Distinguishing Two Types of Prior Knowledge That Support Novice Learners

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Abstract

Prior knowledge has long been recognized as an important predictor of learning, yet the term prior knowledge is often applied to related but distinct constructs. We define a specific form of prior knowledge, *ancillary knowledge,* as knowledge of concepts and skills that enable learners to gain the most from a target lesson. Ancillary knowledge is not prior knowledge of the lesson's target concepts and skills, and may even fall outside the domain of the lesson. Nevertheless, ancillary knowledge affects learning of the lesson, e.g., lower ancillary knowledge can hinder performance on lesson-related tasks. We measured ancillary knowledge, prior knowledge of the domain, and controlled for general ability, and found that (a) stronger ancillary knowledge and general ability predicted better performance on transfer tasks, but (b) prior knowledge of the domain did not. This research suggests that enhancing instruction by remediating gaps in ancillary knowledge may improve learning in introductory-level courses.

Keywords: prior knowledge; ancillary knowledge; domain-general knowledge; far transfer; introductory courses

Introduction

Learners in any given class often vary widely with respect to their knowledge of both the current material and the skills and concepts that may be considered ancillary to and supportive of the current material. At the college level, this is perhaps most evident in introductory-level courses, which by definition enroll many learners who are novices in a domain, and yet who bring all types and degrees of prior knowledge into the classroom. Before attending Introduction to Cognitive Psychology, for example, students may or may not have taken a general psychology course that included a high-level introduction to many topics. They are also likely to have had different degrees of exposure to and practice with concepts and skills that could be considered supportive of learning Cognitive Psychology, e.g., graphing and experimental design. These topics, which may have been learned in the context of psychology or a different science or math context, are likely useful to students as they learn about cognitive psychology hypotheses, study designs, graphed results, and whether the data support these hypotheses. Despite the clear relevance of graphing and experimental design knowledge, rarely are they measured or their gaps addressed during instruction.

We wished to evaluate whether such ancillary knowledge would predict performance on assessment items related to a new lesson better than prior domain (cognitive psychology) knowledge or knowledge of the specific lesson, which would suggest that this unmeasured and often unaddressed type of knowledge plays an important role in learning.

Background

Researchers have long considered prior knowledge critical for learning (Ausubel, 1968; Dochy, 1988; Jonassen & Grabowski, 1993). Across studies, it represents one of the largest sources of variance in pre/post-test measures, accounting for 30 to 60 percent of the difference in scores (Dochy, 1988). Prior knowledge explains performance over and above general ability. For example, it predicted learning of science concepts better than mental capacity and developmental level (Lawson, 1983) or formal reasoning ability (Zeitoun, 1988), and comprehension of text passages after accounting for IQ (Langer & Nicolich, 1981).

The importance of prior knowledge for learning is well established, yet many studies do not provide explicit definitions of prior knowledge or use similar terms to reference distinct constructs (Dochy & Alexander, 1995). Consequently, important dimensions of prior knowledge may be overlooked, and research becomes inconclusive. In addition, some benefits of prior knowledge may be due to prior knowledge in the domain, ancillary knowledge, or both; similarly, learning difficulties may be due to knowledge gaps of either type. More generally, if learners vary in both types of prior knowledge, but the two types are not distinctly assessed, their role in learning cannot be clearly understood.

Our research aims to distinguish these two types of prior knowledge: *prior knowledge in the domain,* i.e., concepts and skills within the target domain, from *ancillary knowledge*, i.e., knowledge of the concepts and skills that are outside of the target domain (but may be utilized in the target domain and additional domains; see Dochy, 1988). See *Figure 1* for a graphical representation. In order to be considered ancillary knowledge, these concepts and skills should enable better learning of the new material, such as knowledge of graphing and experimental design may for many cognitive psychology topics. Bloom's (1976) term for this idea was "cognitive entry behaviors," which he defined as "those prerequisite types of knowledge, skills, and competencies which are essential to the learning of a particular new task or set of tasks" (p. 122).

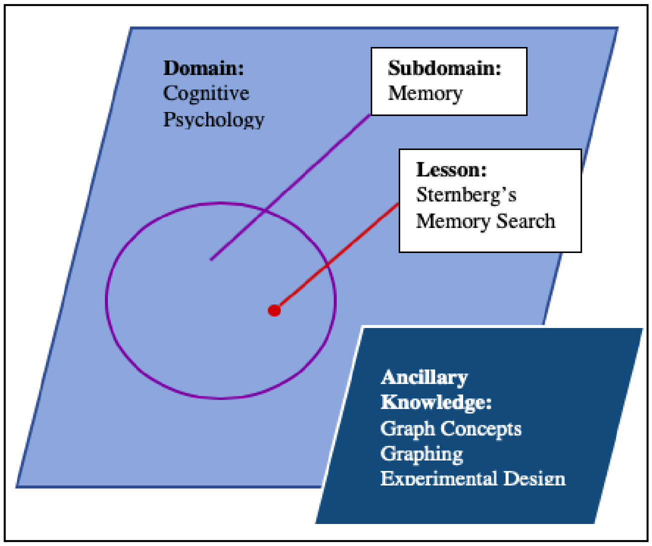

Figure 1: Levels of domain knowledge include the domain, subdomains, and concepts and skills within the domain. Ancillary knowledge is domain-independent, but may nevertheless support learning in the domain.

The mechanisms of support for learning are likely the same for both types of prior knowledge, including freeing up attentional resources and enabling greater comprehension and problem solving (Fincher-Kiefer, Post, Greene, & Voss, 1988; Kintsch, 1994; Schauble, Glaser, Raghavan, & Reiner, 1991; Siegler, 1986; Willingham, 2007). The key difference is that prior knowledge in the domain is obviously relevant and ancillary knowledge is often overlooked or deemed out of scope of the current instruction.

This is particularly problematic for undergraduates, who are likely to have gaps in the types of ancillary knowledge that readily support experts as they encounter new topics. Schunn and Anderson (1999) contrasted experts' and undergraduates' performance on an experimental design task and found that the latter did not demonstrate the experimental design skills of using theory to design their experiment and relating results back to the theories at a proficient level. On the other hand, experts have a wealth of domain knowledge and tools they can bring to bear in new situations, such as knowledge of related studies or formulas typically used.

Despite this, undergraduates have often acquired a measurable degree of general knowledge (Means & Voss, 1985), general strategies (de Jong & Ferguson-Hessler, 1996), and even subject-specific knowledge (Dochy & Alexander, 1995). Variability is heightened because the knowledge may have been learned and forgotten, partially learned, or not abstracted at a high enough level to be useful in new contexts. In other words, undergraduates' base levels of knowledge are more sophisticated (tending toward greater richness) than younger students, but also more tenuous and incomplete than experts' knowledge. Therefore, instead of categorizing subjects as experts or novices, we took a quantitative measure of ancillary and domain knowledge in our target population in order to pick up on this variability.

In addition, in order to investigate the role of ancillary knowledge in undergraduate learning, we utilized a situation typical in introductory courses, namely one in which ancillary knowledge and domain knowledge were expected to vary greatly, but prior knowledge of the lesson was uniformly low (i.e., not at play). The specific lesson we chose was the Sternberg memory search paradigm and experimental results, as taught in an introductory Cognitive Psychology course at Carnegie Mellon University. A key advantage of this lesson was that several questions on the assessments were adapted from materials that had been used in the course and therefore already deemed suitable (i.e., challenging but within grasp) for the average ability level of our sample.

We analyzed the lesson to determine what would qualify as ancillary knowledge – i.e., independent of the target lesson and yet expected to enhance learning of that lesson. We identified the following as relevant ancillary knowledge: variable selection and measurement, facility with graphed data and the lines that fit these data, and interpretation of graphed results in terms of theoretical relationships between variables. Consistent with this list, a reviewer of this paper shared that a lack of ancillary knowledge related to graphing prevented his or her students from fully understanding Sternberg's hypothesis, his various independent variables and study results. In other words, missing ancillary knowledge (i.e., an inability to apply knowledge about y-intercept and slope) affected the extent to which students were able to gain lesson-specific knowledge.

In order to separate ancillary knowledge fully from the domain of cognitive psychology, we situated the pre-test questions in other domains, such as physics (for graphing questions) or social psychology (for experimental design questions). We measured prior knowledge in the domain by assessing knowledge of the subdomain of memory (e.g., chunking, serial position effect), as well as prior knowledge of the lesson (e.g., Sternberg's paradigm, hypothesis, and results). See *Table 1* for sample questions.

Conceptual and Procedural Knowledge

Our measures also differentiated between types of ancillary knowledge based on another dimension that is often included in studies of learning and performance: conceptual versus procedural knowledge. The classification of knowledge as conceptual or procedural is both common (Baroody, Feil, & Johnson, 2007; Crooks & Alibali, 2014) and useful for studying learning and performance. Researchers and educators sometimes call conceptual knowledge "knowing that" and procedural knowledge "knowing how," or, even more simply, concepts (conceptual) and skills (procedural).

Determining *how* to measure conceptual apart from procedural knowledge became a secondary focus of our work. Even though the labels conceptual and procedural suggest the idea of two independent categories, these knowledge types are often related. Rittle-Johnson and Siegler (1998) reported positive correlations between amounts of conceptual and procedural knowledge in four areas of math learning.

Table 1: Sample item from each of the six (6) knowledge types assessed at pre-test.

Knowledge Type		Sample Item
Ancillary Knowledge – Graphing	*(1) Conceptual*	Here is a Boxplot (also called a Box and Whisker plot). Circle any feature that can be determined.
	(2) Procedural	What does the slope of an object accelerating uniformly look like on an acceleration vs. time graph? Hint: Sketch a graph with acceleration on the x-axis.
Ancillary Knowledge – Experimental Design	*(3) Conceptual*	A social psychology researcher is interested in whether cheerfulness and extroversion determine a person's attractiveness. She does an experiment in which several participants view videos of interviews of everyday people and then rate the interviewee's perceived cheerfulness, extroversion, and attractiveness […] Are the results correlational or causal?
	(4) Procedural	Advertisements for an herbal product, ginseng, claim that it promotes endurance. As a researcher, how would you design a controlled experiment to test this claim? Describe each of the following: (e.g., groups, controls, dependent measure)
Prior Knowledge – Subdomain (Memory)	*(5) Conceptual*	While recalling a mobile phone number, splitting it into groups of 3 or 4 digits tends to be easier to remember than a single long number. *Why* does this chunking process work?
Prior Knowledge – Lesson (Sternberg)	*(6) Conceptual*	What did some researchers find surprising (counter-intuitive) about the mental search process Sternberg proposed?

Furthermore, Rittle-Johnson, Siegler, and Alibali (2001) described conceptual knowledge as knowledge of principles, concepts, and rules and when to apply those principles, and procedural knowledge as routinized knowledge acquired from explicit practice of a given problem type. From this view, any novel problem requires conceptual knowledge, because it has been neither practiced nor routinized. This presented a challenge, as we wished to gauge procedural knowledge of graphing and experimental design via the pre-test and then assess performance on novel procedural transfer problems at post-test. As stated, at pre-test, we addressed this issue by giving problems from outside the domain of cognitive psychology with the assumption that the procedural skills had been learned elsewhere. However, this was not possible at post-test, which was given in the context of the current lesson.

At post-test, we assessed procedural knowledge as knowledge of steps that we considered scriptable, and therefore teachable, whether or not students actually learned that procedure in the context of our lesson. Procedural assessment items included finding a slope, determining the ratio of two slopes, designing an experiment, determining the nature of a novel search process by executing a learned algorithm, etc., all in the context of lesson-specific concepts. By contrast, conceptual items tested facts, principles, or declarative knowledge, for example asking students to recall a fact, explain an answer, label a diagram, graphically depict a concept, etc.

Research Questions

We tested two research questions. First, does ancillary knowledge predict performance on near and/or far transfer questions, controlling for both general ability (i.e., SAT scores) and prior knowledge in the domain (i.e., the subdomain of memory)? We hypothesized that ancillary knowledge would predict learning but that prior knowledge of the domain would not.

Second, did we sufficiently distinguish conceptual and procedural knowledge types in the psychology domain? We measured concepts and procedures separately, on both the pre- and post-tests. Evidence that these variables are acceptably independent in terms of their correlations would be suggestive that our operationalization was successful. In addition, evidence that conceptual or procedural ancillary knowledge had differential patterns of association with the various post-test measures would also provide some support.

Method

Participants

80 undergraduate students (M_{age}=19.85 years, 63.8 percent female) completed the study for course credit.

Design and Procedure

A correlational design was used to study how natural variation in ancillary knowledge (pre-test question types 1-4 below) would relate to performance at post-test. On the pre-test, four questions each assessed (1) graphing conceptual knowledge, (2) graphing procedural knowledge, (3) experimental design conceptual knowledge, and (4) experimental design procedural knowledge. In addition, four questions assessed (5a) prior knowledge of memory, and two questions assessed (5b) prior knowledge of the lesson. These last two questions (5b) were the only ones that repeated between pre- and post-test. They were ultimately not used as a pre-test measure, because we determined that participants' knowledge of the target lesson was uniformly low/absent.

Due to limited time for the experiment, our goal on the pre-test was to sample sufficiently from each area of prior knowledge in order to determine a quantitative measure of probable degree of knowledge in each area, not to try to assess each area in depth.

Next, participants read a two-page lesson, which was about 700 words with several figures, adapted from J.R. Anderson's 8th Ed. Textbook, *Cognitive Psychology and Its Implications*. Then, participants completed a practice activity that was either conceptual or procedural in nature. The results of the practice manipulation and two additional measures of conceptual knowledge following the practice manipulation are not reported in this paper.

Next, participants completed the Post-Test. To measure participants' learning, we created four types of questions (and therefore four outcome measures): (1) Text-based Questions could be answered successfully if participants formed an adequate mental model of the text as they read. Participants did not need to bridge inferences, but rather draw from their memory of the text in order to recall information (see Kintsch, 1994; McNamara et al., 1996). (2) Near-transfer conceptual items were related to the lesson, but had not been stated directly in the text and therefore required bridging inferences. (3) Near-transfer procedural items required participants to perform procedures in the context of newly learned lesson concepts. For example, participants were asked to determine and compare the slopes of lines depicting the relationship between lesson-specific variables. This drew on preexisting knowledge of procedures (i.e., finding slopes and comparing their ratios) in the context of the lesson concepts. (4) Far-transfer items required participants to apply knowledge and skills they had learned (i.e., types and levels of variables, graphed data, and underlying hypotheses from Sternberg's memory search paradigm) to other types of mental processes, including a visual search task and a mental rotation task. See *Table 2* for sample post-test questions. Finally, participants were asked to provide demographic data and aptitude scores.

In sum, there were nine predictor variables. Five were taken from the pre-test: (1) Ancillary Graphing, conceptual, (2) Ancillary Graphing, procedural, (3) Ancillary Experimental Design, conceptual, (4) Ancillary Experimental Design, procedural, and (5) Prior Knowledge Memory, conceptual. As stated, knowledge of the lesson was excluded from analysis because the pre-test items related to the Sternberg lesson were answered incorrectly or left blank (with only one subject answering one item correctly).

The other four variables were covariates: (6) SAT Verbal scores, (7) SAT Math scores (if ACT scores were given, they were converted), (8) Reading Time, a measure of how long the participant spent on the lesson, and (9) English Native, a categorical variable indicating whether the student was a native English speaker from at least the age of six.

Table 2: Sample item from each of the four (4) outcome measures assessed at post-test.

Knowledge Types		Sample Items
Text-based	*(1) Conceptual*	What did some researchers find surprising (counter-intuitive) about the mental search process Sternberg proposed?
Near Transfer	*(2) Conceptual*	Which independent variable from the list above has the greatest influence on the slope of the line in the graph?
	(3) Procedural	The graph below shows the relationship between Memory Set Size and Response Time for Foil trials (A) and Target trials (B). Compared with the increase in reaction time for B, the increase in reaction time for A is…
Far Transfer	*(4) Conceptual & Procedural (mixed within each question)*	Consider a new type of mental task. This one involves conducting a visual search for an item, such as a red circle in a field of distractors (similar items). In Feature search, a person is asked to find the red o in a field of green x's and o's. (a) A feature search is most like a _____________ (parallel/serial) search. (b) Graph the lines for Target and Absent trials on the graph below. Label the lines.

Analyses and Results

Predictor Variables

Predictor variables were tested for normality. Several of the variables were negatively skewed and/or kurtotic, including both pre-test concept variables (graphs, experimental design) and SAT scores. In these cases, each score was reflected and then logarithmically transformed. These transformations resulted in acceptable normality, and these variables were re-reflected after transformation to aid in interpretation of beta coefficients.

Procedural Knowledge types (i.e., Graphing, Experimental Design), Reading Time, and Prior Knowledge-Memory, were normally distributed. The categorical variable English Native Speaker was answered "yes" seventy-percent of the time. Four cases did not report SAT scores and so the variable means were imputed for those cases.

Tests to see if the data met the assumption of collinearity indicated that multicollinearity was not a concern, with all $VIF < 2$. Correlations between each pair of predictor variables are reported in *Table 3*. The highest pairwise correlation was 0.55, between SAT Math and Verbal, below the conservative cutoff of 0.7 for multicollinearity. Seven pairs of predictor variables were significantly, positively correlated.

Table 3: Correlations between predictor variables.
** Correlation is significant at the 0.01 level (2-tailed). * Correlation is significant at the 0.05 level (2-tailed).

	Graphing Concepts	Graphing Procedures	Exp. Design Concepts	Exp. Design Procedures	Memory Concepts	SAT Verbal	SAT Math	Reading Time
Graphing Concepts	1							
Graphing Procedures	**0.336********	1						
Exp. Design Concepts	0.060	0.135	1					
Exp. Design Procedures	0.090	**0.252***	0.183	1				
Memory Concepts	0.209	0.172	0.169	0.095	1			
SAT Verbal	**0.254***	**0.241***	-0.026	-0.032	0.035	1		
SAT Math	**0.477********	**0.345********	0.063	-0.127	0.159	**0.547********	1	
Reading Time	-0.170	0.009	-0.177	0.072	-0.159	-0.064	-0.067	1

Linear Regressions

We regressed each of the Post-Test measures (Text-based Questions, Near Transfer Concepts, Near Transfer Procedures, and Far Transfer) on the nine explanatory variables in order to determine whether ancillary knowledge, prior knowledge in the domain, or general ability predicted performance. The model for Text-based Questions was the only model that was not significant.

The Near Transfer Concepts model was significant, $F(9,70) = 3.508$, $p = 0.001$, $R^2 = .311$, *Adj.* $R^2 = .222$. Greater Ancillary Knowledge of Graphing Concepts ($\beta = 4.426$, $t = 1.957$, $p = 0.054$) predicted better performance on near transfer concept questions.

The Near Transfer Procedures model was significant, $F(9,70) = 4.542$, $p = 0.001$, $R^2 = .369$, *Adj.* $R^2 = .288$. Greater Ancillary knowledge of Graphing Procedures ($\beta = 0.779$, $t = 3.574$, $p = 0.001$) predicted better performance on near transfer procedural questions.

The Far Transfer model was significant, $F(9,70) = 5.814$, $p = 0.001$, $R^2 = .428$, *Adj.* $R^2 = .354$. Higher SAT Math score ($\beta = 2.259$, $t = 2.330$, $p = 0.023$) and greater Ancillary Knowledge of Experimental Design Procedures ($\beta = 1.370$, $t = 4.114$, $p = 0.001$) each predicted better performance.

Finally, to test whether model fit was better when the four types of ancillary knowledge were entered as separate predictors in the model, as we had done, versus entered as a single predictor (and therefore treated as having a similar effect on learning), we compared *Adj.* R^2, AIC score, and BIC score for each of the models. *Adj.* R^2 and BIC are more sensitive to number of predictors and therefore penalize more for model size than AIC. The remaining predictors entered into the model were the same: SAT scores, Prior Knowledge of Memory, Reading Time, and English Native.

Model fit scores are shown in *Table 4*. All six models were significant at the 0.001 level. In addition, the single score for ancillary knowledge was a significant predictor in each of those three models. There was a slightly higher *Adj.* R^2 (0.005 more variance explained) for the single predictor model for Near Concepts, and a lower *Adj.* R^2 with the single predictor model for Near Procedures (0.009 less variance explained) and for Far Transfer (0.045 less variance explained). BIC, which penalizes more for number of predictors than AIC, was unsurprisingly lower in the single predictor models than the separate predictor models, signifying less overfitting. AIC was similar across the models, with the AIC for the single predictor model being slightly lower for Near Concepts and Near Procedures, but slightly higher for Far Transfer.

Table 4: Model fit for separate vs. combined (i.e., a single, additive score) ancillary knowledge predictors. The separate ancillary predictor models had nine predictors, whereas the single ancillary predictor models had six.

	Separate Ancillary Predictors Model (df=9)				*Single Ancillary Predictor Model (df=6)*			
For Outcome Measure:	R^2	*Adj.* R^2	*BIC*	*AIC*	R^2	*Adj.* R^2	*BIC*	*AIC*
Near Concepts	0.311	0.222	437.24	411.04	0.286	0.227	428.20	409.15
Near Procedures	0.369	0.288	356.78	330.58	0.334	0.279	347.44	328.38
Far Transfer	0.428	0.354	439.22	413.02	0.362	0.309	432.46	413.41

Discussion

This research identified ancillary knowledge and skills that predicted performance on near and far transfer assessment questions related to a cognitive psychology lesson. In each case, more ancillary knowledge led to better performance. We measured four types of ancillary knowledge that had a low degree of intercorrelation, namely conceptual and procedural knowledge of graphing and experimental design. Furthermore, specific ancillary measures predicted the various post-test measures, and statistical models that treated the ancillary knowledge as distinct accounted for the same or more variance than those that treated the ancillary knowledge as monolithic.

In addition, we found encouraging evidence that it is possible to operationalize assessment questions that differ on the conceptual and procedural knowledge dimension, and thereby measure them as distinct constructs, in this domain (i.e., cognitive psychology) and at this lesson and instructional level (i.e., introductory college coursework). Even though procedural assessment items are clearly dependent on a grasp of the lesson concepts in this context, we crafted procedural post-test questions that were predicted by ancillary procedural knowledge as assessed by pre-test problems in a different domain, suggesting that the procedural knowledge itself was uniquely important and domain independent. We do not interpret these results as implying that only procedural knowledge was needed for any of the assessment questions we labeled procedural (that is, independent of conceptual knowledge of the lesson).

SAT Math scores were also predictive of success in the Far Transfer model. And while not reported above, SAT Verbal was nearly significant (p = 0.068) in the Near Transfer Concepts model, and SAT Math was nearly significant (p = 0.076) in the Near Transfer Procedures model. It is not surprising that aptitude played a role in learning, particularly unsupported learning (e.g., no instructor) of a novel lesson, as students had to make sense of the material for themselves. Even so, ancillary knowledge was predictive over and above aptitude in the models.

In contrast to ancillary knowledge and general ability, prior knowledge in the memory subdomain of cognitive psychology was not predictive in any of the models. This should not be interpreted as domain-specific knowledge failing to predict performance in general, however. Schunn and Anderson (1999) found that domain-specific knowledge contributed to the performance of experts, and we expect that if students continued studying in the domain, domain-specific knowledge would be more and more predictive of their performance. In this study, however, the novice status of the participants lent greater importance to the variability in their ancillary knowledge and its role in their learning.

Finally, neither time spent reading the lesson nor native English speaker status from the age of six was predictive of performance, which is not surprising given that all students in our sample regularly do coursework in English, and that we also included a verbal aptitude measure in the model.

One final note about the specific assessment questions written for each of the outcome measures, some of which came from an actual cognitive psychology course and some of which were written for this lab study. The type of ancillary knowledge that predicted greater success on each transfer measure was arguably both a function of the outcome type (conceptual or procedural) and also the specific questions written for the category. As seen in Table 2, many of the questions written for the Near Transfer Concepts measure asked students to assess the relative influence of study variables in graphs of data and as they related to various theories, and so knowledge of graphing concepts is a logical predictor. Many of the questions written for the Near Transfer Procedures measure asked students to apply procedures related to graphing and experimental design in the context of the newly learned topic. For example, they were asked to predict values of various independent variables (e.g., stimulus quality, biasing) in Sternberg's experiment, imagine a graph for Accuracy instead of Reaction Time in Sternberg's experiment, etc., and so knowledge of graphing procedures is likewise a logical predictor.

For the Far Transfer measure, questions required students to apply their new lesson knowledge to mental processes that they had not previously encountered in their reading. Applying knowledge of the Sternberg paradigm in order to graph data and predict results for novel mental processes would likely benefit from greater knowledge of experimental design. Had we written different assessment questions, we expect that different ancillary knowledge structures would have been useful to the students, and a task analysis would have revealed that relevant knowledge. Furthermore, we consider it probable that ancillary knowledge structures beyond graphs, graphing, and experimental design could be measured and found predictive of better success at post-test.

Our study had several limitations. First, we tested our hypotheses regarding ancillary knowledge in the context of one lesson, so demonstrating the generalizability of these findings will be critical. Psychology is a domain that is conceptually rich, and therefore future studies should include a greater number of ancillary constructs. Second, the design was correlational, so we could not rule out other possible causes of performance differences. Third, we did not attempt to remedy gaps in knowledge structures that we identified in order to determine how such intervention would impact learning. Studying methods of remediating specific skills in the context of a new lesson versus outside the context of the lesson could suggest productive instructional practices once gaps are identified. Finally, work to further differentiate conceptual and procedural ancillary knowledge would be useful. Due to time limits, we were only able to take gross measures of ancillary knowledge at pre-test. A greater depth of pre-assessment, paired with the use of methods such as think-aloud protocols, to detect conceptual or procedural processing during the assessment would aid our understanding of how undergraduates construct, structure, and utilize their knowledge when encountering a new lesson.

Conclusion

We have defined a type of prior knowledge, ancillary knowledge, that differs from other types of prior knowledge in important ways. It is both domain-independent and yet relevant to learning of a target lesson. We also provide evidence that ancillary knowledge can be productively differentiated into various subtypes of knowledge (i.e., graphing vs. experimental design; conceptual vs. procedural).

The distinction between ancillary knowledge and prior knowledge of the domain is relevant for researchers who study learning, and may have bearing on the design of pre-tests. If the target population of students varies in level of domain-independent knowledge that may still have direct bearing on the lesson, pre-testing for ancillary knowledge (in addition to prior knowledge of the domain or lesson) would be relevant and potentially important for understanding patterns of learning.

In addition, distinguishing ancillary knowledge has implications for the design of instructional materials. Finding ways to identify and close gaps in ancillary knowledge could enhance the effectiveness of instruction for novice learners and ultimately improve learning and transfer.

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References

Ausubel, D. P. (1986). *Educational psychology: A cognitive view.* New York: Holt, Rinehart & Winston.

Baroody, A. J., Feil, Y., & Johnson, A. R. (2007). An alternative reconceptualization of procedural and conceptual knowledge. *Journal for Research in Mathematics Education*, 115-131.

Bloom, B. S. (1976). *Human characteristics and school learning.* New York: McGraw-Hill.

Crooks, N. M., & Alibali, M. W. (2014). Defining and measuring conceptual knowledge in mathematics. *Developmental Review*, *34*(4), 344-377.

De Jong, T., & Ferguson-Hessler, M. G. (1996). Types and qualities of knowledge. *Educational Psychologist*, *31*(2), 105-113.

Dochy, F. J., & Alexander, P. A. (1995). Mapping prior knowledge: A framework for discussion among researchers. *European Journal of Psychology of Education*, *10*(3), 225-242.

Dochy, F. J. R. C. (1988). *The "Prior Knowledge State" of Students and Its Facilitating Effect on Learning: Theories and Research*. Available from Open University, Herleen, OTIC Research Report 1.2.

Fincher-Kiefer, R., Post, T. A., Greene, T. R., & Voss, J. F. (1988). On the role of prior knowledge and task demands in the processing of text. *Journal of Memory and Language*, *27*(4), 416.

Jonassen, D. H., & Grabowski, B. L. (1993). *Handbook of individual differences, learning, and instruction*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Kintsch, W. (1994). Text comprehension, memory, and learning. *American Psychologist*, *49*(4), 294.

Langer, J. A., & Nicolich, M. (1981). Prior knowledge and its relationship to comprehension. *Journal of Reading Behavior*, *13*(4), 373-379.

Lawson, A. E. (1983). Predicting science achievement: The role of developmental level, disembedding ability, mental capacity, prior knowledge, and beliefs. *Journal of Research in Science Teaching*, *20*(2), 117-129.

Means, M. L., & Voss, J. F. (1985). Star Wars: A developmental study of expert and novice knowledge structures. *Journal of Memory and Language*, *24*(6), 746.

McNamara, D. S., Kintsch, E., Songer, N. B., & Kintsch, W. (1996). Are good texts always better? Interactions of text coherence, background knowledge, and levels of understanding in learning from text. *Cognition and Instruction*, *14*(1), 1-43.

Rittle-Johnson, B., Siegler, R. S., & Alibali, M. W. (2001). Developing conceptual understanding and procedural skill in mathematics: An iterative process. *Journal of educational psychology*, *93*(2), 346.

Rittle-Johnson, B., & Siegler, R. S. (1998). The relation between conceptual and procedural knowledge in learning mathematics: A review. In C. Donlan (Ed.). *The Development of Mathematical Skills.* UK: Psychology Press.

Schauble, L., Glaser, R., Raghavan, K., & Reiner, M. (1991). Causal models and experimentation strategies in scientific reasoning. *The Journal of the Learning Sciences*, *1*(2), 201-238.

Schunn, C. D., & Anderson, J. R. (1999). The generality/specificity of expertise in scientific reasoning. *Cognitive Science*, *23*(3), 337-370.

Siegler, R.S. (1986). *Children's thinking.* Englewood Cliffs, NJ: Prentice-Hall.

Willingham, D. T. (2007). Critical thinking. *American Educator*, *31*(3), 8-19.

Zeitoun, H.H. (1988). *The relationship between abstract concept achievement and prior knowledge, formal reasoning ability, and sex among some Egyptian secondary school students*. Paper presented at the annual meeting of the National Association for Research in Science and Teaching, Lake of the Ozark, MO.