be to present a principle using the most dissimilar cases that still allow a learner to compare the cases and recognize the basis for their similarity.

Prior Knowledge

Several lines of research have established that an individual's existing knowledge can provide a significant advantage in his or her ability to recognize and take advantage of deep structural content. One of the classic findings in this area comes from the work of Chi, Feltovich, and Glaser (1981) examining the differences between experts and nonexperts in the domain of physics. The researchers found that experts (advanced physics PhD students) overwhelmingly tended to group physics problems on the basis of the general principles underlying their solution (e.g., conservation of energy, Newton's second law). In contrast, relative novices (undergraduates who had just completed an introductory mechanics course) were much more likely to group problems by their concrete features (e.g., the presence of springs, inclined planes, pulleys, etc.). This general pattern, with experts using meaningful structural commonalities to assess similarity and novices using surface features, has been replicated in a wide range of domains. For instance, expert programmers tend to sort computer programs on the basis of their underlying algorithms, whereas novices are more likely to sort on the basis of application type (Weiser & Shertz, 1983). Similarly, trained musicians were found to group musical pieces exclusively by similarities in their melodic and harmonic structure, whereas nonmusicians had a strong bias to group them by similarities in instrumentation (Wolpert, 1990). Likewise, when expert and novice subjects were asked to solve the Tower of Hanoi puzzle and judge the similarity between the goal and various states, experts' judgments were more likely to be based on the number of moves required to transform one position to the other, rather than number of shared superficial features (Suzuki, Ohnishi, & Shigemasu, 1992). Although most of this research has examined individuals that are already experts in their field, similar effects can be induced experimentally through training. For example, Schoenfeld and Hermann (1982) found that students were more likely to sort mathematical problems on the basis of their underlying structure after an intensive training course on mathematical problem solving.

Important for our purposes, these expertise differences appear to have a strong influence on the likelihood of spontaneous analogical reminding and use. For example, Novick (1988) found that students with greater expertise in mathematics (as assessed by scores on the mathematical section of the SAT) were much more likely to make use of previously seen problems that were analogous but overtly dissimilar to a new test problem. In contrast, the nonexpert students were more likely to be influenced (negatively) by remindings of prior problems with surface commonalities (also see Ball, Ormerod, & Morley, 2004; Gentner et al., 2009).

Of course, experts are not completely immune to the influence of surface features (e.g., Blessing & Ross, 1996; Hardiman, Dufresne, & Mestre, 1989). In fact, in some circumstances, experts' greater knowledge and experience can leave them susceptible to new kinds of surface influences. For instance, Blessing and Ross (1996) asked experienced math students to solve story problems that varied in both their surface features (the cover story of the problem) and their underlying structure (the formula necessary to solve them correctly). According to prior research, one might predict that these experts would have learned simply to ignore the irrelevant contextual information and focus solely on the abstract relationships within each problem. However, these students' prior experience had provided them with additional relevant information: that certain kinds of mathematical problems tend to be presented in certain kinds of contexts. The researchers found that students' performance was impaired when the problems involved content that was typically associated with a different type of solution formula (also see Bassok, Wu, & Olseth, 1995; Hinsley, Hayes, & Simon, 1978).

Overall, however, expertise provides significant advantages for transfer. There are many factors that might contribute to this fact. Experts may have simply had more practice construing situations in terms of the abstractions that are relevant to their field. For instance, physicists are likely to be quite good at thinking about specific problems in terms of abstract objects and forces. Because of this, their mental representations of two problems that involve the same underlying principles are likely to be fairly similar, which would facilitate both reminding and mapping. One of the most important factors in experts' transfer, as we discuss in the next section, is that their rich background knowledge allows them to overcome limitations in working memory.

Cognitive Load and Task Difficulty

Potentially the greatest constraint on learning in general, and therefore on transfer, is the severe cognitive restriction on the amount of information that can be processed at any one time. Research on working memory (see Baddeley, 2000; Baddeley & Hitch, 1974) has provided a wealth of evidence that individuals are only capable of keeping a handful of units of information active simultaneously and are able to actively manipulate even fewer. Furthermore, this kind of knowledge is typically very short-lived. In the absence of active rehearsal, information tends to remain active for only a few seconds.

These facts are especially relevant for transfer because there are reasons to suspect that structural knowledge in particular could be disproportionately influenced by such restrictions. In general, learners need to represent the individual entities in a situation before they are able to represent the relationships between those constituent parts (e.g., Goldstone & Medin, 1994). This suggests that when an individual has limited resources to devote to a set of facts—perhaps because new content in a lecture is displacing it quickly—it is the representation of the relational structure that is most likely to suffer (see Halford, Wilson, &

Phillips, 1998). Similarly, this limited capacity means that learners have fewer opportunities to elaborate on the new information by generating new inferences, making connections to existing knowledge, and developing more general schemas from the information (e.g., Sweller, 1994). Given this, limitations in cognitive capacity could lead to serious difficulties in both recognizing and making use of analogous structures.

There is empirical evidence to support this idea. Waltz and colleagues (Waltz, Lau, Grewal, & Holyoak, 2000) examined people's ability to recognize structural commonalities between pairs of visual scenes, each of which portrayed various people and objects interacting in some way. For example, one picture showed a woman receiving groceries from a man from a food bank, while the paired picture showed the same woman giving food to a squirrel (see Figure 1). In this and all of the pairs, one of the entities was "cross-mapped" between the images—for example, the woman in the first picture corresponded to the woman in second picture on the basis of their similar physical appearance, but she corresponded to the squirrel in terms of their shared role as "recipient of food" (see Markman & Gentner, 1993). The question of interest was which of these alternatives participants would select

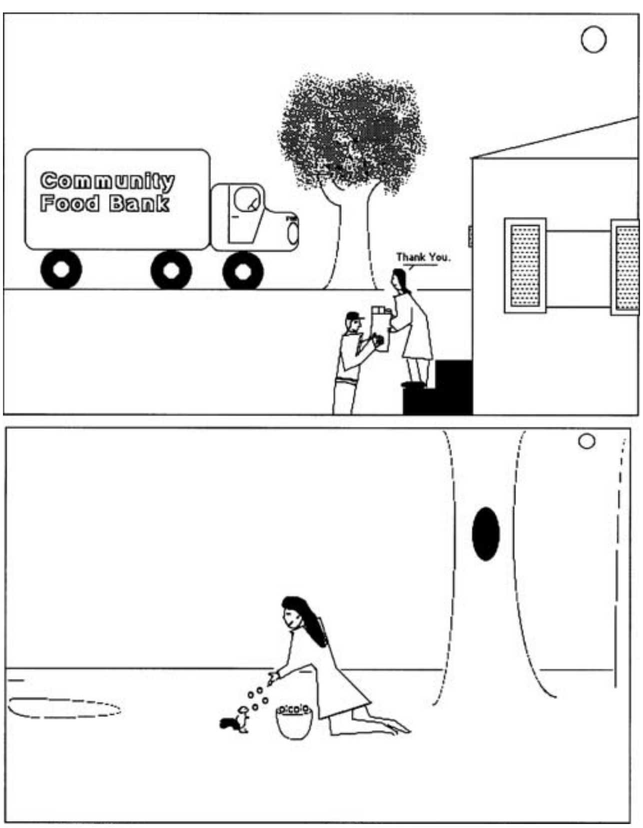

FIGURE 1 Sample stimuli used by Waltz et al. (2000). From "Structural alignment during similarity comparisons," by A. B. Markman and D. Gentner, 1993, *Cognitive Psychology, 25,* p. 436. Copyright 1993 by Elsevier. Reprinted with permission.

when asked which entity corresponded to the first woman. Under normal conditions, the relational match (the squirrel) and the perceptual match (the woman) were chosen about equally often. However, when participants were put under a cognitive load during the task—for example, by asking them to maintain a string of digits in memory—they were far more likely to ignore the structural features and prefer the perceptually similar match. Similar results have been found from manipulations that deplete working memory capacity indirectly, such as inducing anxiety in participants (Tohill & Holyoak, 2000).

Because of the critical role that working memory constraints play in learning and transfer, researchers have been very interested in determining effective ways of managing processing demands during learning. *Cognitive load theory* (CLT; Sweller, van Merrienboer, & Paas, 1998), which distinguishes between different kinds of cognitive demands based on their relevance to learning, has provided a productive framework for examining these issues. For example, several studies have reported superior learning and transfer after students had been shown several worked examples (see Renkl, 2005; Renkl & Atkinson, 2010). This *worked-example effect* is typically explained in terms of learners having the opportunity to develop meaningful schemas without having unnecessary demands placed on their cognitive processing. Other research has shown that learning can benefit from manipulations such as removing irrelevant, distracting content (e.g., Garner et al., 1989), using cues to direct attention to relevant content (e.g., Lorch, 1989; Mautone & Mayer, 2001), allowing learners to pace their own training in order allow sufficient processing time (e.g., Lusk et al., 2009; Mayer & Chandler, 2001), and "pretraining" students on relevant subcomponents of a system prior to the complete training phase (e.g., Mayer, Mathias, & Wetzell, 2002; Pollock, Chandler, & Sweller, 2002).

CLT also takes into consideration the fact that auditory and visual working memory systems appear to be relatively independent (e.g., Baddeley, 1986; Paivio, 1990). That is, a heavy processing demand from one kind of information (e.g., auditory or verbal content) typically does not significantly interfere with processing for a different kind of information (e.g., visual content). Because of this, it is often possible to more effectively balance the information load between these two subsystems. For instance, Mayer and colleagues report several studies in which the presentation of visual material that was accompanied by oral narration led to better learning and transfer than the simultaneous presentation of visual material and text (e.g., Mayer & Moreno, 1998; Moreno & Mayer, 1999; Moreno, Mayer, Spires, & Lester, 2001). In this case, presenting the visual and verbal content in different modalities avoids overloading a single system. Other studies have found benefits associated with aligning images and text spatially (e.g., Hegarty & Just, 1989; Moreno & Mayer, 1999) and synchronizing their presentation temporally (e.g., Mayer & Anderson, 1991, 1992; Mayer & Sims, 1994), both of which should reduce the length of time that information must be maintained in working memory.

In all of these examples, the degree to which learners' working memory is taxed has an important influence on their ability to acquire new knowledge, and particularly their ability to develop knowledge structures that can generalize to new situations. In fact, constraints on cognitive processing almost certainly play a role in many of the transfer effects that have already been discussed. For example, both the facilitation observed in analogical mapping between similar objects and the impairment associated with "cross-mapping" entities to dissimilar roles (e.g., Gentner & Toupin, 1986; Ross, 1987, 1989) are likely to reflect the relative difficulty of maintaining similar versus dissimilar correspondences in working memory. Likewise, the labeling of relational structures (e.g., Catrambone, 1996, 1998) may be beneficial in part because it serves to reduce cognitive demands by grouping and thereby simplifying the information to be stored and processed.

One of the clearest examples of the role of processing constraints on transfer is in the differences between experts and novices. Specifically, expertise seems to involve specialized kinds of processes and representations that allow an individual to efficiently work around these severe cognitive constraints. A considerable amount of evidence supports the idea that proficiency in a content domain is not associated with improved storage or processing capacity per se. Rather, individuals are able to become much more *efficient* at processing information through the acquisition of long-term knowledge structures. Through the process of *chunking*, experts may reduce very large quantities of information into a much smaller number of representational units. For instance, although a novice looking at a chessboard in mid-game is confronted with an overwhelming amount of information, chess experts are able to quickly recognize and classify large groups of pieces into a small number of meaningful structures (e.g., Chase & Simon, 1973; de Groot, 1966). Important for our purposes, chunked knowledge structures such as these do not only allow individuals to encode content far more quickly and remember configurations much more effectively. They also serve as a kind of classification which enables experts to associate appropriate procedures and strategies with different kinds of complex situations. For example, a physics expert may classify diverse problems into structurally meaningful categories (e.g., Chi et al., 1981) that highlight relevant relationships and suggest specific kinds of solutions.

Although there are many clear examples of benefits from reducing the cognitive demand associated with learning, the story is made somewhat more complex by the seemingly contradictory evidence for the benefits of cognitive difficulty. "Desirable difficulties" (Bjork, 1994) are aspects of a learning situation that make immediate learning and encoding more difficult but that also enhance long-term retention and retrieval. Although such effects have typically been examined in terms of basic information recall, several studies suggest that certain kinds of difficulties during training may enhance transfer as well. For instance, Kornell and Bjork (2008) showed participants several examples of paintings from each of 12 different artists and then looked at the participants' ability to generalize their knowledge by recognizing new paintings by those artists. Participants overwhelming preferred conditions in which the paintings by any particular artist were grouped together consecutively, and believed that this presentation improved their test performance. In reality, however, the more challenging "spaced" presentation, in which paintings by each artist were presented "interleaved" with those of other painters, led to reliably better generalization.

In a more typical problem-solving transfer test, Chen and Mo (2004) found that although greater variability in training examples led to slower, more difficult learning, it also left participants better equipped to generalize their knowledge to new transfer problems. Similarly, researchers have found that participants' ability to transfer a solution to an insight problem was improved when the source problem was presented in a way that made structural relationships within the problem *less* salient, and therefore more difficult to encode (Didierjean & Nogry, 2004; Gick & McGarry, 1992). In all of these cases, the introduction of difficulty during training improved later transfer performance.

The recommendations from CLT and Desirable Difficulties are, on the face of it, conflicting, and each has its share of empirical support. One possible reconciliation of these conflicting results is that introducing difficulties into learning can confer benefits for transfer so long as solid learning is nonetheless achieved. Reminiscent of Nietzsche's aphorism "What does not destroy me, makes me strong," the recommendation would be to introduce learning challenges that do not completely derail learning. Adaptive learning technologies that adjust the difficulties of materials while learning is ongoing represent a promising way of implementing this recommendation.

Types of Processing and Strategic Approaches

All of the effects discussed thus far have related to influences outside of the learner's immediate control—features inherent in the learning materials and situations themselves, or knowledge that individuals bring from their prior experience. However, transfer can also be affected by a variety of online factors, reflecting different kinds of processing used during encoding or transfer.

Surprisingly little evidence exists regarding one of the most direct potential processing influences—namely, whether individuals can be in a cognitive state that causes them to interpret things more or less relationally in general. In one of the few studies on this question (Bliznashki & Kokinov, 2010), researchers recently reported evidence that engaging in one task that requires relational construal of information can prime participants to interpret subsequent situations more relationally. Specifically, after attempting several items from the Raven Progressive Matrices test, which involves solving visual analogies based on structural relationships between a series of diagrams, participants were more likely to judge the similarities between new scenes based on structural rather than featural information. Relatedly, in research with young children, A. L. Brown and Kane (1988) found that 3- and 4-year-old participants seemed to "learn to learn," quickly developing a mind-set to look for relational similarities between cases after previous exposure to other analogous situations. However, much work remains to be done on this fundamental issue.

Another way in which learners may influence their own encoding is in terms of the specific goals with which they approach a given task. A great deal of research over the past two decades has examined the influence of achievement goals on learning, primarily in terms of *mastery* versus *performance* goals (see Ames, 1992). Although mastery goals relate to basic competence, with the aim of personal learning and improvement, performance goals relate to success on the immediate task, particularly in terms of demonstrating one's ability relative to others. These competing goal types have been shown to have a significant impact on learning in general (see Elliot, 1999; Pintrich, 2000), with mastery goals being associated with greater engagement and long-term success, as well as correlating well with a variety of factors beneficial to learning, such as persistence and the adoption of appropriate cognitive strategies. Recent research has revealed similar effects on knowledge transfer more specifically. For instance, Bereby-Meyer, Moran, and Unger-Aviram (2004) put groups of participants into a negotiation task and examined their ability to maximize their gains through the use of mutually beneficial strategies. Some participants were given instructions that emphasized immediate performance and the minimization of errors, whereas others received instructions that emphasized content mastery. All participants' performance improved on subsequent versions of similar tasks. However, when participants transferred their knowledge to a new scenario in which important conditions and details were changed, those in the performance-oriented condition performed no better than a control group, whereas those who had been given mastery-oriented instructions improved reliably. Other research has extended this finding to situations in which such achievement orientations were primed at the time of transfer rather than during initial learning (Bereby-Meyer & Kaplan, 2005). Similar results have been found by simply varying the specificity of learners' goals during training (Vollmeyer, Burns, & Holyoak, 1996). When participants in that study were provided with a specific goal to achieve in the training phase, immediate performance was good. However, transfer to a task with a new goal was reliably poorer than for participants who had freely explored during training without any specific goal.

Finally, there is evidence that individuals may vary greatly in the quantity and quality of explanations that they spontaneously generate when studying examples and that these differences can have an important influence on their ability to learn and transfer from studied materials. Influential research by Chi and colleagues (Chi, Bassok, Lewis, Reimann, & Glaser, 1989) found that students who self-explained well—explaining and justifying steps in an example problem, and considering goals, consequences, and the relationships between subsequent actions—were far more successful at solving later transfer problems. Renkl (1997) replicated and expanded on these findings, reporting large effects of self-explanation even when controlling for time on task, and distinguishing between several qualitatively different types of explanation styles, which he found to be quite stable within individuals across situations. This *self-explanation effect* seems to benefit learning via multiple routes, both by supplementing the presented information through the generation of relevant inferences and by helping learners to recognize and correct disparities between their own mental models and the ones suggested by the examples (see Chi, 2000).

Following on these correlational results, researchers have had some success in improving transfer by eliciting self-explanations from learners, particularly in combination with other favorable learning conditions. For instance, Renkl, Stark, Gruber, and Mandl (1998) used multiple worked examples to teach participants about compound interest calculation and found that participants who had been trained to generate appropriate self-explanations (through the observation of good self-explanation, followed by practice with feedback and coaching) exhibited reliably better transfer performance. In another study (Atkinson, Renkl, & Merrill, 2003), researchers found that transfer following training through a "fading" procedure, in which worked-out steps were successively removed from training examples, was improved when participants were prompted for self-explanations at each step of the training problems.

Challenges to the Traditional View

Although the traditional approach to transfer has generated an enormous body of research, it has also come under an increasing amount of criticism. Many of the basic themes of this criticism are captured by the influential work of Lave (1988), who lays out several interrelated points of concern. Most fundamentally, she questions the model of knowledge representation that underlies (explicitly or implicitly) the basic cognitivist approach. Traditional psychological research tends to view knowledge as a stable mental entity, which under the right conditions may be brought forth and applied to new situations. For example, a student may learn a general rule for applying the distributive property to a mathematical formula. When confronted with a problem in which this method would be appropriate, the student may retrieve this existing knowledge structure and apply it to the new problem. Although there are many ways in which this process could break down—a failure to successfully retrieve the existing knowledge, an inaccurate mapping between the known method and the new situation—the relevant knowledge itself is typically treated as a discrete, reified entity. In fact, the very word "transfer" seems to reflect this assumption—that a discrete piece of knowledge is being "carried over" intact from one context to another.

Lave (1988) presented a very different view of knowledge, both in terms of acquisition and use. In this view, all knowledge is a by-product of participation in particular situations and is very much tied to those specific contexts. Because of this, the most traditional kind of knowledge transfer between dissimilar cases is simply not possible, because there is no knowledge that is in a sufficiently abstracted form to be applicable across highly variable contexts. Rather, new knowledge is constructed in the course of understanding and participating in new situations, a process generally referred to as "situated learning." (As Greeno, 1997, p. 12, noted, however, Lave does not explicitly say that far transfer cannot occur, but that there are serious concerns about the underlying theory on which this assumption is based.)

In particular, Lave and colleagues emphasized the social and interactive nature of learning, observing that learning typically takes place in "communities of practice," or groups of people who interact in the service of shared interests and goals. For example, when Lave and Wenger (1991) analyzed the process of learning within several different communities of shared interest (e.g., Yucatan midwives, apprentice tailors, members of Alcoholics Anonymous), they found a general pattern in which newcomers to a group gradually acquired knowledge from more experienced members as an incidental by-product of group participation. Apprentice tailors, for instance, typically begin their careers by performing a number of seemingly trivial tasks—running errands, preparing the tailor's materials and workspace at the beginning of each day, adding finishing details to garments that the tailor has completed—that serve to familiarize the novice with the framework of fundamental knowledge of that community. The apprentice's responsibilities gradually progress "backward" to cutting and sewing jobs, and this progress "can be arranged and interrelated in ways that gradually transform that skeletal understanding" (p. 96).

In addition to questioning the established views of what constitutes learning, Lave also took issue with many practical aspects of the experimental research on transfer. For instance, transfer research is typically designed to measure participants' application of one particular principle or strategy, which is chosen or designed by experts whose knowledge may be quite different from that of the learners. In so doing, most transfer studies prioritize expert knowledge while overlooking or disregarding the relationships that novice participants find relevant. As an example, Lave cited a study (Williamson, Hollan, & Stevens, 1983) that describes an individual attempting to understand and make predictions about a heat exchange mechanism (a system in which cool fluids are used to reduce the temperature of hotter fluids). Over the course of answering questions about this system, the individual generated multiple, distinct models of its operation. New questions allowed the learner to recognize flaws in his previous models, and in trying to integrate and coordinate these different models, he both improved his models and furthered his overall understanding of the system. Lave argued that traditional studies of learning and transfer that are based solely on matches to experimenter-generated "normative" models and solutions would have failed to capture this individual's learning and knowledge.

Lave also noted that the most common experimental design for assessing transfer involves training with a single artificially constructed example, followed by measurement of that example's influence on a single subsequent case (which has been judged analogous by an expert). This "two-problem" design seems to severely restrict the scope of what prior knowledge a participant can meaningfully bring to bear on a new situation.

These critiques have resonated with many researchers interested in learning and education and have been adapted and expanded upon in various ways, both in terms of theory and application. For example, Carreher and Schliemann (2002) argued that the idea of transfer itself represents a theory rather than an actual phenomenon to be investigated or explained. Furthermore, they believe it is a theory that is largely incompatible with existing empirical findings, and one which should therefore be abandoned. In reviewing the literature, and in their own studies examining fifth-grade students' acquisition of the concept of negative numbers, they found little evidence for any of the passive "carrying over" of knowledge between cases that the transfer metaphor implies. Instead, in-depth interviews with their student participants suggested that they were "drawing upon a broad history of experience regarding numbers, general arithmetical operations, money, notation and diagrams, and so forth" (p. 19), and integrating and adapting that diverse knowledge during the online processes of comprehension and learning. Thus, they argued that existing knowledge is often altered to accommodate new information. Schwartz, Chase, and Bransford (2012/this issue) describe this process as seeing the new in the old—interpreting previous situations in new ways. In contrast, traditional views of knowledge transfer seem to allow only the assimilation of new information into static existing knowledge structures—seeing the old in the new.

Other researchers are more open to the value of traditional transfer research, while still agreeing with many of Lave's specific concerns. Lobato and her colleagues (e.g., Lobato, 2012/this issue; Lobato & Seibert, 2002) have done work addressing two of the major issues raised by Lave—the emphasis in transfer research on conforming to expert knowledge, and the reliance on simple "two problem" transfer designs. In her work, Lobato has performed in-depth analyses of verbal protocols collected from students over the course of several days of training. Through these analyses, she has been able to identify ways in which students' understandings during training are reflected and adapted during later transfer episodes. In this way, her research allows a much richer picture of what information is being drawn upon during application, and also highlights how that knowledge may develop gradually throughout learning experiences.

In one example (Lobato & Seibert, 2002), a student was observed and interviewed while learning about slope, ratios, and proportionality. In analyzing those protocols, the researchers found evidence that an approach discovered by the student in an earlier session (partitioning a particular rise/run "unit," which could then be iterated any number of times) was brought to bear on a later problem in a very different context. However, this use did not appear to reflect a straightforward importing of a previous piece of knowledge. Rather, the interview suggested an extended process that required both a reinterpretation of the new problem and an adaptation of the original knowledge.

James Greeno and his colleagues (e.g., Greeno, Smith, & Moore, 1993) offered a reconceptualization of transfer that is related to, but somewhat distinct from, Lave's. Greeno interpreted transfer on the basis of the *affordances* (Gibson, 1977) that a situation offers—in other words, the ways in which an agent may meaningfully interact with a situation. When similar affordances are shared across different situations, there is a possibility for transfer to occur.

As an example, Greeno examined Judd's (1908; replicated by Hendrickson & Schroeder, 1941) classic study in which participants practiced hitting an underwater target with a dart or an air rifle. Some of those participants received an explanation of light refraction and how it could lead to deceptive perceptions of the target's location. Although all participants performed equally well on the initial task, those who had received the additional instruction performed much better on a transfer task in which the depth of the target was changed. Greeno suggested that success on this task depends on attending to the affordances of the situation that are invariant across the contexts—namely, the relative angle of the apparent path of the projectile after hitting the water—rather than attending to any of the other means of adjusting one's aim that would not be invariant across contexts. According to this interpretation, those participants who had received information about refraction were more attuned to the relevant, task-invariant affordances, and thus more likely to interact with the modified version appropriately.

As this example highlights, for Greeno these affordances do not reflect a quality of the external situation itself, but rather a relationship between the situation and the agent who is acting upon it. Greeno argued that just as the idea of motion reflects a relationship between an object and a point of reference, so too does cognition necessarily depend on a relationship between an agent and a context. It is therefore incorrect to treat context as simply an influence on cognition—by his interpretation, the very idea of cognition without context is meaningless.

One of the most influential reconsiderations of learning and transfer is through the idea of *preparation for future learning* (e.g., Bransford & Schwartz, 1999; Schwartz & Martin, 2004). Several decades ago, educational philosopher Harry Broudy (1977) suggested three different ways in which knowledge could be manifested in an individual: replicative knowledge ("knowing that" something is true), applicative knowledge ("knowing how" to accomplish some task), and interpretive knowledge ("knowing with" some existing knowledge). Although traditional tests of transfer have looked extensively at the first two ways of understanding, they have largely ignored the third—the ways in which our prior experience shapes our *interpretations* of new information (see Schwartz, Bransford, & Sears, 2005). Through this kind of application, specific prior knowledge serves as a *lens* for the construal of new content rather than being the direct *focus* of cognition itself. Consistent with the themes of recent transfer critiques, research has demonstrated powerful interpretive effects of knowledge that would have been overlooked by more conventional measures. For instance, most transfer studies involve a simple manipulation during the study phase (e.g., viewing a relevant analog vs. viewing an unrelated control example), followed by an assessment of this manipulation's effect on a transfer task (e.g., solving a problem). In contrast, Schwartz and Martin (2004) designed a "double-transfer paradigm," in which some participants received additional training between the study and test phases.

In one of their studies, ninth-grade algebra students learned about standardized scores, which allow comparison of individual values across groups with different averages and variabilities (e.g., how does one performance on the high jump compare to another performance on the long jump?). One group of students began by attempting to invent a way of standardizing scores on their own, whereas another group was shown an intuitive way of visually understanding standardization, which they then practiced themselves. The researchers found no difference between the groups in terms of direct transfer to transfer problems given immediately after the manipulation. Typically, this would be interpreted to mean that the manipulation had no effect. However, the study involved an additional manipulation: Prior to testing, half of the students in each group were given additional training on the conventional method of calculating standardized scores. It is important to note that this training was identical for the two conditions. The researchers found that for these students, the initial condition *did* influence transfer performance. Specifically, those students who began by trying to invent their own procedure and *then* received more formal training performed markedly better than the other three groups, whose performance was essentially identical. Apparently, the initial manipulation influenced the way in which individuals were able to *learn* from the supplemental training.

In general, mainstream psychologists have not responded to (or even acknowledged) the critiques from education researchers. In the most prominent direct response, Anderson, Reder, and Simon (1996, 1997) disputed the general claims of situated learning on empirical grounds, pointing to evidence that transfer is possible even across situations that are concretely very dissimilar. Others have complained that the arguments presented by Lave and others are largely untestable and unfalsifiable. However, some of the research and ideas from mainstream psychologists are at least consistent with the points raised by situated thinkers.

For instance, many transfer researchers have discussed an adaptation or "re-representation" phase in transfer, during which one or both of the representations involved is altered to make analogical mapping more consistent (e.g., Clement, 1988; Gentner & Colhoun, 2010; Holyoak, Novick, & Melz, 1994; Keane, 1996). For example, when Clement (1988) analyzed protocols collected during physics problem solving, he found that individuals often transformed or modified prior cases in order make them applicable to new problems. Furthermore, he reported that problem solving often involved the generation of *Gedanken* experiments, or novel, artificially constructed thought experiments. Such mental constructions would clearly not involve transferring knowledge from a specific prior case but would instead require learners to draw on and adapt multiple sources of experience.

Consistent with this last point, several studies have examined transfer from "real-world" episodes outside of any experimental context, helping to address issues with the standard "two problem" design. For example, Dunbar (2001) used an "in vivo" approach, in which he recorded weekly meetings from biology laboratories. In analyzing these discussions, he discovered numerous examples of scientists drawing on outside analogies to help them formulate new theories, design experiments, and explain new ideas to one another (also see Ball et al., 2004; Bearman, Ball, & Ormerod, 2007; Christensen & Schunn, 2007). Other research has looked at individuals' ability to retrieve autobiographical examples that are structurally similar to new experimentally presented cases. For instance, Chen, Mo, and Honomichl (2004) found evidence that people were likely to spontaneously retrieve and use relevant folk tales in order to solve new analogous problems. Similarly, Gentner et al. (2009) found that just as comparison of multiple cases can improve transfer to new situations, it can also facilitate retrieval of previously known, structurally similar episodes, including autobiographical memories from an individual's own past.

Traditional cognitive approaches have generally considered analogical reasoning to be a very active, deliberative process in which two situations are explicitly mapped to one another. This characterization is difficult to reconcile with arguments for the importance of "knowing with," or using prior knowledge as an interpretive lens for understanding new situations. However, there is some evidence for less deliberative, more implicit forms of analogical transfer. For instance, Schunn and Dunbar (1996) presented participants with a simulated biochemistry problem that required a strategy of *inhibition* in order to be solved (other participants were given a problem with a different solution strategy). On a molecular genetics problem the following day, these participants were better able to generate the correct inhibition-based solution. Despite this transfer, however, the participants appeared to be unaware of the relationship between the two problems and did not mention the earlier simulation in their verbal protocols or in a questionnaire given after the transfer task. Other recent studies have reported similar effects, even when participants were explicitly asked about the relationship between the training and transfer tasks (e.g., Day & Gentner, 2007; Day & Goldstone, 2011; also see Gross & Greene, 2007). Kostic and colleagues (Kostic, Cleary, Severin, & Miller, 2010) found further evidence for this phenomenon, showing a dissociation between familiarity and recall for previously seen analogical relationships. Participants in that study often knew that they had seen a structurally similar example earlier in the session, even when they could not explicitly remember the content of that example. This further suggests the likelihood of situations in which the structure of prior experiences may influence later processing without requiring explicit analogical mapping between specific cases.

The critiques of the traditional view of transfer present serious challenges to mainstream transfer research. By pointing out potential problems with the models on which such research is based, such critiques seem to call into question the very foundations and justification for this extensive body of literature, not to mention its findings. On the other hand, it is often not clear to psychologists how these criticisms can be addressed within a straightforward experimental framework. Contemporary researchers are making progress in bridging this apparent divide, however. The work on preparation for future learning and Lobato's approach of iterating explicit manipulations with in-depth qualitative analysis provide prime examples of taking these issues seriously while simultaneously maintaining scientific rigor. And as discussed earlier, research by mainstream psychologists is increasingly producing findings that bear on these issues, whether or not that is their explicit goal. The extent to which the critiques of Lave and others will ever be satisfactorily addressed is of course an open question, but examples such as these provide reason for optimism.

PERCEPTION, COGNITION, AND TRANSFER

Taken as a whole, a review of the literature on transfer provides a story of challenges and frustrations, but also reasons for hope. In one way or another, each of the articles in this special issue draws creatively on broad swaths of this literature—including recent critiques—in order to advance our understanding of how we can best foster generalizable knowledge. In this section, we would like to propose our own suggestion for reconceptualizing transfer, which is, ironically enough, to shift transfer from an abstract, high-level conceptualization to perception–action processes. Specifically, we believe the evidence suggests that perceptual learning and perceptual processes provide a critical foundation for both knowledge representation and knowledge use, and that we can leverage this fact in order to facilitate learning and transfer.

This proposed connection is by no means new. For instance, in their seminal work on expertise and problem solving, Chase and Simon (1973) asserted that "it is no mistake of language for the chess master to say that he 'sees' the right move; and it is for good reason that students of complex problem solving are interested in perceptual processes" (p. 56). Later in his career, Herb Simon (2000) maintained that "an audience of scientists will very likely agree that thinking doesn't always (or maybe not even usually) use the medium of words," and that often, "seeing is the most efficient way of reasoning" (pp. 119–120). This idea has also intrigued education researchers. For instance, the views of J. S. Brown, Collins, and Duguid (1989) on situated cognition assume a primary role for perception in knowledge acquisition and use. However, both the interest and the empirical evidence for a relationship between perception and cognition have been expanding rapidly in recent years, and a more thorough consideration seems warranted. There are at least two productive ways in which one can draw connections between perception and cognition. The first, weaker connection is in the terms of the general *kinds* of characteristics that are typically associated with each type of processing; the second, stronger potential connection is the suggestion that cognition may rely on perceptual processes and representations in a very literal way.

Relative to most views of how cognition operates, perceptual processes tend to be very fast, to occur automatically without conscious deliberation, and to rely largely on pattern-matching with respect to existing representations. This, of course, is not to say that perception is either simple or content-free. In fact, the efficiency and subjective ease of perceptual experience belies both the complexity and the flexibility of the processes involved. Some of this efficiency may derive from the availability of general, possibly innate organizing principles, such as those suggested by the Gestaltists (e.g., Metzger, 1936; Wertheimer, 1938) or more recently by developmental psychologists such as Spelke (1990) and Baillargeon (1987). However, perception is also strongly influenced by prior experience. For instance, expertise in a given domain is often accompanied by a kind of perceptual "tuning" that leaves the individual more sensitive to perceptual features and patterns that are relevant to their field (see Gauthier, Tarr, & Bub, 2010). Such gradual adaptation is consistent with other kinds of "nondeliberate" learning, such as the acquisition of procedural knowledge and automaticity (e.g., Shiffrin & Schneider, 1977). However, lasting changes in perceptual interpretations can also result from much briefer experiences. A classic example of this is the well-known "young woman/old woman" illusion (Boring, 1930), an ambiguous drawing which can be interpreted as either a relatively young or very old woman. Leeper (1935) found that preceding the viewing of this image with an unambiguous version of the drawing, which was not open to alternative construals, overwhelmingly biased participants' subsequent interpretation of the ambiguous figure. Similarly, DeSchepper and Treisman (1996) found that a single exposure to an abstract figure influenced individuals' perception for several weeks, even when they demonstrated no conscious recognition for that figure. In one dramatic demonstration of this type of effect, individuals exhibited facilitated recognition for picture fragments after a single, brief exposure during an initial study conducted 17 years earlier (Mitchell, 2006). Participants in the follow-up experiment frequently reported having no memory for the previous study itself, much less for the specific items.

There are clear parallels between these kinds of perceptual effects and the idea of "knowing with," in which prior conceptual knowledge is used to interpret new situations. In fact, one recent study (Day & Gentner, 2007) represents a fairly straightforward replication of the young woman/old woman demonstration with conceptual materials (narrative passages). In this study, participants' interpretations of an ambiguous passage were strongly influenced by an unambiguous analogous passage they had recently read, with two different versions of the first passage leading to two different interpretations of the subsequent passage. As in the perceptual task, the structure of a recent stimulus served to guide the interpretation of a new case, although in this instance it was conceptual, relational structure that was being affected. Also paralleling the young woman/old woman demonstration, this influence did not appear to be deliberate or effortful. When participants were asked afterward, they reported that the ambiguous target passage had been completely understandable on its own and that they had not referred to any prior passages in trying to understand the new one. As in the perceptual task, participants in this study not only were unaware of the influence of the first stimulus on the second but also appeared to be unaware of the ambiguity in the second case altogether. Consistent with the concept of *knowing with*, the earlier scenario was not an explicit focus of attention but rather provided a framework through which new incoming information could be structured (also see Day & Goldstone, 2011, discussed next).

However, there are reasons to suggest an even stronger, more direct connection between perceptual and conceptual processes. Specifically, we would suggest that a considerable amount of cognitive activity—even those aspects which seems relatively "abstract"— relies on mental representations that are perceptually and spatially concrete. As such, the relationship between our conceptual and perceptual processes and representations could be considered a very literal one. For example, individuals are reliably faster when responding to smaller numbers with their left hands and to larger numbers with their right hands, a phenomenon known as the "SNARC" effect (Dehaene, Bossini, & Giraux, 1993). Follow-ups and extensions to this study strongly suggest that these individuals are relying on a spatial mental representation such as a number line when performing the seemingly abstract task of assessing magnitude.

Some of the most extensive evidence for the role of perceptual representations in cognition comes from research on mental models. Such models provide a simplified spatial and mechanical representation of a situation, allowing individuals to reason about relationships within a system and about consequences of different possible actions. In a recent review, Hegarty (2004) discussed a considerable body of evidence supporting the use of such analog spatial models in a variety of mechanical reasoning tasks. For instance, the ability to solve simple mechanical problems is highly correlated with independent measures of spatial ability but not measures of verbal ability (e.g., Hegarty & Sims, 1994). Similarly, such problems experience more disruptive interference from a simultaneous secondary task that involves visuospatial working memory than from one involving verbal working memory (e.g., Sims & Hegarty, 1997). Studies have also found patterns of reaction times for such problems that are consistent with reliance on an analog mental simulation (e.g., Schwartz & Black, 1996). Such phenomena are not limited to mechanical problem solving situations, of course. For instance, research on text processing has repeatedly found evidence for the construction of mental "situation models" in the course of comprehending text passages (see Zwaan & Radvansky, 1998). Through the use of such models, readers are able to quickly and automatically infer the physical affordances of the entities described in text (e.g., Glenberg & Robertson, 2000). In fact, there is evidence that reading comprehension may actually be fostered by asking individuals to "act out" written passages with physical objects (Glenberg, Gutierrez, Levin, Japuntich, & Kaschak, 2004).

Mental models can also play an important role beyond such literal approximations of real-world situations. Individuals may also use models that are only analogically or metaphorically similar to novel cases. For example, Gentner and Gentner (1983) reported that learners were very likely to understand concepts related to electrical currents in terms of mental models of flowing water or moving crowds of people. Similarly, Johnson-Laird and colleagues have reported extensive evidence that seemingly very abstract types of logical reasoning are often performed through the use of analog, perceptually-concrete mental representations (see Johnson-Laird, 2006).

The role of perceptual representations in comprehension and reasoning suggests that such content may be important in transfer as well, and there is a growing body of evidence that this is the case. Some of the earliest evidence involved problems that were inherently and literally spatial in nature. For instance, Dreistadt (1969) reported that individuals were better able to solve a spatial insight problem (e.g., "organize 10 items into five rows of exactly 4 items each") when a perceptual image that was relevant to the solution (e.g., a star) was present as an incidental feature of the environment. The author reported anecdotally that participants were largely unaware of this influence on their reasoning. In an even earlier example, Maier (1931) reported that participants were much more likely to solve the "two-string" insight problem after witnessing the researcher "accidentally" brush against one of the strings and cause it to swing (a crucial component of the solution). Again, this influence was reported to occur largely outside of conscious awareness.

Recently, we (Day & Goldstone, 2011) examined the possibility of achieving "far" transfer through similar means. Specifically, we hypothesized that because knowledge transfer appears to be contingent on the psychological (rather than objective) similarity between two situations, and because individuals often seem to represent complex situations through simplified, concrete mental models, it is possible that transfer could occur between cases that appear quite dissimilar on the surface but are in fact represented similarly.

In our study, participants began by interacting with a computer simulation of a ball that was suspended between two elastic bands, and oscillated horizontally between them (see Figure 2). In addition, there was a fan located to the left of this system that could blow rightward across it, adding an additional force in that direction. Participants were given the goal of using the fan to cause the ball to either (a) stop in the middle between the two poles connected to the ball by the bands or (b) reach the far right-hand side of the system. In either case, the goal could be accomplished by coordinating one's actions with the inherent frequency of the ball's oscillations. For instance, by applying the rightward force from the fan only when the ball was traveling leftward, and not when it was traveling rightward, the amplitude of the ball's oscillations could quickly be reduced and the ball would eventually stop in the middle of the system. (The alternate goal required the opposite strategy, applying force from the fan only when the ball was moving rightward.) Next, participants moved on to a second, seemingly unrelated task that was quite dissimilar to the ball simulation in a number of important ways. First, rather than being a perceptually rich simulation of moving, interacting parts, the second task was entirely text based. Furthermore, although the ball task displayed actions and interactions unfolding in real time, this task progressed in discrete time steps, controlled by the users' button presses. Finally, the domain itself was quite dissimilar: The second simulation involved managing the population of a city. Specifically, some participants were assigned the goal of stabilizing the city's population at 500,000, whereas other participants attempted to reach a population of 1,000,000. To achieve these goals, participants decided whether or not to invest in media advertisement for the city at each time step, which would inject a temporary positive "force" on the population level.

Despite the numerous overt differences between the first and second simulation, they were in fact governed by the same underlying dynamics. Both involved oscillatory motion (of the ball or the population) that could be manipulated

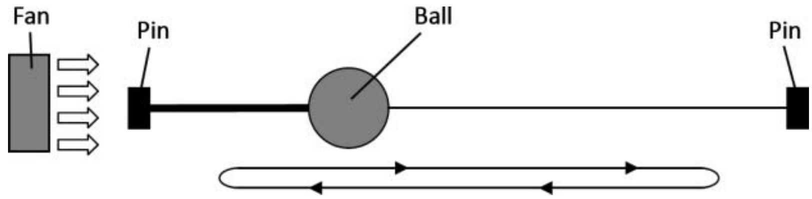

FIGURE 2 Schematic of the ball simulation used by Day and Goldstone. From “Analogical Transfer From a Simulated Physical System,” by S. B. Day and R. L. Goldstone, 2011, *Journal of Experimental Psychology: Learning, Memory, and Cognition, 37*, p. 553. Copyright 2011 by the American Psychological Association. Reprinted with permission.

by a force in one direction, to either stabilize or maximize the relevant value (ball location or population size). Likewise, the appropriate methods for achieving these goals were completely analogous between the two tasks. We predicted, and found, that participants would achieve the goal in the second task more quickly when it was structurally similar to the goal they were assigned in the previous simulation (e.g., both goals involved either stabilization or maximization). Of interest, participants in our study were unlikely to report noticing the relationship between the tasks, and such noticing was not related to more successful transfer.

We argue that, although the two situations are quite dissimilar from one another on the surface, the physical dynamics of the ball and fan simulation provided a useful mental model for representing the (less overtly spatial) population task. Consistent with this interpretation, when the order of the tasks was reversed (with the more decontextualized population task presented first), no evidence for transfer was observed. In other words, the overtly perceptual and spatial nature of the training task appeared to be critical for this kind of transfer to occur.

Other research is consistent with our general conclusions. For example, Beveridge and Parkins (1987) used a concrete perceptual model to improve performance on a Duncker’s (1945) radiation problem. As noted earlier, previous research has shown that participants have a very difficult time solving this problem independently and are unlikely to make spontaneous use of relevant analogous examples (Gick & Holyoak, 1980, 1983). However, Beveridge and Parkins found that participants were much more likely to transfer their knowledge successfully when they had previously been shown a physical model that captured the relevant “convergence” structure of the problem. Specifically, they were shown a set of colored transparent strips of plastic that fanned out from a central location, where they overlapped. These strips demonstrated a darker, “stronger” color in that central location, analogous to the greater summed intensity of the converging rays in the radiation problem. Similar results have been obtained after showing an animated diagram depicting moving lines of arrows converging at a central point (Pedone, Hummel, & Holyoak, 2001).

Grant and Spivey (2003), also using Duncker’s radiation problem, demonstrated the important role of online perceptual processing in understanding and transferring knowledge. Those researchers tracked participants’ eye movements while viewing a simple diagram of the described of the situation, with parts labeled *tumor*, *healthy tissue*, *skin*, and *outside*. They found that individuals who successfully solved the problem had spent considerably more time looking at the *skin* area of the diagram, and suggested that this pattern reflected more eye movements crossing the skin boundary while looking between the inside and outside of the body. In other words, successful problem solvers’ eye movements were effectively “acting out” the convergence pattern. Thomas and Lleras (2007, 2009a) subsequently reported achieving similar effects through experimental manipulation. Participants in their studies were more likely to solve the radiation problem after performing a visual task that guided their eye movements (2007) and/or visual attention (2009a) in a convergence pattern on the diagram, alternating between various locations inside and outside the body.

Such perceptual effects on thinking are not limited to visual representations. In fact, a large body of research on “embodied” cognition (see Barsalou, 1999; Glenberg, 1997; Wilson, 2002) has focused on the important relationship between physical action and thought. For example, the “action compatibility effect” (Glenberg & Kaschak, 2002) refers to the fact that individuals’ speed at judging the sensibility of a sentence is influenced by the physical action involved in their response. For instance, participants take longer to confirm that “close the drawer” is a sensible phrase when their response involves a motion toward their own bodies (which is incompatible with the motion required to actually close a drawer). Similarly, Goldin-Meadow and colleagues (see Goldin-Meadow, 2005) have repeatedly demonstrated the importance of gesture in learning and comprehension and have even shown that experimental manipulations of individuals’ gesturing can help or hinder their learning (e.g., Cook, Mitchell, & Goldin-Meadow, 2008). Effects such as these suggest the possibility of similar embodied effects on problem solving and transfer, and there is some preliminary evidence for this. For instance, just as acting out a passage with physical objects can lead to greater comprehension (Glenberg et al., 2004), Catrambone, Craig, and Nersessian (2006) found that acting out an analog to Duncker’s radiation problem with wooden blocks increased the likelihood of transferring the convergence solution. In a different kind of paradigm, Thomas and Lleras (2009b) found that participants were better able to solve Maier's two-string problem after performing an exercise which involved swinging their arms, although most participants remained unaware of this effect.

It is important to note, however, that most of the effects described in this section would not necessarily arise from "raw" perceptual representations, containing only information about form, location, color, and so forth. Rather, our explanation assumes that these mental models are integrated representations of both perceptual and meaningful conceptual content. Thinking back to the ball and fan simulation, for example, it is clear that a model based on this simulation would need to include information about properties such as "force" to be effective, properties that are not directly perceivable themselves but must be inferred from the visible components. Furthermore, that particular example requires additional conceptual content in order to assign meaningful directionality to the systems. That is, although the population task that follows it has an inherent positive direction, the ball task is horizontal, with neither direction explicitly "higher" or "lower" than the other. However, as discussed previously, there is evidence that individuals rely on a mental number line that automatically associates the rightward direction with increase. If this conceptual content were included in participants' mental models of the ball task, it would help to explain the mapping between our two simulations—in both cases, the participants' interventions would be perceived to provide a net positive force. Consistent with this interpretation, when we ran a follow-up study in which the direction of the fan was reversed, such that it was on the right-hand side blowing leftward across the ball system, no transfer to the population task was observed. A mapping that included this additional conceptual content appeared to be fundamental to the usefulness of the model.

This inherent integration of perceptual and conceptual content also highlights the fact that these mental models are not equivalent to actual perception. A recent study involving physics students (Thaden-Koch, Dufresne, & Mestre, 2006) demonstrated this distinction clearly. In that study, participants observed a simulation of two balls rolling along adjacent tracks. When one of the balls moved in an unrealistic manner—accelerating on an uphill portion of the track—honors physics students were *less* likely to notice this error than were physics novices. In this case, the physics students' (still-developing) knowledge about the principles operating in the simulation led them to ignore overt perceptual information in favor of their own expectations about the behavior that "should" occur. We would suggest that these students' observations may, in fact, be guided by models that are perceptual in that they involve dynamic and spatial representations. However, perceptually grounded models need not be veridical models, and they can possess systematic distortions. With systematic training, the students' perceptual expectations might be brought into better alignment with the real behavior of the rolling balls, with revisions to their underlying interpretations possibly resulting. Knowledge is both influencing, and is influenced by, perceptual interpretations.

Mathematics provides an interesting domain for examining the interplay between perception and cognition. On one hand, mathematics is, by definition, abstracted from any specific content domain. Ideas such as "three" or "multiplication" are by design theoretically unattached to any particular concrete instantiation. On the other hand, individuals (particularly experts) routinely report a subjectively strong perceptual component to their mathematical reasoning. Because of reports such as these, researchers have recently been giving more attention to the potential importance of perceptual representations and perceptual processing in mathematics. Most of the research conducted thus far has specifically examined the role of perception in the processing of external representations of mathematical concepts, such as equations or graphs.

For instance, Kellman and his colleagues (e.g., Kellman, Massey, & Son, 2009) created an interactive classification task that trained participants to recognize the relevant perceptual features underlying accurate transformations between representations (e.g., matching a graph to an equation). Individuals who completed that task were subsequently much more accurate in generating their own transformations between representations, a crucial step in successful problem solving. Similarly, David Landy and colleagues have focused on the role of perceptual processes in understanding and interacting with mathematical formulas. For instance, in practice, the perceptual grouping of terms (i.e., which terms are closer together in space on the page) can interfere with and even trump groupings based on operator precedence (e.g., grouping by multiplication before grouping by addition; Landy & Goldstone, 2007a, 2007b). On the other hand, experience with mathematical formulas can lead to the automatic deployment of attention to operators with higher priority (Landy, Jones, & Goldstone, 2008). People also appear to *interact* with equations in ways that seem concretely grounded. For instance, students may learn to use a strategy of transposition, or "moving" a term from one side of an equation to the other (and then applying the inverse operation). So, for example, the equation $5x + 7 = 12$ may be rewritten as $5x = 12 - 7$ by moving the 7 to the right. There is evidence that for experienced students, this operation is conceived in terms of actual spatial movement. Goldstone, Landy, and Son (2010) reported a study in which an equation was presented on a computer screen with a subtle moving grating in the background, and participants were asked to solve the equation for a particular variable. Performance was reliably worse when this grating was moving in the *opposite* direction of the implicated spatial transposition of the term—for instance, when a solution required "moving" a term rightward but the grating was moving to the left. This suggests that the grating's motion was interfering with participants' imagined spatial movements of terms within the equation.

Taken together, findings such as these provide a way of extending and enriching our understanding of traditional transfer phenomena while also addressing many of the concerns and critiques that have been raised against the standard cognitivist approach. For example, the suggestion that transfer is often a largely perceptual process is inherently consistent with the idea of "knowing with." Perception is by nature a process of interpretation, in which existing knowledge structures guide and constrain the organization of new incoming information. Many of the phenomena described in this section could best be explained in terms of providing a model by which new information may be structured and understood (e.g., Beveridge & Parkins, 1987; Day & Gentner, 2007; Day & Goldstone, 2011; Pedone et al., 2001). This differs in important ways from the more traditional account of transfer, which *begins* with the *recognition* of structural commonalities. Instead, perception and action routines can provide the basis for linking two situations, and once linked, more formal, more generalizable structures that are compatible with the linking can be constructed. This kind of mechanism may also underlie the advantage that Kotovsky and Gentner (1996) found for progressively removing perceptual support for connecting two structurally similar situations.

Consistent with construing existing knowledge as a "lens" rather than a focus of cognitive processing, the effects described here frequently appear to be implicit, often occurring without deliberation or even conscious awareness (e.g., Day & Gentner, 2007; Day & Goldstone, 2011; Dreistadt, 1969; Maier, 1931; Schunn & Dunbar, 1996; Thomas & Lleras, 2009b). The notion of perceptually grounded models underlying interpretation also provides a productive way of considering new means for promoting transfer. If transfer between overtly dissimilar situations is possible when those cases involve similar mental models (e.g., Day & Goldstone, 2011), transfer research may be most successful when it focuses on understanding underlying models used by novices and experts in a domain (see Lobato, 2012/this issue).

These ideas are consistent with the themes of several of the critiques, and they link particularly well with the ideas and research of Lobato, described earlier (e.g., Lobato & Seibert, 2002). The student described in that example appeared to be forming a model of slope and proportionality as a discrete, integrated unit that could be combined iteratively to fit different situations. Such a model would seem to lend itself to a fairly perceptual, spatial representation. Such a model would also be consistent with her general finding that prior knowledge was not imported wholesale in order to solve an analogous case, but rather that knowledge provided a means of working through and organizing new information—which allowed the original model to be simultaneously modified and adapted.

A perceptual interpretation of transfer is also consistent with the idea that knowledge is not typically transferred from a single source. The knowledge that underlies one's understanding of a concrete, analog system seems to exist in a variety of independent, sometimes conflicting pieces (e.g., Collins & Gentner, 1987; diSessa, 1982). To the extent that comprehension often involves interplay between new facts and existing knowledge working together to construct appropriate models (e.g., Clement, 1988), transfer may often draw on a lifetime of knowledge and experience. This fits well with the analysis by Carreher and Schliemann (2002) described previously. Students in their research were informed and influenced by knowledge from multiple domains at once, and their learning involved an active process of novel integration across those domains. Of course, this is not to say that such "interpretation"-based transfer invariably relies on multiple sources. As with literal perception, interpretation may also sometimes rely heavily on a single recent episode (e.g., Day & Gentner, 2007; Day & Goldstone, 2011, Schunn & Dunbar, 1996).

Our goal in this section has not been to suggest that perceptual representations are "the" basis for knowledge transfer, or that they supply an explanation for the many varied findings and phenomena reported in the transfer literature. Although such a conclusion would necessarily follow from the strongest claims that all of cognition is inherently perceptual (e.g., Barsalou, 1999), there is at present simply not enough empirical data to support this argument convincingly. Nor are we suggesting that the path to improved transfer is to make learning materials more "perceptual." In fact, there is considerable evidence discussed earlier in this paper that explicitly contradicts this conclusion. Rather, we would argue that acknowledging and leveraging learners' perceptual representations, particularly as they relate to mental models of learned material, is one important, effective, and largely unexplored means of supporting transfer.

CONCLUSIONS

In this article, we have tried to organize the diverse literature on knowledge transfer into a coherent whole. Obviously, however, these broad-ranging ideas and findings sometimes defy straightforward integration. For example, as researchers and educators continue to struggle with the challenges of helping students to achieve generalizable knowledge, it is clear that the critiques of the more traditional models of transfer will need to be taken seriously. It is also possible that by recognizing different approaches as being reflective of differing goals or levels of analysis, and by honestly considering both the advantages and weaknesses of different perspectives, it will prove to be the case that no single approach is sufficient to account for all aspects of transfer. However, as transfer researchers of all stripes continue to become more open and creative in their search for explanations and solutions, the development of theories and principles that are both very general and highly effective remains an enticing possibility. As the other articles in this special issue make clear, the coming decade promises to be a productive and exciting period for transfer research.

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