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LEARNING, INSTRUCTION, AND COGNITION

The Role of Initial Learning, Problem Features, Prior Knowledge, and Pattern Recognition on Transfer Success

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The purpose of this study was to demonstrate that transfer ability (positive and negative) varies depending on the nature of the problems, using the knowledge transfer matrix, as well as being dependent on the individual differences of the learner. A total of 178 participants from the United States and New Zealand completed measures of prior knowledge, pattern recognition, a positive transfer problem, and a negative transfer problem. Nearly 11% of participants could not successfully solve the base problem after the initial learning phase. The problem condition was a significant predictor of positive transfer success, while no significant differences were found for negative transfer, although, there was ample evidence of negative transfer. Furthermore, prior knowledge was only a significant predictor for problems in which the structural features between the problems were different. Future directions are discussed in regard to the initial learning phase, differences in transfer success, and the need for measures of negative transfer.

Keywords *positive transfer, negative transfer, analogical reasoning, prior knowledge, pattern recognition*

TRANSFER, THE PROCESS OF APPLYING what one knows or can do in one situation to a novel situation or varied task, has been a major emphasis in educational and cognitive

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psychology since E. L. Thorndike's (1913) *Psychology of Learning*. Since that time, numerous foundational studies of transfer have been published in an attempt to investigate the extent to which individuals are able to cognitively transfer (e.g., Gentner, 1983; Gick & Holyoak, 1980). The general premise of these studies is to understand when and how students use knowledge learned in one situation and apply it to another (i.e., transfer), and has been posited by some as essential to more efficient and effective learning (e.g., Alexander & Murphy, 1999; Schoenfeld, 1999). For example, for Piaget to be convinced that some prior learning had occurred, he specifically questioned whether generalization from prior learning to future thought was possible (Piaget, 1997/1964). Piaget stated specifically that, "What makes learning interesting is the possibility of transfer of a generalization," (Piaget, 1997/1964, p. 26).

However, others argue that research on transfer is either unneeded or needs to be culturally contextualized (e.g., Detterman, 1993; Lave, 1997). In the case of Lave (1997), she argued that functionalist experiments of transfer (problem-solving approaches that she terms *cognitive transfer*; e.g., Gick & Holyoak, 1980) have limited value because these experiments are dissociated from "socially situated activity" (p. 43), and furthermore, that the poor transfer success of the participants across a number of transfer studies she reviewed indicated that transfer achieved in these laboratory experiments was unlikely to generalize to other contexts. We disagree that poor transfer success in previous studies is an indicator of the usefulness of research on transfer. Instead, we contend that transfer success is dependent on individual differences of the learner (e.g., prior knowledge) as well as the features of the problem (e.g., superficial vs. structural features).

Further complicating the issue of transfer in the literature is the lack of commonality among researchers in how transfer is conceptualized and operationalized (Lobato, 2006; Loughlin, Dinsmore, Baggetta, Doyle, & Alexander, 2011). Recently, a review of studies in the educational psychology literature that examined transfer from 2003–2009 revealed that often there was *no* conceptual definition of transfer offered (Loughlin et al., 2011). Given this lack of clarity, it is no surprise then that there have been inconsistent findings on the relation between transfer and learning. (e.g., Butterfield & Nelson, 1991; Carraher & Schliemann, 2002).

This poor consensus in the literature on the nature of transfer can often create problems in that evidence for transfer (i.e., transfer success) in studies may not be equivalent. Several attempts have been made to bring clarity to the literature on transfer through the development of taxonomies or heuristics (e.g., Salomon & Perkins, 1989). For example, using Barnett and Ceci's (2002) taxonomy, a transfer study can be classified on the dimension of learned skill being transferred (e.g., procedure or principle) and on the knowledge domain (e.g., biology to botany or science to art). However, by their very nature, taxonomies typically only consider one dimension at a time. This linear treatment of transfer does not reflect the complex, multidimensional nature of learning (Alexander, Schallert, & Reynolds, 2009).

The purpose of the present study is fourfold. First, we aimed to empirically test different conceptions of transfer using a transfer matrix proposed by Loughlin and colleagues (2011). Here, we seek to demonstrate that transfer success depends on the transfer situation and that it is important that the nature of transfer differs from situation to situation in a multidimensional manner. This extends past research, which has typically only investigated one dimension of transfer (near vs. far), using a multidimensional framework (i.e., the Knowledge Transfer Matrix [KTM]) to simultaneously investigate two dimensions of transfer (i.e., near vs. far and surface vs. structural). Second, we aimed to examine the extent to which individuals' initial learning of the base problem (or lack thereof) may explain the relatively poor transfer rates in previous studies. Our intent here is to demonstrate that low rates of successful transfer may not be solely the result of an inability to transfer, but may also be the result of a failure to initially learn a concept. Third, we included a measure of negative transfer in the experiment. The purpose of including negative transfer in the design was to examine if not only whether individuals were able to apply the knowledge from the base task to target task, but could also recognize when this transfer was not appropriate. In other words, we aimed to extend what is meant by *transfer success*. Last, we investigated the role that individual cognitive differences may play in individuals' transfer performance (i.e., pattern recognition and prior knowledge) to extend our understanding of some of the precursors of transfer success. First, we turn to a discussion of our conceptualization of positive and negative transfer.

Positive and Negative Transfer

One surprising finding from the Loughlin and colleagues (2011) literature review was that only 2 of the 43 studies tabled from 2003–2009 mentioned negative transfer. Both of these studies explicitly contrasted positive and negative transfer. Campbell and Robert (2008) defined positive transfer as retrieval facilitation and negative transfer as retrieval interference similar to the definitions proposed by Greeno, James, and DaPolito (1971) and framed according to information processing theory. On the other hand, Keung and Ho (2009) defined positive transfer as the use of cognitive skills that promote learning, while negative transfer is the use of cognitive skills that hinder learning. These are similar to the definitions proffered by those working in the area of analogical transfer (e.g., Gentner & Landers, 1985; Holyoak & Koh, 1987; Novick, 1988). Novick (1988) hypothesized that the features of the problem (i.e., surface vs. conceptual) will affect both positive and negative transfer. We agree with Novick (1988) that a focus solely on positive transfer may not provide a complete picture of transfer; hence, the present study considers both types.

Specifically this study examined three types of transfer: positive transfer, transfer failure, and negative transfer. *Positive transfer* is defined as using concepts from an analogous problem (i.e., a base problem) to successfully solve a target problem (Novick, 1988). For example, if individuals use the concept of multiplicative probability that they had learned from a problem about a student correctly guessing joint items on a math test (i.e., the base problem) to solve a problem in which they were asked to estimate the joint likelihood of the existence of aliens (i.e., the target problem) successfully, this would be considered positive transfer. *Transfer failure* is defined as the failure to use concepts from an analogous problem (i.e., the base problem) to successfully solve a target problem (Novick, 1988). If individuals fail to use the concept of multiplicative probability that they had learned from a problem about a student correctly guessing joint items on a math test (i.e., the base problem) to solve a problem in which they were asked to estimate the joint likelihood of the existence of alien (i.e., the target problem), this would be considered transfer failure. Last, we define *negative transfer* as the use of concepts from a nonanalogous problem to solve a target problem (Novick, 1988). In other words, negative transfer would hinder effective future problem-solving (i.e., produce the incorrect solution). For example, if individuals use the concept of multiplicative probability that they had learned from a problem about a student correctly guessing joint items on a math test (i.e., the base problem) to incorrectly solve a problem about the probability of guessing independent items on a math test (a nonanalogous problem), this would be considered negative transfer.

We contend that the demonstration of an episode of positive transfer is not sufficient evidence that successful transfer occurred. Rather, we contend that the demonstration of successful transfer

		Knowledge Domain	
		Near	**Far**
Problem Type	**Surface**	**Quadrant I (Near Surface)** Transfer of knowledge between tasks with the same surface features to the same or similar topic as the initial task	**Quadrant III (Far Surface)** Transfer of knowledge between tasks with the same surface features to a subject or domain that is different from than the initial task
	Structural	**Quadrant II (Near Structural)** Transfer of knowledge between tasks with different surface features but the same structural features to the same or similar topic as the initial task	**Quadrant IV (Far Structural)** Transfer of knowledge between tasks with different surface features but the same structural features to a subject or domain that is different from than the initial task

FIGURE 1 Conceptual model for examining the interrelation between knowledge domain and knowledge type in studies of transfer.

is dependent on the ability of the individual to have an understanding of when not to apply declarative or procedural knowledge in a given situation. In other words, individuals need to demonstrate that they possess conditional knowledge (i.e., knowing when and why to apply declarative or procedural knowledge; Alexander & Judy, 1988; Alexander, Schallert, & Hare, 1991; Pintrich, 2002; Schraw, 1998). Without this additional piece of evidence (i.e., an instance where they should not apply knowledge to a given situation) it is possible that an individual could appear to transfer, yet they might not possess the conditional knowledge that stops them from applying this knowledge to inappropriate situations.

Theoretical Framework

In addition to the bifurcation of transfer to both positive and negative dimensions, we further define different types of positive transfer. Loughlin and colleagues (2011) proposed a two-by-two matrix, the KTM, to categorize transfer. The KTM is a multidimensional matrix that considers the intersection of two important aspects of transfer, namely the level and domains of knowledge. The matrix was based on the variations in the concept of transfer found within the extant literature. In the KTM, transfer was positioned in the matrix on the basis of what level transfer was occurring on (i.e., levels of understanding) and how the base and target tasks differed in terms of academic domain (i.e., similarity of academic domains between the base and target tasks). For the present study, we adapted the KTM by differentiating transfer by the problem features (i.e., superficial versus structural) rather than levels of understanding given that it was the problem features (as well as similarity between base and target) that we manipulated (Figure 1).

Similarity Between Base and Target

The first of these dimensions, similarity between base and target refers to the degree of similarity between the initial and target transfer tasks (commonly distinguished as near and far; Clark &

Voogel, 1985; Mayer & Greeno, 1972; Royer, 1979). We define *near* transfer to be transfer tasks that are in the same topic or subject as the initial task and *far* transfer to be tasks that are in different academic domains. For example, near transfer would be between two tasks both in the educational testing domain, while far transfer would be between tasks in educational testing and astrobiology.

Problem Representation

The second dimension, problem representation, refers to how the features of the problem differ either perceptually or conceptually. The perceptual problem representation refers to the surface features of the problem. Surface features include the specific items and terms of the problem as well as the specific wording of the problem (Novick, 1988). These surface features may be either solution-relevant (i.e., promote positive transfer) or solution-irrelevant (i.e., promote negative transfer) cues for solving the target problem. The conceptual problem representation refers to the structural features of the problem. Structural features include abstract and solution-relevant features that provide cues to similar patterns and relations between problems that can aid the learner in solving the target problem (Gentner, 1983; Holyoak, 2004; Novick, 1988). For example, tasks that share a perceptual level of understanding could be two different multiplicative probability problems that both include two events (same surface features of two items). While, tasks that share a conceptual level of understanding could be two different multiplicative problems of which one problem includes two events and the other problem has three events (different surface features but the same structural feature of multiplicative probability).

Specifically, in this investigation, we empirically test whether positive transfer, failure to transfer, and negative transfer differs across the two dimensions of the KTM. The research literature on transfer is rife with proposals of different dimensions of transfer (see Beach, 1999; Leberman, McDonald, & Doyle, 2006 for reviews). However, this is the first such study to our knowledge that empirically tests positive and negative transfer in a multidimensional framework such as the one we propose here.

The Problem of Initial Learning

Within the transfer literature the role of initial learning is often overlooked or assumed rather than verified. In general, exposure to the source problem is taken as learning (e.g., Escribe & Huet, 2005), with little or no attention paid to either the influence of prior knowledge on learning from the source, or what is actually learned from the source problem (e.g., Gick & Holyoak, 1980). Transfer success is then measured only on an individual's success on the target task, not necessarily their understanding of the base task (i.e., initial learning; e.g., Reed, Ernst, & Banerji, 1974). For example, in a well-known series of experiments, participants exposed to military stories, such as storming the fortress, were expected to recognize the structure of the problem and its solution, and through analogical transfer apply the successful solution of Duncker's radiation problem (Gick & Holyoak, 1980, 1983). Exposure to the source problem was implicitly taken as learning, however, no explicit measure assessed what the participants learned from the source problem. In other words, the assumption is made that there was failure to transfer, when it could be the case that learning never occurred in the first place. Piaget (1997/1964) contended that before the question about generalization can be answered, the question must be asked, "Is learning lasting?" (p. 26). It is certain that if no learning occurred from an initial problem or situation, there would be no expectation that a concept could be transferred from one situation to the other.

For this investigation, we specifically asked participants to summarize the base problem after reading it and solve the identical problem in the second part of the procedure. We hypothesized, in part, that the low transfer success rates that Lave (1997) cited may actually be failure to learn in the first place.

Cognitive Influences on Transfer

Next, we turn to the role of individual cognitive differences to help explain why some succeed at transfer where others fail. Two promising cognitive differences that may promote transfer success are; one, what people have already learned (i.e., prior knowledge) and, two, what they are able to perceive as potential relations between the known and the novel (i.e., pattern recognition). Prior knowledge helps to facilitate future learning and the application of current understanding to new problem representations (Carey, 2000; Dufresne, Mestre, Thaden-Koch, Gerace, & Leonard, 2005). Without prior knowledge, learners may not have a mental model to map the base and target problems and thus, may be unable to transfer. Mental models are knowledge representations that learners' use to think about and understand concepts (Alexander, 2006; Vosniadou, 1999). Mental models help provide a foundation for learners to understand relations between problems, to activate, select and apply prior knowledge to respond to a novel problem (Dufresne et al., 2005), and to attend to the relevant cues to derive or recognize meaningful patterns (Holyoak, 2004; Shadrick & Lussier, 2009).

The ability to positively transfer may also be influenced by the ability to notice, recognize, or create patterns of meaning in the target problem and connect or map it to a learner's current mental model about a similar concept. Learners who are more successful at positively transferring may be better at generating and recognizing patterns among different concepts and problems due to noticing cues about both surface and structural features (Novick, 1988). Learners who negatively transfer may miss the relevant cues because they focus on surface features, while learners who are able to positively transfer draw on a store of knowledge that is represented and organized around domain-specific concepts and principles that allows them to focus on deeper features (Ross, Shafer, & Klein, 2006). Learners who lack the knowledge of knowing what information is relevant as well as lacking the understanding and skills needed to see the patterns will often either try to attend to everything or overlook important pieces of information. As a consequence, they will either fail to transfer or negatively transfer. The present study explores the role of both individuals' prior knowledge and pattern recognition to explain transfer success or failure.

Research Questions and Design

The present investigation seeks to address the issues discussed previously and extend the current literature on transfer through three guiding questions. First, how many individuals were able to learn the base problem? We hypothesize that although we had individuals read and summarize the problem, some of the participants would fail to complete the base problem successfully. Identified individuals who did not demonstrate initial learning were then not included in further analysis of transfer, as they had not demonstrated initial learning.

Second, does positive transfer, failure to transfer, and negative transfer differ as a function of the similarity of the base and target task (i.e., near and far) and the problem features (i.e., surface versus structural features) in the KTM? We hypothesize that transfer success will vary across the four cells of the KTM. Specifically, we hypothesize that near-surface transfer will have higher rates of positive transfer than far-structural transfer. Positive transfer for far transfer has been shown to be more difficult than near transfer (e.g., Barnett & Ceci, 2002). Furthermore, positive transfer tasks across problems with different structural features are notoriously difficult for individuals (e.g., Gick & Holyoak, 1983). To test this hypothesis, we used a between-subjects design in which we manipulated the relation between base and target problem (both in terms of similarity and problem features) and randomly assigned participants to one of four conditions (near-surface transfer, near-structural transfer, far-surface transfer, or far-structural transfer). In addition to testing for positive transfer, we also investigated the extent to which individuals possessed the requisite conditional knowledge to not apply procedural knowledge to a situation in which this procedural knowledge was inappropriate.

Third, how do individuals' cognitive differences (i.e., prior topic knowledge and pattern recognition) affect positive transfer success across the four study conditions? We hypothesize that prior knowledge and pattern recognition would aid transfer, particularly more difficult forms of transfer (e.g., the far-structural type we have described here; Gentner, 1983; Gentner & Gentner, 1983). To test this hypothesis, we used participants' prior knowledge and pattern recognition scores as covariates in the between-subjects design used for the second question.

METHOD

Participants

Participants for this study were 178 undergraduate and graduate students from the United States and New Zealand. The U.S. sample was drawn from a large mid-Atlantic university. This sample consisted of 131 participants (79% female) who were primarily social science majors (87%) and were ethnically diverse (66% Caucasian, 12% African American, 12% Asian, 5% Hispanic, and 4% other). These participants reported an average age of 20.53 years and the majority were second- (27%), third- (42%), and fourth-year (27%) undergraduates. A large majority of the participants reported English as their native language (98%).

The New Zealand sample was drawn from a large research university on the north island of New Zealand. This sample consisted of 47 participants (79% female) who were primarily social science majors (91%) and were ethnically diverse (21% European, 62% Asian, 12% Hispanic, and 17% other). These participants reported an average age of 21.26 years and were predominately second- (43%) and third-year (57%) undergraduates. Thirteen participants reported English as their native language, 25 reported some other language as their native language, and nine did not respond to this item.

Measures and Tasks

The measures for this study consisted of a subject-matter knowledge measure and pattern recognition measure. Participants also completed an initial additive probability task as well as follow-up problem-solving tasks including problems related to their initial learning on the additive probability task, a positive transfer problem (with four different conditions), and a negative transfer problem.

Subject-Matter Knowledge

The subject-matter knowledge measure consisted of five items about statistical probability. These five items were selected from an initial set of ten items that were piloted on a similar population to those from the present study. These five items were selected from the initial pool of ten because they reached the highest discrimination values (i.e., an item difficulty closest to .5).

For the present study, the answer choices for each item were on a graduated response scale (Alexander, Murphy, & Kulikowich, 1998) representing four categories. The rationale for using the graduated response scale was that this scale can account for participants' partial knowledge, unlike a dichotomously scored item (i.e., correct or incorrect). The first of these four categories was the in-topic correct response that was scored a 4. The second of these four categories was the in-topic incorrect response and was scored a 2. This response was not correct, however, the response was within the same topic as the correct response. The third category was the in-domain incorrect response and was scored a 1. This response was also incorrect, was from a different topic than the correct response, but was still in the domain of research methods. The fourth category was the popular lore option which was scored a 0. This incorrect response was one in which a participant with little or no subject-matter would chose and was not associated with the domain of research methods. Using the graduated response, we hoped to obtain more information about each participant's knowledge for use in the statistical analysis (rather than just simply correct or incorrect). An example item from the subject-matter knowledge follows:

The probability that one rolls a 3 with one die given that they have already rolled a 3 on the other die is referred to as follows:

a. exclusive probability (0)
b. conditional probability (1)
c. dependent probability (2)
d. independent probability (4)

The correct response for this item was choice *d*, and was scored a 4. Answer choice *c* was incorrect but was a very closely related response to the correct answer (i.e., same topic) and was scored a 2. Answer choice *b* was also incorrect and is a type of probability, but is more distantly related to the correct answer and was scored a 1. Last, answer choice *a* was incorrect and was not a probability term and was scored a 0.

Instead of summing the scores to form a composite, we chose to create factor scores in an attempt to parse out error from the items under consideration (Hancock & Mueller, 2001). These factor scores yielded sample dependent scores ($M = 0$, $SD = 1$). The factor analysis suggested a one factor solution that accounted for 23.75% of the total variance in these five items. Construct validity of these items was assessed by examining the factor loadings of each item. It is suggested that factor loadings that are greater than 0.50 provide good construct validity evidence (Crocker & Algina, 1986). Questions 1 and 4 did not meet this criteria with factor loadings of .053 and .10, respectively. Reliability was calculated using maximal reliability because we were using factor scores instead of composite scores. Maximal reliability was calculated using Coefficient H (e.g., Hancock & Mueller, 2001). Coefficient H is an estimate of the correlation the factor is expected to have with itself over repeated administrations, with values greater than .70 being desirable

(Mueller & Hancock, 2010). Coefficient H for the knowledge measure was only slightly less than this value at .66.

Pattern Recognition

The pattern recognition measure consisted of six items from the Wechsler Abbreviated Scale for Intelligence (Wechsler, 1999). We used only the pattern recognition items because these particular items validly measure the cognitive influence on transfer we were interested in investigating in our study, the construct of pattern recognition. These six items were selected from an initial set of ten items that were piloted on a similar population to those from the present study. These six items were selected from the initial pool of ten because they reached the highest discrimination values (i.e., an item difficulty closest to .5). The directions for each of these items were to "please examine each picture and then choose the missing piece from the five choices below the picture by circling the number. There is only one correct answer to each problem. If you believe that more than one answer is right, choose the best one."

The answer choices for each item were on a graduated response scale, similar to the prior knowledge questions, representing five categories. A panel of three experts examined the responses for each of the six pattern recognition items and created the graduated response scale. The graduated responses were based on the number of surface features that differed from the correct response. The first of these five categories was the correct response that completed the pattern and was scored a 5. The remaining four categories were all incorrect responses to which picture completes the pattern and were scored 4, 3, 2, and 1, respectively, as each response moved further away from resembling the correct response. The response that was scored a 4 was the response that most closely matched the correct response with only a slight surface feature difference while the response scored a 1 was the most different from the correct response. As with the subject-matter knowledge test, we used the graduated scale to obtain more information about the participants' pattern reasoning than simply correct or incorrect.

With the Wechsler Abbreviated Scale for Intelligence items, we again chose to create factor scores using the same procedure as the prior knowledge items. The factor analysis suggested a one factor solution that accounted for 25.40% of the total variance in these six items. In terms of construct validity two of the items were a bit lower than the suggested value of .5, these were items 2 and 3 with values of .043 and .26, respectively. Coefficient H for this scale met Mueller and Hancock's (2010) suggested value of .7 (H = .71).

Initial Task (Base Task)

Participants were asked to read a passage that introduced the concept of multiplicative probability with two events (Appendix A). Specifically, the passage introduced the calculation for the probability of guessing two multiple choice questions correctly on a quiz given that the student does not know the correct answer to either item. After participants read the passage, they were instructed to "please summarize this passage, giving both the overall main idea and the major points addressed."

Problem-Solving Tasks

The problem-solving tasks consisted of four items. The first item was a check of the participants' initial learning of multiplicative probability for two events from the initial task (i.e., the same problem in the initial task). The item read:

> A statistics instructor writes a two-item pop quiz for her class. Each item was multiple choice with four possible answer choices. The instructor would like to know what the chance is that a student who does not know the answer to either item could guess both items correctly. What is the chance that a student who does not know either item would guess both items correctly?

The second item was a distracter item on statistical variance. The distracter task was added because we agree with Lave (1997) that participants should not have to be prompted to cognitively transfer. Therefore, the purpose of this item was to avoid having the base and target tasks in consecutive order. This problem did not use the concept of multiplicative probability for the problem solution. The item read, "A researcher wants to know the variance of three people's test scores. Her students' test scores are 5, 10, and 15." Participants were given the equation for variance and asked to calculate it.

The third item consisted of a near-surface, near-structural, far-surface, or far-structural transfer question that aligned with our conceptual framework (i.e., the KTM). All four of these items are included in Appendix B. The near-surface item was similar in domain (asking about the probability of correctly guessing items on a quiz) and was structurally similar to the initial problem in that there were two events (i.e., two items). However, the items for the near-surface problem were true/false instead of multiple choice (changing the percentages entered into the calculation). The far-surface item was different in domain (i.e., astrophysics) and asked participants to calculate the probability that life exists on other planets given two events (i.e., same structure as the base). The near-structural item was in the same domain (i.e., educational tests) as the initial task, but contained different structural features (i.e., five items instead of two). The far-structural item was in a different domain (i.e., astrophysics) and also had different structural features (i.e., five events instead of two) from the initial task.

The fourth item was a problem on additive probability for which prior training would be counterproductive (negative transfer). This item read:

> A statistics instructor writes a two-item pop quiz for his class. Each item was multiple- choice with four possible answer choices. The instructor would like to know what the chance is that a student who does not know the answer to either item could guess one or the other item correctly. What is the chance that a student who does not know either item would guess one or the other item correctly?

Procedures

The participants completed all research tasks during or following their regularly scheduled class time. Participants were reminded ahead of time to bring a calculator with them. Students had the option of using a calculator or the calculation function on their mobile phone if they desired. Participants then gave informed consent to participate in this study.

Participants then completed the demographics measure, the subject-matter knowledge measure, completed the initial task (i.e., base task), and the Wechsler Abbreviated Scale for Intelligence items. Participants then completed the four problem-solving tasks (i.e., initial learning problem, distracter problem, positive transfer problem, and negative transfer problem). Participants were randomly assigned to one of the four positive transfer conditions (i.e., near surface, near structural, far surface, or far structural). As soon as participants completed these items, they were permitted to leave. Participants took between 10 and 20 min to complete these measures and tasks.

Before data collection, the first and second authors developed a coding scheme for positive transfer, failure to transfer, and negative transfer. For the positive transfer item (i.e., item number three of the problem-solving tasks) we scored a correct answer as a 1, a partially correct (the correct equation but incorrect answer) as .5, and an incorrect answer (incorrect formula and answer) as a 0.

For negative transfer (i.e., item number four of the problem-solving tasks), we coded the response into one of four categories: responses that used multiplicative probability to solve the problem incorrectly (negative transfer), responses that used the additive probability to solve the problem correctly (no evidence of negative transfer – additive probability), responses that used a calculation other than additive or multiplicative transfer (no evidence of negative transfer – other), or no work shown (no evidence of negative transfer – indeterminate). For the analysis, responses were coded as either evidence of negative transfer or no evidence of negative transfer for each participant. Interrater agreement for both the positive and negative transfer items was 96% agreement across 25% of the total participants. Any discrepancies were resolved in conference. This was deemed acceptable and the first author coded the remainder of the participants.

RESULTS

To examine differences in positive and negative transfer by levels of understanding and similarity from the transfer matrix (Figure 1) and the role of subject-matter knowledge and pattern recognition in these two types of transfer two factorial logistic regressions were performed (for more information, see Cohen, Cohen, West, & Aiken, 2003, Chapter 13; Pedhazur, 1997, Chapter 17). Because the dichotomous dependent variables (i.e., presence or absence of positive or negative transfer) violate the assumptions of linear regression (i.e., a nonlinear relation between the dependent and independent variables, untenability of the assumption of homoscedasticity, and nonnormally distributed errors; Pedhazur, 1997, p. 714).

The first of these regressions used positive transfer as the dichotomous dependent variable with transfer condition (i.e., near surface, near structural, far surface, and far structural), prior subject-matter knowledge, and pattern recognition as the independent variables (a between-subjects analysis). The second regression used negative transfer as the dichotomous dependent variable with the same independent variables as the previous regression. A priori contrasts by condition were also run for each of these regressions with the near-surface condition as the reference condition. The near-surface condition was chosen as the reference condition because it was the most prevalent identified in a recent literature review on transfer using the transfer matrix (Loughlin et al., 2011).

Before the analyses were run, cases in which the participant failed to answer the initial learning problem correctly were excluded from the positive transfer analyses. This resulted in 19 cases (10.67%) being excluded from this analysis. The number of excluded cases were nearly equal by condition (near surface = 4, near structural = 6, far surface = 4, and far structural = 5).

TABLE 1
Frequency and Percentage of Unsuccessful and Successful Positive Transfer, by Condition

	Unsuccessful positive transfer		*Successful positive transfer*	
	n	%	n	%
Near perceptual	7	18.42	31	81.58
Near conceptual	20	51.28	19	48.72
Far perceptual	23	54.76	19	45.24
Far conceptual	21	52.50	19	47.50
Total	71	44.65	88	55.35

Note. Percentage totals reflect the total of participants who were unsuccessful or successful at the positive transfer task.

Differences in Transfer by Levels of Understanding and Similarity

Positive Transfer

Table 1 presents the frequency and percentages of positive transfer success by condition. Overall, transfer condition was a significant predictor of positive transfer success (Wald $=$ 8.83, $df = 3$, $p = .032$). Furthermore, a priori planned contrasts indicated that the near-surface condition differed significantly from the other three conditions (e.g., Wald $=$ 6.44, $df = 1$, $p = .011$, in the case of near-structural transfer). However, the near-structural, far-surface, and far-structural conditions did not differ significantly (e.g., Wald $=$ .119, $df = 1$, $p = .73$, for near-structural and far-surface transfer). The odds ratios for the conditions in reference to the near-surface condition were 4.66, 5.36, and 4.89 for the near-structural, far-surface, and far-structural conditions, respectively. This means that participants were about five times more likely to positively transfer in the near-surface condition than in the other three conditions.

Negative Transfer

Table 2 presents the frequency and percentages of negative transfer by condition. Overall, transfer condition was not a significant predictor of negative transfer (Wald $=$ 3.68, $df = 3$, $p =$ .30). In addition, an examination of negative transfer performance of only those who successfully transfer ($n = 88$) indicated that nearly a quarter of these participants ($n = 21$) also exhibited negative transfer.

The Role of Subject-Matter Knowledge and Pattern Recognition in Transfer

Neither subject-matter knowledge or pattern recognition was a significant predictor of positive transfer performance (Wald $=$ 2.37, $df = 1$, $p = .12$; and Wald $=$ 1.33, $df = 1$, $p = .25$, respectively). Furthermore, contrasts for positive transfer performance were also nonsignificant except for the far-structural condition. For the far-structural condition, subject-matter knowledge was a significant predictor of positive transfer performance (Wald $=$ 5.22, $df = 1$, $p = .022$).

TABLE 2
Frequency and Percentage of Negative Transfer, by Condition

	No negative transfer demonstrated		*Negative transfer demonstrated*	
	n	%	n	%
Near perceptual	32	76.19	10	23.81
Near conceptual	40	88.89	5	11.11
Far perceptual	36	78.26	10	21.74
Far conceptual	33	73.33	12	36.36
Total	141	79.21	37	20.79

Note. Percentage totals reflect the total of participants who exhibited negative transfer performance.

DISCUSSION

The Problem of Initial Learning

Our first question examined the rate at which the participants could successfully demonstrate that initial learning could occur (i.e., they could solve the multiplicative probability problem presented in the short passage). The finding here that nearly 11% of the participants in this study failed to complete the base task correctly was rather surprising to us given the reproductive nature of the task. In other words, the problem they were asked to solve to demonstrate initial learning was identical to the one that they had just read about. In addition, a short time period had elapsed between the reading and their demonstration of initial learning. We assume that an extended amount of time between reading the passage and solving the base problem would raise this percentage even further. This would further lower the rates of positive transfer seen in any kind of delayed transfer test (e.g., Johnson & Mayer, 2009).

Differences in Transfer by Levels of Understanding and Similarity

Positive Transfer

These data did support our hypothesis that positive transfer success differed across conditions of the KTM (Figure 1). As with previous research, this study provides evidence that positive transfer success (and transfer failure) differ depending on the academic domains (e.g., Barnett & Ceci, 2002) and the structural features (e.g., Gick & Holyoak, 1983; Novick, 1988) of the problems (i.e., base and target) presented. Furthermore, this study extends previous research by demonstrating different rates of positive transfer along multiple dimensions of transfer. Specifically, we demonstrated significant differences between near-surface transfer and the other three cells of the KTM (i.e., near-structural, far-surface, and far-structural). In other words, transfer success is conditional on the nature of the problems at hand. Transfer is often more likely to occur between near-surface problems—in this case, 81.58% of the time. However, when the problems differed by academic domain or structurally, we see much lower occurrences of successful transfer (slightly less than 50%). Although we agree with Lave (1997) that the prevalence of successful transfer was low in the studies she reviewed (i.e., Gentner, 1983; Gick & Holyoak, 1980; Hinsley, Hayes, & Simon, 1977), we disagree, however, with her criticism that low transfer success in those studies is evidence that building generalized knowledge structures are not helpful to individuals in transferring knowledge from one situation to another. The studies she examined resembled the far-structural types of transfer and we would expect lower rates of transfer. This argument ignores the higher levels of transfer success in the near-surface cell of the KTM.

Significant differences were not detected between the other three transfer conditions (i.e., near structural, far surface, and far structural). One possible explanation for this is that transfer success between these conditions simply does not differ (or that the effect sizes are so small these differences are relatively unimportant). This explanation would suggest that the either the dissimilarity of the domains or the dissimilarity in problem structure is enough to stymie successful transfer. Having dissimilar domains and structure does not appear to lower the chances of successful transfer in this case. The second explanation, however, may be that the dissimilarities between the problem conditions (either in the structure of the nature of the academic domains) was not sufficiently far apart enough to detect differences. This so called restriction of range problem has been well documented (e.g., Mendoza & Mumford, 1987). Given that the academic domains were relatively far apart in our estimation (i.e., educational statistics and astronomy), it may be the case that the structural features of the problem were not different enough to detect a significant difference.

Negative Transfer

For negative transfer, no significant differences existed across the four study conditions. In other words, the features of the problem (i.e., structurally or the nature of the academic domain) did not differentially affect participants' use of the multiplicative concept for the additive probability problem. However, the high percentage of individuals (25%) who demonstrated successful transfer and negative transfer should serve as a reminder that demonstrating positive transfer success only partly explains the usefulness of the generalized knowledge structures individuals have constructed. If individuals do not possess the conditional knowledge to apply these learned concepts only to those problems in which they are useful, they are not much better off, and perhaps worse off, than those who were unable to transfer the concept successfully in the first place. So, while 55.35% of the individuals in this study demonstrated positive transfer, only 41.51% demonstrated the conditional knowledge to not only transfer successfully, but also when not to apply the learned concept when it was not appropriate. Furthermore, we caution that individuals who demonstrated positive transfer success and negative transfer is a lower bound. This is due to the inability in some cases to observe negative transfer (i.e., individuals who did not show their work). Hence, we assume that negative transfer was slightly higher than the conservative estimate reported here.

The Role of Subject-Matter Knowledge and Pattern Recognition in Transfer

We found limited evidence of the influence of individual's cognitive differences on their ability to positively transfer. Our results demonstrated no evidence of pattern recognition as a significant predictor of positive transfer performance. This may be due to the fact that the pattern recognition measure used in this study is a measure of both perceptual and cognitive ability while the problem-solving tasks were a measure of cognitive ability only. In addition, our results found prior knowledge significantly predicted positive transfer for the participants in only the far-structural condition and not in the other three study conditions. This result may be due to the fact that the far-structural condition was the hardest task and required prior knowledge to help solve the problem, while the other tasks that were not as difficult did not require prior knowledge. For tasks that are relatively easier, prior knowledge may not be necessarily needed to solve the problem.

CONCLUSIONS

Given the importance that many place on the role of transfer in learning (e.g., Alexander & Murphy, 1999; Piaget, 1964; Schoenfeld, 1999), moving forward it is crucial that studies of transfer are precise in defining what (i.e., the features of the problem) is being transferred, what situations it is being transferred between (i.e., the nature of the knowledge being transferred), and *who* (i.e., individual characteristics of the learning) is doing the transfer.

With regard to what is being transferred and what situations transfer is occurring between, we have presented evidence that the attributes of the situation (i.e., base and target task in this case) matters. Despite the participants being relatively similar in terms of their backgrounds, transfer performance did differ as a function of the transfer condition (i.e., near surface, near structural, far surface, and far structural). In other words, in some cases, we should expect that transfer will be relatively rare (i.e., far structural) as Gick and Holyoak (1980) and others had found, yet in other cases (e.g., near surface) rates of transfer success will be significantly higher. So, although critics of transfer (e.g., Lave, 1997) correctly point out that seminal studies of transfer such as Gick and Holyoak's (1980) study seem to offer evidence that generalizations are relatively rare in laboratory-type experiments, we propose that this is merely a function of the type of transfer those participants were asked to demonstrate. These findings underscore the need to be precise in designing and describing transfer success for future studies. At the very least researchers should take sufficient care to describe how the base and target tasks relate to each other using some continuum or matrix such as the KTM that we have used here. More useful, however, would be research designs that incorporate multiple types of transfer as described by the KTM or some other framework. In this way, interventions designed to foster transfer can be more carefully evaluated in terms of the effectiveness of the intervention. For example, by only examining one type of transfer from the KTM, that may mask differences in transfer across intervention conditions, when the effectiveness of the intervention may only be significant for certain types of transfer.

Furthermore, we note that the low transfer success reported previously may also be a function of inadequate learning of declarative or procedural knowledge for the base task. Simply reading a base problem is likely not enough to ensure adequate learning. For this investigation, participants read the problem and summarized it, and nearly 11% of our respondents still failed to get the base problem correct when asked about it a few minutes later. This issue would likely become even more salient if a significant amount of time elapsed between the base and transfer tasks.

On the other hand, transfer success may be overestimated if only declarative (i.e., facts or "knowing that") or procedural (i.e., algorithms or "knowing how"; Paris, Cross, & Lipson, 1984, p. 1241; Schunk, 2008) knowledge are demonstrated by participants. For this study, we included a problem in which the procedural knowledge in the base would not be useful to the target task (i.e., negative transfer). This was a test of the participants' conditional knowledge (i.e., when to use declarative or procedural knowledge and why it should be applied; Paris et al., 1984; Schunk, 2008). Although it is certainly helpful to know whether an individual can transfer between a base and target, in our view it is essential that the individual has an awareness of when this knowledge should be used. For example, an engineer who has learned how to design and construct suspension bridges should have the knowledge of when to use this knowledge. Certainly the designers of the Tacoma Narrows Bridge in the United States (see Washington State Department of Transportation, 2005, for more information) knowing the specifics of the target task (building a bridge across the Tacoma Narrows in Washington State) may have avoided this disaster. Future studies should incorporate mechanisms to assess not only declarative or procedural knowledge, but also conditional knowledge.

Regarding who is transferring, there is no shortage of evidence that individual differences (i.e., cognitive and motivational) play a role in the one's ability to successfully engage in transfer. This is not a new idea; Novick (1988) and others have previously shown the importance that an individual's expertise may play in transfer. By framing transfer studies in models of expertise development (e.g., the Model of Domain Learning; Alexander, 1997) this will allow us to organize these findings into a more coherent set of findings. Although the evidence presented in this study is far from conclusive, the measures used here offer some insight for future research. First, specifically recruiting individuals with wide ranges of knowledge and motivation should be a priority in study recruitment. This issue becomes more salient when we are asking individuals to transfer across academic domains (e.g., education to astronomy). Further investigation into knowledge and motivation for each of the two domains adds complexity to the design and analysis.

Examining these dimensions (i.e., the nature of the problems, the knowledge being assessed, and the nature of the individual) should contribute to more valid judgments about the nature of transfer. The critics of transfer are correct that many studies—particularly the seminal studies such as Gentner and Gentner (1983) and Gick and Holyoak (1980)—do not demonstrate that transfer occurs effortlessly or often, but this criticism misses the aim of many studies of transfer; specifically, how do we foster individuals' ability to transfer? Furthermore, we can help ourselves in making the case for transfer by being more precise in how we describe and measure instances of successful, unsuccessful, positive, and negative transfer.

Future Directions for Research

While we believe that this study contributes a great deal to the existing literature, there are facets of the present study that can certainly be both improved and extended upon. In this section, we address sampling strategies, the contribution of individuals' differences on transfer success, and expansion of the KTM.

Sampling

The first issue we turn to is the nature of the sample in the present study. The present sample was homogenous in terms of their level of education (i.e., college students) and their prior knowledge about probability. Despite this relative homogeneity, difference in transfer rates across the four study conditions still existed. Investigations into the developmental differences of successful transfer rates across different age groups would be an important extension of the present research. Longitudinal or cross-sectional studies may yield interesting insights into how heterogeneity both in terms of age and prior knowledge impact transfer rates along the KTM.

Individual Differences

We did not find that prior knowledge influenced positive transfer across three of the four study conditions. Prior knowledge was found to only influence positive transfer in the far-structural condition. This may be due to our prior knowledge measure only assessed the participants' declarative knowledge regarding statistical probability. We did not assess participants' conditional knowledge in multiplicative probabilities, which may be a better predictor of positive transfer than simply declarative knowledge. Future studies could examine the relation between conditional knowledge and transfer performance.

In regards to pattern recognition, we found no evidence in this investigation that pattern recognition was a significant predictor of positive transfer performance which was surprising as the ability to consider relations and identify patterns from multiple mental representations has been recognized as key to underlying transfer of learning from one area to another (Bereby-Meyer & Kaplan, 2005; Bulloch & Opfer, 2009). This may be a result that the pattern recognition measure we used was more of a measure of perceptual or visuospatial ability, which focused on only surface feature representations, while our problem-solving tasks was more of a measure of cognitive ability, which focused on both surface and structural features. Future studies examining the role of pattern recognition in transfer performance should use cognitive pattern recognition measures that asks participants' to recognize patterns that coincide with the problems being transferred (e.g., in this investigation both the surface and structural features).

Furthermore, motivation may be another factor that influences transfer success. While we examined two cognitive factors in the present investigation, it is possible that motivational variables might play a key role. Two such motivational variables may be individual and situational interest (Hidi & Renninger, 2006; Schiefele, 1999). For example, situational interest in either the base or target task may improve performance by focusing attention more closely on relevant details of the problem.

Expansion of the KTM

Last, this study examined only two possible points along each dimension of the KTM (i.e., one conception of near vs. far along the knowledge domain and one conception of structural versus surface on the problem representation dimension). As Alexander (2012) pointed out, it is not likely that there is a true dichotomy between types of transfer (e.g., near vs. far). Extensions of these dimensions allows for many possibilities for future research. For example, future studies may want to investigate transfer as occurring along an intersecting axis or continuum of the KTM instead of just positioned between two points or two dimensions within the KTM. In addition, studies may also want to examine the processes of how individuals attempt to transfer within each dimension. If differences are found in how individuals transfer within the KTM this may provide further support that all transfer is truly not equal.

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APPENDIX A

A statistics instructor writes a two-item pop quiz for her class. Each item was multiple choice with four possible answer choices. The instructor would like to know what the chance is that a student who does not know the answer to either item could guess both items correctly. The instructor calculates that for each item a student has a probability of .25 (or 25%) chance of guessing correctly. By multiplying these two probabilities together he calculates that a student has a probability of .0625 (or 6.25%) of guessing both items correctly.

APPENDIX B

Near Surface Problem
A statistics instructor writes a two-item pop quiz for his class. Each item is true/false with two possible answer choices. The instructor would like to know what the chance is that a student who does not know the answer to either item could guess both items correctly. What is the chance that a student would guess both items correctly?

Near Structural Problem
An educational psychology professor writes a five-item pop quiz for his class. Each item was multiple choice with five possible answer choices. The instructor would like to know what the chance is that a student who does not know the answer to any of the five items could guess three items correctly. What is the chance that a student who does not know any of the items would be able to guess three correctly?

Far Surface Problem
An astronomy professor wants to calculate the chances that intelligent alien life exists in the universe. He postulates that the existence or nonexistence of intelligent alien life depends on the fraction of stars that possess planets and the fraction of alien species that develop a technology that releases detectable sign of their existence into space. The astronomy professor estimates that about half of all stars (.5) possess planets and 1% (.01) will possess alien species that develop technology that releases detectable signs of their existence. What is the chance that we will detect intelligent an alien species?

Far Structural Problem
An astronomy professor wants to calculate the chances that intelligent alien life exists in the universe. He postulates that the existence or nonexistence of intelligent alien life depends on three parameters: the fraction of stars that possess planets; the fraction of alien species that develop life at some point; and the fraction of alien species that develop a technology that releases detectable sign of their existence into space. The astronomy professor estimates that about half of all stars (.5) possess planets, 75% (.75) go on to produce life, and 1% (.01) will possess alien species that develop technology that releases detectable signs of their existence. What is the chance that we will detect an intelligent alien species?