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Examining the Relationship Between Knowing and Doing: Training for Improving Food Choices

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Abstract

Food is essential for maintaining human life; however, our food choices can have negative impacts on the health of our bodies and our planet. For example, obesity and diet-related diseases are increasing at alarming rates. In addition, agricultural chemicals are detectable in many rivers and streams, contaminating drinking water. Thus, understanding what factors contribute to food choices is essential for those interested in social change. This paper reviews some principles of learning and memory and how applications of those principles contribute to our understanding of food choices. Experiments that examine different ways to promote learning, retention, and generalization of knowledge, specifically focused on ways to enhance learning of nutritional information and food choices, are also reviewed. The practical applications of this research to training, health, and public policy are also discussed.

Keywords

learning; retention; transfer; nutrition; decision-making; seeding the knowledge base

The relationship between knowing and doing is complex, and knowledge does not always lead to its intended action. For example, roughly 46.6 million American adults smoke cigarettes despite the fact that 8.6 million live with a serious illness attributed to smoking (aCenter for Disease Control and Prevention [CDC], 2011a). Perhaps one way to decrease the gap between knowing and doing is to promote a deep level of understanding, one that promotes both long-term retention and transfer of knowledge. Research has demonstrated, however, that, in many cases, retention and transfer are competing goals (e.g., Lohse & Healy, 2012). That is, learning is often highly specific to the particular material to be learned as well as to the conditions under which it occurred, and a number of theoretical explanations for specificity effects have been proposed (e.g., Healy & Wohldmann, 2012). For example, Thorndike (1906) proposed that transfer of learning depends on how many “identical elements” are shared between the learning task and the transfer task. More recent, but conceptually similar, theories include encoding specificity (Tulving & Thomson, 1973),

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transfer appropriate processing (Morris, Bransford, & Franks, 1977; Roediger, Weldon, & Challis, 1989), and our own work on procedural reinstatement (e.g., Healy, Wohldmann, & Bourne, 2005). Understanding how to facilitate transfer of learning is one goal of the research reviewed in this paper, and the findings from this program can be applied to create potential solutions to some of the most challenging dilemmas faced by society today.

One such social dilemma involves comprehending how and why people make decisions about food consumption because our choices have widespread implications on the health of our bodies and our planet. For example, the CDC (2011b) reports that obesity (defined as a Body Mass Index equal to or greater than 30) has been steadily increasing since 1985, when rates were less than 10% in most states. By 1999, obesity rates exceeded 20% in more than half of the country, and as of 2010, surpassed 20% in every single state and were greater than 30% in 13 states. Moreover, four out of the six leading causes of death (heart disease, cancer, stroke, and diabetes) in this country are said to be diet-related, and obesity-related Type 2 diabetes is on the rise (e.g., Calle, Rodriguez, Walker-Thurmond, & Thun, 1999; Chan, Rimm, Colditz, Stampfer, & Willett, 1994). Especially alarming, however, is the rapidly increasing rate of childhood obesity, which has more than tripled in the last 30 years (CDC, 2011c). Many of the food preferences formed during early childhood remain throughout the lifespan (e.g., Birch, 1999), and the stigma associated with obesity has lifelong negative effects (e.g., Puhl & Heuer, 2009).

Beyond health, our food choices impact the planet in a number of ways. The production and distribution of food is resource intensive and environmentally costly, for example, contributing to our loss of clean drinking water due to agricultural runoff (e.g., Environmental Protection Agency, 2005; Postel, 2000), higher rates of certain types of cancer in farm workers (e.g., Parent, Desy, & Siemiatycki, 2009), and a loss of biodiversity and pollinators (e.g., Ratnieks & Carreck, 2010), to name a few.

The need for large-scale changes to our food system is apparent, and because consumer behavior drives change, psychologists who investigate factors that influence decisions have a unique opportunity to contribute to the discussion of how to create such change. An entire field of research is devoted to the study of food choices, such as environmental, contextual, and social factors (e.g., Schuldt, Muller, & Schwarz, 2012; Wansink, 2006), as well as biological and evolutionary adaptations (e.g., Gearhardt, Grilo, DiLeone, Brownell, & Potenza, 2011). In this paper, however, I take a new approach by reviewing studies aimed to reveal how the science of learning and, more specifically, how principles developed in the field of cognitive psychology, can be applied to inform our understanding of food choices.

Learning Nutritional Information

Americans spend approximately 48% of their food dollars dining outside the home (Pomeranz & Brownell, 2008). Unlike processed foods that are purchased in the grocery store, food consumed in restaurants is not required to contain a Nutrition Facts Panel, which lists the nutritional characteristics (e.g., total calories, grams of fat, sugar, etc.) in those foods. Thus, knowing what is healthy (i.e., low in calories, high in nutrition) is especially difficult when dining out because the ingredients and nutritional information are not always

available. Moreover, portions are often more than one serving, and added sugars and fats are not easily detectable, posing additional challenges to health-conscious consumers. Take, for example, a taco salad offered in a popular fast-food restaurant, which contains roughly 1450 calories. Based on a 2000-calorie diet, this taco salad represents nearly three-quarters of the daily-recommended calories, leaving little room for one to consume additional foods throughout the day without exceeding the 2000-calorie limitation.

Without being provided calorie information for the foods we are eating, we are unable to make fully informed food choices because people are generally poor at estimating the number of calories in foods. Several factors influence the accuracy of those estimates. For example, people more often underestimate the caloric content of main dishes when eating at restaurants that are perceived as healthy (e.g., Subway) than when eating at those that are perceived as unhealthy (e.g., McDonalds; Chandon & Wansink, 2007a). Overweight individuals are more likely to underestimate the calorie content of foods than normal weight individuals, likely because overweight individuals tend to select larger meals and people are more likely to underestimate the calories in large meals (Chandon & Wansink, 2007b). In fact, even registered dietitians (i.e., experts) often underestimate the caloric values of foods (Backstrand, Wootan, Young, & Hurley, 1997). To eliminate the need for guessing, recent regulations have been put into place requiring that some food chains offer calorie counts on their menus. But not all restaurants will be required to post calories, and because it would be impossible to learn the calorie content of all foods available, discovering how to promote generalization of this knowledge could be helpful for those who wish to make informed food choices. Looking towards theories of learning and transfer can provide a better understanding of ways to minimize specificity and promote a deep level of knowledge, which may help to shrink the gap between knowing and doing.

Theories of Learning and Transfer

As stated previously, knowledge is often highly specific to the learning conditions, such that little to no transfer may be evident between original learning and subsequent recall. Thus, one goal of my research has been to understand ways of reducing specificity effects and promoting positive transfer. Seeding the knowledge base has been shown to encourage transfer of learning, and this technique has been used to improve quantitative estimates in a variety of domains (e.g., estimating distances between cities and population sizes)--because it is not just calories we have trouble estimating, but quantitative values more generally (e.g., Brown & Siegler, 1996). The typical paradigm involves three experimental phases. First, participants are presented with a series of items (e.g., city names) and are asked to estimate the quantitative values for a specific property (e.g., populations). Next, participants learn the actual values (i.e., seed facts) for a subset of those items. Finally, participants estimate the values for all of the original items and, in some cases, new items as well. Generally, seeding improves overall estimation accuracy, including accuracy for the items not included during the second phase, demonstrating transfer of learning.

Although the theoretical explanations for the effectiveness of the seeding paradigm have been debated, several robust findings from cognitive psychology can potentially account for the benefits to learning and transfer found after seeding the knowledge base. For example,

inherent in the seeding paradigm is the opportunity to practice making quantitative estimates for a variety of items, and placing task variations, known as *variability of practice*, within the learning context is important for the development of the schemata responsible for retention and transfer of knowledge (e.g., Schmidt & Bjork, 1992). Although typically applied to the acquisition of procedural knowledge (e.g., motor skills), the variability of practice hypothesis might also help to explain any positive transfer effects found when the seeding technique is used to learn declarative knowledge. However, the advantages of variable practice are limited to certain conditions that are not well understood (e.g., Healy, Wohldmann, Sutton, & Bourne, 2006).

Alternatively, the benefits to learning and transfer after seeding might be explained by the fact that generating information to be learned often produces greater recall than merely reading the information, a robust finding referred to as the *generation effect* (e.g., Jacoby, 1978; Slamecka & Graf, 1978). Some researchers have claimed that the activation of specific item features stored in semantic memory is important for the occurrence of this effect (e.g., Nairne, Puse, & Widner, 1985). Other researchers have argued for a transfer appropriate processing account (e.g., deWinstanley, Bjork, & Bjork, 1996). Although the mechanisms of the underlying benefits found through generation are not fully understood, seeding the knowledge base requires that participants actively generate quantitative information, which could help to explain why seeding improves retention and transfer of quantitative information relative to passively viewing that information.

Applying the Science of Learning to a Laboratory Task

In two recent experiments from my lab, the seeding technique was applied to a calorie estimation task in order to evaluate whether or not seeding is beneficial for learning and transfer of calorie information (Wohldmann & Quilici, 2012). Although the design of these particular experiments did not allow for a test of the variability of practice hypothesis, it was conducive for testing the generation effect. More specifically, in the first experiment, a list of food items was selected from the six USDA food groups (meat, dairy, vegetables, fruits, grains, and fats). Each food item, described quantity, and any corresponding calorie information designated one serving. For example, “Bagel (1 large, 4.5” in diameter)” belonged to the grain group; “Nectarine (1 medium, 2.5” in diameter)” to the fruit group; and “Spinach (1 cup, raw)” to the vegetable group. There were three between-subjects conditions (seeding, view only, control), with 33 participants in each condition, and three experimental phases (familiarization, training, testing). During familiarization, items from each of the food groups appeared on the screen, one at a time, and participants were asked to estimate the number of calories contained in the item. Participants were given five foods from each food group, presented in a mixed fashion, and no feedback was given on the accuracy of their estimates. During training, different items than those shown during familiarization appeared on the screen, again, one at a time.

Participants in the seeding condition were asked to estimate the calorie content of the item being presented, as during familiarization; however, during training these participants received immediate feedback on their estimates in the form of the actual number of calories contained in that food item. Participants in the view only condition were provided with the

actual number of calories contained in each item (presented next to the described quantity), and they were asked to read aloud the name, quantity and calorie count of each item being presented. Participants in the control condition neither estimated nor saw calorie information; instead, they were asked merely to read aloud the name and described quantity of each food item being presented. Each block of training included 30 items, five from each food group, and each block was shown in a different random order four consecutive times. Finally, during testing, all participants made calorie estimates, as during familiarization. Some of the items on the test were old, having been shown previously during either familiarization or training, and some of the items were new, not having been shown previously. Testing included all 60 of the old items and 30 new items.

Performance was measured by calculating proportional absolute error, which is the absolute difference between the estimated caloric value and the actual caloric value of each food item divided by the actual caloric value. This measure provides a normalized assessment of error magnitude. Although relative error (which is the same measure as absolute error except uses the signed difference) was examined, the findings from the measure of absolute error are most pertinent to the discussion of learning and transfer; thus, relative error is not reported in this paper. Figure 1 shows the percentage of error (i.e., proportional absolute error multiplied by one-hundred) on calorie estimates during familiarization and testing as a function of condition and item type (old, new). All conditions were equivalent at familiarization, which occurs before the condition manipulation. Having been given no caloric values and no feedback on their estimates, participants in the no calorie control condition learned essentially nothing between familiarization and testing. In contrast, participants in both the view only and seeding conditions showed significant improvement in estimation accuracy between familiarization and testing on old items, demonstrating that being given either calorie information or feedback on estimates of calorie counts results in learning.

As can also be seen in Figure 1, participants in the no calorie control condition showed no improvement in estimation accuracy between familiarization and testing on new items, suggesting no transfer of learning. Those in both the view only and seeding conditions, however, did show significant improvement between the two phases, demonstrating transfer of learning. In fact, estimation accuracy was essentially equivalent (i.e., not statistically different) for both old and new items, indicating perfect transfer.

The results of this experiment suggested benefits to learning and transfer when either viewing or receiving feedback on estimates of calorie information. Contrary to previous studies, the seeding technique did not yield greater transfer than did merely reading calorie information; that is, participants in the view only condition performed just as well on the final test as those in the seeding condition. These findings also, then, suggest no benefit to generating to-be-learned information over passively reading the information.

The items used in this first experiment, however, were fairly simple—single serving sizes of various foods sampled from the USDA food categories. The domain of food is much more complex than, for example, one ounce of cheese or a medium-sized apple. Thus, a second experiment was conducted to examine learning and transfer for more complex food

categories. Specifically, the items presented were selected from actual restaurant menus (including five national chain restaurants), and foods were categorized according to the restaurant's designated menu categories (appetizer, entrée, side-dish, dessert, drink). As in the first experiment, the item name and a description were shown, and the descriptions were taken directly from restaurant menus. For example, "steak tacos entrée (Two Baja-style tacos with grilled steak, fresh shredded cabbage and homemade ranchito sauce) served with white and blue corn tortilla chips and homemade roasted tomato salsa" was included in the entrée category; "small Sichuan-style asparagus side dish (Wok-fired with Sichuan preserves, onion, chili flakes and garlic)" was included in the side-dish category; a "goblet of fresh strawberries (Bowl of fresh strawberries served with whipped cream on the side)" was included in the dessert category. In all other respects, the methods used in the second experiment were the same as those used in the first. Seventy-five participants were tested, with 25 in each between-subjects condition.

Figure 2 shows proportional absolute error on calorie estimates during familiarization and testing as a function of condition and item type (old, new). As can be seen, the pattern of results looks very similar to that of the first experiment. Specifically, participants in the view only and seeding conditions performed significantly better on the final test than those in the control condition, despite the fact that all conditions performed similarly during familiarization (prior to the condition manipulation). As in the first experiment, between familiarization and testing, performance improved on both old items, demonstrating learning, and new items, demonstrating transfer of learning.

Across the two experiments, the seeding technique was effective for learning and transfer of knowledge, supporting previous studies demonstrating the benefits of seeding for learning quantitative information. However, viewing calorie information was just as effective for learning and transfer as seeding calorie information, a finding that is contrary to data supporting the generation effect, which claims better memory for information that is generated than information that is merely read. Other researchers have demonstrated that, under certain conditions, the generation effect can be reduced or eliminated entirely. For example, when instructions encouraged participants to process the material to be learned in a manner that was similar to the processing requirements of the generation condition, the generation effect disappeared (e.g., McDaniel, Waddill, & Einstein, 1988). Similarly, when the processing strategy involved imagery rather than passively reading, no advantage for the generation condition was found (e.g., Begg, Vinski, Frankovich, & Holgate, 1991). Finally, other research has shown a reduced generation effect when the material presented was unfamiliar (e.g., non-words) to the participants (e.g., Lutz, Briggs, & Cain, 2003). Because calorie counts are likely unfamiliar to most people and somewhat meaningless unless one is on a particular diet that involves counting calories, unfamiliarity alone could account for the results of the present experiments. Moreover, although participants were not told explicitly that they would be asked to estimate calorie counts on a test following training, it is possible that they anticipated a test and, therefore, processed the information presented during training in a manner that was similar to the processing requirements in the seeding condition.

Regardless of why no difference was found between the seeding and view only conditions, from an applied perspective and in light of studies examining the impact of menu regulation, finding a benefit to learning and transfer for participants in the view only condition is an especially important finding. That is, recent research has shown that posting calories on menus may not reduce the calorie content of meals purchased in fast food restaurants (Elbel, Gyamfi, & Kersh, 2011; Elbel, Kersh, Brescoll, & Dixon, 2009). Thus, one might argue that such regulations have little benefit to society, and merely pose an additional financial burden on businesses. The findings from these two experiments, however, suggest that the benefits of presenting calorie information extend beyond immediate decision-making. That is, viewing calorie information might have unexpected benefits to learning; because menu labeling is not required in all restaurants, generalization of knowledge is key. Furthermore, while knowledge might not be sufficient for influencing decisions, it is certainly necessary.

Applying the Science of Learning to Understanding Real Decisions

The two seeding experiments described above demonstrate how to improve general knowledge, promoting transfer of learning, by applying the seeding technique to a laboratory task. Making decisions in the real world, however, can be very different from the laboratory experience. For example, anyone trying to reduce their calorie intake through dieting probably understands how difficult it can be to put knowledge into action when it comes time to reject a slice of rich, calorie-laden cake. Thus, another goal of the research program described in this paper is to examine how learning influences actual decisions, in this case food choices. More importantly, this research focuses on whether or not a deep understanding of material can be used to shrink the gap between knowledge and action. To this end, in another recent experiment from my lab, we examined how learning about nutritional information influences actual food choices (Wohldmann, Quilici, & Chilet, 2012). In this particular experiment, the nutrition interventions targeted Latino American adults because obesity rates (38.6%) are higher than those in Caucasian American adults (32.6%; Flegal, Carroll, Ogden, & Curtin, 2010), and are rising rapidly.

During the first phase of this study, all participants (who were self-described Latinos) were trained to record 3-day food journals by a nutritionist who met with them individually. During training, participants were taught how to record portion sizes and food characteristics (e.g., ingredients, brand, quantity consumed). Upon completion of the 3-day food journal, participants returned for an intervention, and were assigned to one of three between-subjects conditions. Participants in one of the two Food Pyramid conditions were given a detailed diet analysis based on their 3-day food journal entries. As part of this diet analysis, participants were shown how much of the recommended level of macro- and micronutrients (e.g., saturated fat, unsaturated fat, transfat, protein, fiber, sugar, sodium) they were consuming, and were given tailored advice about how to improve their diets including a list of fruits and vegetables that could be introduced into their diets. This advice, and the foods suggested for consumption, was based on either a culturally relevant traditional diet described by the Latino Nutrition Coalition (LNC) or a culturally irrelevant diet based on the USDA guidelines for healthy eating. Participants were also shown food pyramids provided by each of the organizations, which included images and general quantity guidelines of suggested foods. Those in the control condition completed questionnaires unrelated to food

and diet (e.g., religious beliefs, mood, demographics). Finally all participants completed a second 3-day food journal approximately 1-week later, and received \$50 upon completion of the study. One-hundred and three participants completed all phases of this study.

Figure 3 shows the number of total calories and fat calories consumed during the 3-day food journal period as a function of condition (culturally relevant, culturally irrelevant, control) and session (Week 1, Week 2). Participants in both intervention conditions significantly reduced their caloric intake between the two sessions, with no statistical difference between the two intervention conditions. The reduction in calories consumed, if maintained, would equate to losing nearly one pound per week—a healthy amount according to medical and nutrition professionals. Participants in the control condition, however, showed a much smaller and non-significant calorie reduction between the two sessions.

To examine what specific food choices were influencing this reduction in calories, the changes between the two sessions in total fat calories, sugar calories, and total servings of fruits and vegetables, grains, meats and beans, and dairy consumed were assessed. As can be seen in Figure 3, for participants in the intervention conditions, the reduction in total fat calories consumed between the two phases was significant. This is an important finding in the context of the results of Brady, Lindquist, Herd, and Goran (2000), who found that the average 10-year old child reportedly consumes 46% of his or her daily calories from added sugars and fats, when guidelines for healthy eating recommend that only 5% of our daily calories come from fat and sugar. The control condition showed no significant reduction in fat calories. Changes in other categories were not significant, although participants in the intervention conditions showed a marginally significant reduction in sugar calories, suggesting that the calorie reduction found for participants in the intervention conditions came primarily from a decrease in fat and sugar consumption rather than an increase in fruit and vegetable consumption or other changes in dietary behaviors. During the diet analysis, the nutritionist emphasized the importance of increasing fruit and vegetable consumption, but the reduction in calories consumed between the two sessions came largely from fat and sugar. Thus, possible demand characteristics on the part of participants cannot fully explain the present findings.

The results of this experiment suggest that concrete information, specific advice about the healthfulness of certain foods and how those foods relate to the needs of our bodies, might be an important predictor of behavioral change. Participants in the intervention conditions were given detailed diet analyses upon completing the first food journal, and were offered suggestions for alternative foods in order to meet their nutritional needs in the form of specific advice about fruits and vegetables that could be added to their diets. Thus, having access to detailed nutrition information and concrete advice improves immediate food choices.

Conclusions

The experiments described here demonstrate ways in which transfer is achieved, as well as how learning results in subsequent changes to behavior. More specifically, the first two experiments described in this paper demonstrate how to promote learning and generalization

of calorie information. The results suggest that calorie labeling might have unintended benefits to learning and transfer of knowledge. That is, restaurant menu labeling, already in effect in some cities, might help people to more accurately estimate the calorie content of foods when calorie information is not available, thus, allowing them to make informed choices and possibly influencing their choices. This small change to menus could have large effects on nutritional knowledge, more generally. The third experiment shows that, although the relationship between knowing and doing is complex, making information concrete by giving tailored nutritional advice might possibly help to shrink the gap between knowing and doing. While the long-term effects of this type of nutritional intervention, or tailored nutrition training, are still unknown, the manipulation did have immediate benefits to dietary choices. This preliminary finding supports the idea of taking a proactive approach to healthcare policy, potentially one involving visits to a nutritionist. This is a preventative measure not covered under many insurance plans.

More broadly, findings and learning principles from the field of cognitive psychology can be applied to a wide range of social dilemmas, for example, improving nutritional awareness so that people can make informed choices. As discussed earlier, improving food choices has the potential to decrease obesity-related diseases and healthcare costs associated with obesity, enhance psychological well-being, and improve overall quality of life. Moreover, decreasing the demand for highly processed foods by educating consumers about the effects of those foods could shift the way our agricultural system operates, potentially lessening the negative environmental and social impacts.

To create changes to our food system that minimize health and social impacts, we must understand the psychological processes that drive consumer behavior. I believe such change necessitates decreasing the gap between knowing and doing. We hear a lot of “common wisdom” about people and change, for example, that people are resistant to change, afraid of change, and so on. The results of the studies described in this paper, however, demonstrate that people can change if they know more precisely what to do—clarity dissolves resistance.

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References

- Backstrand, J.; Wootan, MG.; Young, LR.; Hurley, J. Fat chance: A survey of dietitians' knowledge of the calories and fat in restaurant meals. Washington, D.C: Center for Science in the Public Interest; 1997.
- Begg I, Vinski E, Frankovich L, Holgate B. Generating makes words memorable, but so does effective reading. *Memory & Cognition*. 1991; 19:487–497.10.3758/BF03199571 [PubMed: 1956309]
- Birch LL. Development of food preferences. *Annual Review of Nutrition*. 1999; 19:41–62.10.1146/annurev.nutr.19.1.41
- Brady LM, Lindquist CH, Herd SL, Goran MI. Comparison of children's dietary intake patterns with US dietary guidelines. *British Journal of Nutrition*. 2000; 84:361–367.10.1017/S0007114500001641 [PubMed: 10967615]

- Brown NR, Siegler RS. Long-term benefits of seeding the knowledge base. *Psychonomic Bulletin & Review*. 1996; 3:385–388.10.3758/BF03210766 [PubMed: 24213943]
- Calle EE, Rodriguez C, Walker-Thurmond K, Thun MJ. Overweight, obesity, and mortality from cancer in a prospectively studied cohort of U.S. adults. *New England Journal of Medicine*. 1999; 348:1625–1638.10.1056/NEJMoa021423 [PubMed: 12711737]
- Center for Disease Control and Prevention. Tobacco use: Targeting the Nation's Leading Killer at a Glance 2011. 2011a. Retrieved from <http://www.cdc.gov/chronicdisease/resources/publications/AAG/osh.htm>
- Center for Disease Control and Prevention. Obesity trends by state 1985–2010. 2011b. Retrieved from <http://www.cdc.gov/obesity/data/trends.html>
- Center for Disease Control and Prevention. Childhood obesity facts. 2011c. Retrieved from <http://www.cdc.gov/healthyyouth/obesity/facts.htm>
- Chan JM, Rimm EB, Colditz GA, Stampfer M, Willett WC. Obesity, fat distribution, and weight gain as risk factors for clinical diabetes in men. *Diabetes Care*. 1994; 17:961–969.10.2337/diaclin.23.3.130 [PubMed: 7988316]
- Chandon P, Wansink B. The biasing health halos of fast-food restaurant health claims: Lower calorie estimates and higher side-dish consumption intentions. *Journal of Consumer Research*. 2007a; 34:301–314.10.1086/519499
- Chandon P, Wansink B. Is obesity caused by calorie underestimation? A psychophysical model of meal size estimation. *Journal of Marketing Research*. 2007b; 44:84–99.10.1509/jmkr.44.1.84
- deWinstanley PA, Bjork EL, Bjork RA. Generation effects and the lack thereof: The role of transfer-appropriate processing. *Memory*. 1996; 4:31–48.10.1080/741940667 [PubMed: 8821084]
- Elbel B, Gyamfi J, Kersh R. Child and adolescent fast-food choice and the influence of calorie labeling: A natural experiment. *International Journal of Obesity*. 2011; 35:493–500.10.1038/ijo.2011.4 [PubMed: 21326209]
- Elbel B, Kersh R, Brescoll BL, Dixon LB. Calorie labeling and food choices: A first look at the effects on low-income people in New York City. *Health Affairs*. 2009; 28:1110–1121.10.1377/hlthaff.28.6.w1110
- Environmental Protection Agency. Protecting water quality from agricultural runoff. 2005. (EPA Publication No. 841-F-05-001). Retrieved from http://www.epa.gov/owow/NPS/Ag_Runoff_Fact_Sheet.pdf
- Flegal KM, Carroll MD, Ogden CL, Curtin LR. Prevalence and trends in obesity among U.S. adults, 1999–2008. *Journal of the American Medical Association*. 2010; 303:235–241.10.1001/jama.2009.2014 [PubMed: 20071471]
- Gearhardt AN, Grilo CM, DiLeone RJ, Brownell KD, Potenza MN. Can food be addictive? Public health and policy implications. *Addiction*. 2011; 106:1208–1212.10.1111/j.1360-0443.2010.03301.x [PubMed: 21635588]
- Healy, AF.; Wohldmann, EL. Specificity and transfer of learning. In: Ross, B., editor. *Psychology of Learning and Motivation*. Vol. 57. 2012. p. 227-253.
- Healy, AF.; Wohldmann, EL.; Bourne, LE, Jr. The procedural reinstatement principle: Studies on training, retention, and transfer. In: Healy, AF., editor. *Experimental cognitive psychology and its applications*. Washington, DC: American Psychological Association; 2005. p. 59-71.
- Healy AF, Wohldmann EL, Sutton EM, Bourne LE Jr. Specificity effects in training and transfer of speeded responses. *Journal of Experimental Psychology: Learning, Memory, and Cognition*. 2006; 32:534–546.10.1037/0278-7393.32.3.534
- Jacoby LL. On interpreting the effects of repetition: Solving a problem versus remembering a solution. *Journal of Verbal Learning and Verbal Behavior*. 1978; 17:649–668.10.1016/S0022-5371(78)90393-6
- Lohse KR, Healy AF. Exploring the contributions of procedural and declarative training to performance: A test of the procedural reinstatement principle. *Journal of Applied Research in Memory and Cognition*. 2012; 1:65–72.10.1016/j.jarmac.2012.02.002
- Lutz J, Briggs A, Cain K. An examination of the value of the generation effect for learning new material. *The Journal of General Psychology*. 2003; 130:171–188.10.1080/00221300309601283 [PubMed: 12773019]

- McDaniel MA, Waddill PJ, Einstein GO. A contextual account of the generation effect: A three-factor theory. *Journal of Memory and Language*. 1988; 27:521–536.10.1016/0749-596X(88)90023-X
- Morris CD, Bransford JD, Franks JJ. Levels of processing versus transfer appropriate processing. *Journal of Verbal Learning and Verbal Behavior*. 1977; 16:519–533.10.1016/S0022-5371(77)80016-9
- Nairne JS, Pusey C, Widner RL Jr. Representation in the mental lexicon: Implications for theories of the generation effect. *Memory & Cognition*. 1985; 11:183–191.10.3758/BF03197011 [PubMed: 4033420]
- Parent ME, Desy M, Siemiatycki J. Does exposure to agricultural chemicals increase the risk of prostate cancer among farmers? *McGill Journal of Medicine*. 2009; 12:70–77. [PubMed: 19753293]
- Pomeroy JL, Brownell KD. Legal and public health considerations affecting the success, reach, and impact of menu-labeling laws. *American Journal of Public Health*. 2008; 98:1578–83.10.2105/AJPH.2007.128488 [PubMed: 18633081]
- Postel SL. Entering an era of water scarcity: The challenges ahead. *Ecological Applications*. 2000; 10:941–948.10.1890/1051-0761(2000)010[0941:EAEOWS]2.0.CO;2
- Puhl RM, Heuer CA. The stigma of obesity. *Obesity*. 2009; 17:941–964.10.1038/oby.2008.636 [PubMed: 19165161]
- Ratnieks FLW, Carreck NL. Clarity on honey bee collapse? *Science*. 2010; 327:152–153.10.1126/science.1185563 [PubMed: 20056879]
- Roediger, HL., III; Weldon, MS.; Challis, BH. Explaining dissociations between implicit and explicit measures of retention: A processing account. In: Roediger, HL., III; Craik, FIM., editors. *Varieties of memory and consciousness: Essays in honour of Endel Tulving*. Hillsdale, NJ: Erlbaum; 1989. p. 3-41.
- Schmidt RA, Bjork RA. New conceptualizations of practice: Common principles in three paradigms suggest new concepts for training. *Psychological Science*. 1992; 3:207–217.10.1037/0278-7393.17.5.940
- Schuldt JP, Muller D, Schwarz N. The “fair trade” effect: health halos from social ethics claims. *Social Psychological and Personality Science*. 2012 Advance online publication. 10.1177/1948550611431643
- Slamecka NJ, Graf P. The generation effect: Delineation of a phenomenon. *Journal of Experimental Psychology: Human Learning and Memory*. 1978; 4:592–604.
- Thorndike, EL. *The principles of teaching: Based on psychology*. New York: A. G. Seiler; 1906.
- Tulving E, Thomson DM. Encoding specificity and retrieval processes in episodic memory. *Psychological Review*. 1973; 80:352–373.10.1037/h0020071
- Wansink, B. *Mindless eating: Why we eat more than we think*. New York, NY: Bantam Dell; 2006.
- Wohldmann, EL. Examining the relationship between knowing and doing: Nutrition training for improving food choices. Invited talk delivered at the annual meeting of the American Psychological Association; 2011 Aug.
- Wohldmann, EL.; Quilici, JL. Planting a seed: Using the seeding technique to improve calorie estimates. 2012. Manuscript in preparation
- Wohldmann, EL.; Quilici, JL.; Chilet, PM. The relationship between education and diet: Examining a culturally relevant nutrition program. 2012. Manuscript submitted for publication

Figure 1. Percentage of error on the calorie estimation task as a function of condition, phase, and item type in Experiment 1. Bars represent standard errors of the mean.

Figure 2. Percentage of error on the calorie estimation task as a function of condition, phase, and item type in Experiment 2. Bars represent standard errors of the mean.

Figure 3.

Calorie consumption during the 3-day food journal period as a function of condition, session, and calorie type in Experiment 3. Bars represent standard errors of the mean.