BEYOND A MERE LACK OF SUPPORT: EVIDENCE AGAINST LEARNING STYLE THEORIES FROM INCONSISTENT RECALL SCORES UNDER MULTIPLE PRESENTATION MODES

A Thesis
Presented
to the Faculty of
California State University, Chico

In Partial Fulfillment
of the Requirements for the Degree
Master of Arts
in
Psychology
Psychological Science Option

by
Adelaide K. Kreamer
Spring 2013
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DEDICATION

This thesis is dedicated to my family without whom I would not have made it to where I am today. Thank you for sticking with me through everything: the good, the bad, and the ugly. Your love, support, and encouragement has been life changing.
ACKNOWLEDGMENTS

Dr. Martin van den Berg is great. And, his instruction, guidance, and friendship has been great as well.
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ABSTRACT

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Spring 2013

Proponents of perceptual Learning Style theories claim that there are individual differences in the modalities through which people learn best. In contrast, critics argue that there is not enough evidence to support such claims. However, mere lack of support is insufficient to refute Learning Style theories. In an attempt to clarify this issue, we predicted that modality-specific recall would be inconsistent over a one-week period. Participants studied short stories using four different presentation modes during two sessions. We compared recall scores in each presentation mode, as well as performance-based learning style categorizations between the two sessions. Differences in recall
performance over time were greater than the differences between the four presentation modes. Additionally, consistency of performance-based learning style categorizations only reached chance level. Finally, Learning Style inventories unsuccessfully predicted performance in corresponding modalities. We interpret these results as evidence against Learning Styles and instead recommend empirically confirmed teaching methods.
CHAPTER I

INTRODUCTION

Background

The field of Learning Styles is complex and full of controversy. In general Learning Styles are thought of as individuals’ preferences for approaching or responding to learning tasks (Cassidy, 2004; Peterson, Rayner, & Armstrong, 2009), however, there are numerous definitions and theories of Learning Styles. The current study focuses on one particular model, namely the Dunn and Dunn Learning Styles Model (Dunn, 1984). In this model, Learning Styles are defined as “the way in which individuals begin to concentrate on, process, internalize, and retain new and difficult academic information.” (Dunn, Griggs, Olson, Beasley, & Gorman, 1995, p. 353).

In their model Dunn and Dunn separate Learning Styles into 21 different factors, which work in combination to create one’s individual learning style (Dunn, 1984). The 21 identified factors are organized in five broad dimensions: Environmental, Emotional, Sociological, Physical, and Psychological stimuli. Within the Physical dimension, Perceptual Modality Preference (Visual, Auditory, Kinesthetic) is an element identified as a contribution to one’s learning style (Coffield, Moseley, Hall, & Eccestone, 2004; Dunn, 1984; Dunn et al., 1995). Although Perceptual Modality Preference is only one element out of 21 identified in the Dunn and Dunn Model of Learning Styles, it has
gained the most popularity in the international education realm (Cassidy, 2004; Coffield et al., 2004; Scott, 2010).

Across the board Learning Style theories hold to the Learning Styles Hypothesis (Pashler, McDaniel, Rohrer, & Bjork, 2009). This hypothesis is two-fold; first, it holds that learning done within one’s learning style will result in optimal learning, whereas learning done outside of one’s learning style will result in poor learning. In terms of Perceptual Modality Preference this means that Visual Learners will have optimal learning performance when they learn in a visual format. For example, a Visual Learner will learn best through the use of videos, diagrams, graphs, charts, and pictures. Second, the Learning Styles Hypothesis assumes that learning done outside of one’s learning style will result in poor learning. In terms of Perceptual Modality Preference this means that Visual Learners will have poor learning performance when they use auditory or kinesthetic formats. For example, a Visual Learner will be negatively affected by listening to verbal explanations or by participating in hands-on activities. This two-fold hypothesis describes an attribution-treatment interaction, an interaction in which the effects of a treatment are dependent upon characteristics of the individual.

The Meshing Hypothesis is based on the Learning Styles Hypothesis, but is directed more for the classroom instructor (Pashler et al., 2009). The Meshing Hypothesis, similar to the Learning Styles Hypothesis, also reports an attribution-treatment-interaction stating that instruction presented in a manner that matches a learner’s learning style will produce optimal learning performance, whereas instruction presented in a mismatched manner will produce poor learning performance. Therefore, in terms of Perceptual Modality Preference, an instructor must present material in a visual
format for Visual Learners, an auditory format for Auditory Learners, and a kinesthetic format for Kinesthetic Learners in order to provide optimal learning opportunities for all students. If an instructor were to present in a visual format for Auditory or Kinesthetic learners he or she would be causing poor learning for those individuals. For example, when teaching algebra the instructor must only present the concepts through speech for Auditory Learners because visual (pictures, diagrams, graphs) or kinesthetic (hands-on activities, writing it out) formats would result in poor learning.

Accommodating learning styles appears to offer poorly performing students a relatively simple solution for improvement. As a result, many learners and instructors are encouraged to incorporate these principles into their learning or teaching regimen (Scott, 2010). However, for teachers especially, this requires extensive changes in how the classroom is run. Instructors would need to first identify their students’ learning styles and then prepare separate materials for each modality. They would also need to present these materials to the individual groups in separate rooms. Given the drastic changes that would be required to put the Learning Styles and Meshing Hypotheses into effect, it is important to know whether Learning Styles are a valid construct and whether there is a strong enough attribution-treatment interaction to warrant this reconstruction of the classroom.

The claims of Learning Style theories have a high impact on teachers and classroom management. Given the implications of the Meshing Hypothesis, one would assume they are well supported, however, the biggest criticism against the Learning Styles field is the overwhelming lack of empirical data supporting the Learning Styles Hypothesis (Cassidy, 2004; Coffield et al., 2004; Pashler et al., 2009; Scott, 2010).
Although the Dunn and Dunn team point to a long list of supporting references (Dunn, 1984; Dunn et al. 1995; Dunn & Griggs, 2003; Dunn & Stevenson, 1997), by far the majority of this support is made up of doctoral dissertations, master’s theses, unpublished conference papers, and non-scientific sources including the popular magazine *Redbook* (Coffield et al., 2004; Dunn et al., 1995).

Furthermore, even the peer-reviewed support cited by Dunn and Dunn is weak at best (Douglass, 1979), most cited research does not approximate what Pashler et al. (2010) considers to be supportive evidence for Learning Style-centered instruction (Kavale & Forness, 1987). Specifically, one study found that survey-identified learning styles did not match performance on memory tasks in the same modality (Kratzig & Arbuthnott, 2006). This finding was in agreement with the results of an extensive meta-analysis, which concluded that no effect was found after using instruction matched to students’ learning styles (Kavale & Forness, 1987).

Perhaps a larger problem than the lack of benefit from accommodating learning styles in the classroom is the overall lack of evidence for attribution-treatment interactions in the educational psychology, special education, or Learning Styles literature (Kavale & Forness, 1987; Pashler et al., 2009; Snider, 1990). Given that memory is stored according to conceptual meaning rather than the perceptual mode in which information is delivered (Collins & Loftus, 1975), it is easy to see why teaching in accordance with learning styles would not produce an interaction (Smith & Jonides, 1997; Willingham, 2009). As Learning Style theories base their claims on the Learning Styles Hypothesis- an attribution-treatment-interaction- the inability to demonstrate this
type of interaction undermines these theories altogether. In short, basing a theory on an interaction that does not exist in the literature should bring that theory under scrutiny.

In addition, critics of Learning Styles point to the lack of reliability and validity of Learning Style measures (Cassidy, 2004; Coffield et al., 2004; Curry, 1990; Snider, 1990; Scott, 2010). In the same way that there are numerous Learning Style theories, there are numerous measures. Although all of these measures should be measuring the same construct, each measure appears to be measuring something different (Ferrell, 1983). Moreover, individuals tend to use general heuristics to answer questions on Learning Style inventories as opposed to providing a critical evaluation of performance after different methods of presentation (Kratzig & Arbuthnott, 2006). This lack of a reliable or valid method of identifying learning styles is particularly problematic if teachers are expected to identify students’ learning styles and then provide instruction accordingly.

Despite the numerous criticisms against Learning Styles, these theories still thrive (Coffield et al., 2004; Scott, 2010; Willingham, 2009). In an Internet search for “Learning Styles,” over two million sites were found (Scott, 2010). Learning Styles have been popular for over 30 years, and even at that time 91% of surveyed teachers believed they should incorporate Learning Styles in their lesson plans (Arter & Jenkins, 1977). But, if there is no support for the theories, why do they persist?

As mentioned earlier, Learning Styles provide an attractive solution for improving student learning. Given that educators find improving student learning important, Learning Styles have become a thriving industry (Coffield et al., 2004; Scott, 2010). Learning Style measures, educational materials, and training are all available for a
price. Given this, Learning Style theorists have monetary motivation for promoting their theories. In addition, as instructors incorporate Learning Styles into their teaching, circumstantial improvements in student performance may be attributed to the use of Learning Style products or techniques (Willingham, 2005). This confirmation bias helps to continue the acceptance of Learning Styles adding to the assumption that it is a valid construct simply because it is so widespread (Scott, 2010; Willingham, 2005).

Present Investigation

Although critics have raised many arguments against Learning Styles, there is no empirical evidence contradicting Learning Styles. The majority of criticisms focus on the lack of support for Learning Styles. However, as Felder (2010) has pointed out, lack of support does not necessarily indicate an invalid construct. It does, however, place Learning Styles as a scientific phenomenon in question. In order to demonstrate that the Learning Styles construct is invalid critics need to produce empirical evidence contradicting Learning Styles.

One field of study that can serve as a blueprint for determining the validity of a construct is the area of synesthesia. In the field of synesthesia the “gold standard” for diagnosis has become the demonstration of consistent and valid synesthetic reports (Baron-Cohen, Wylee, & Binnie, 1987; Eagleman, Kagan, Nelson, Sagaram, & Sarma, 2007). In a similar vein, if Learning Styles are a legitimate scientific phenomenon, individuals should likewise display consistent benefits in learning performance when information is presented in a particular perceptual modality. In addition, individuals should display consistent performance-based learning style categorizations. As a result of
the lack of theoretical and empirical support for Learning Styles, the current study
expected to find empirical evidence contradicting Learning Styles using a methodology
examining consistency.

In line with previous studies, we expected to find a lack of support for an
attribution-treatment-interaction. We also hypothesized that recall performance for each
presentation mode would be unstable across a one-week interval. Our final hypothesis
was that recall performance for a given presentation mode would not correlate with
corresponding survey-identified learning styles or would correlate with non-
corresponding survey-identified learning styles.

Definition of Terms

Attribution-treatment-interaction

Both the Learning Style Hypothesis and the Meshing Hypothesis are examples
of an attribution-treatment-interaction. This type of interaction is one in which
individuals with one set of characteristics benefit from one type of treatment, but are
hindered by another type of treatment (Pashler et al., 2009). For example, Type A people
benefit from Type A treatment, but are hindered by Type B treatment. Type B people, on
the other hand, benefit from Type B treatment, but are hindered by Type A treatment.

Learning Style

Although there are numerous definitions for Learning Styles, in a survey of
Learning Style experts, the majority agreed that “Learning Styles are an individual’s
preferred ways of responding (cognitively and behaviorally) to learning tasks which
change depending on the environment or context. Therefore a person’s learning style is
malleable” (Peterson et al., 2009, p. 520). The current study focuses on the Dunn and Dunn Learning Style Model, which defines Learning Styles as, “the way in which individuals begin to concentrate on, process, internalize, and retain new and difficult academic information” (Dunn et al., 1995, p. 353).

The Dunn and Dunn Model identifies a number of contributing factors that make up an individual’s Learning Style. The current study focuses on one of these factors, Perceptual Modality Preference. This refers to the perceptual mode in which one prefers to receive information: Visual, Auditory, or Kinesthetic. For instance, if one is identified as a Visual Learner, according to the theory, he or she will benefit from receiving information in a visual format, through pictures, graphs, diagrams, etc.

In this thesis when Learning Styles as a theoretical concept are discussed, the term will be capitalized. On the other hand, when specific learning styles of individuals are discussed these will be written in lower case.

**Learning Style Hypothesis**

The Learning Style Hypothesis is one of the main claims of all Learning Style theories including the Dunn and Dunn Learning Style Model. This hypothesis is the idea that learners benefit from interacting with information in a mode that matches their learning style allowing for optimal learning potential, and their learning is hindered when they are dealing with information in a mode that does not match their learning style (Pashler et al., 2009). For example, a Visual Learner will benefit from interacting with information in a visual format, but their learning will be hindered if interacting with information in an auditory or kinesthetic format.
**Meshing Hypothesis**

The Meshing Hypothesis is based on the claims of the Learning Style Hypothesis, but makes implications for classroom instructors. This hypothesis is the idea that learners will have optimal learning potential when instructors present information in a mode that matches their learning style, but their learning will be hindered if instructors present information in a mismatched mode (Pashler et al., 2009). For example, a Visual Learner will benefit when instruction is provided in a visual mode, but their learning will be hindered if instruction is provided in an auditory or kinesthetic mode.
CHAPTER II

LITERATURE REVIEW

In this review, I will provide a thorough examination of the Learning Style construct. In doing so I will discuss the criticisms brought up against the Learning Styles field including the lack of clarity in definitions, lack of support for the Learning Styles Hypothesis, and the lack of reliability and validity for Learning Style measures. In addition, I will describe what type of evidence would be necessary to demonstrate empirical support for Learning Style theories.

To begin it is important to understand how Learning Styles are defined. Learning Styles have become a topic of debate for many researchers, and lack of clarity in their definition has been a great source of criticism for the field (Cassidy, 2004; Curry, 1990; Desmedt & Valcke, 2004; Peterson et al., 2009; Scott, 2010; Willingham, 2009). Not only is there confusion regarding definitions of Learning Styles, there is also confusion in the categorizations between Learning Styles, Cognitive Styles, Cognitive Abilities, and Multiple Intelligences (Peterson et al., 2009; Willingham, 2009). The big difference between these four categories lies in the difference between abilities and styles. In general, abilities refer to one’s capacity for thinking in a particular way whereas styles refer to one’s tendency or preference for thinking in a particular way.

Cognitive abilities refer to what one knows and how successful one is when dealing with a particular type of content (Willingham, 2009). For example, someone who
is very successful in math and learns mathematical concepts quickly would have a great mathematical ability. Howard Gardner based his theory of Multiple Intelligences on this concept of cognitive ability (Gardner, 1983; Willingham, 2009). In his theory, Gardner (1983) identified seven (eventually eight) intelligences or relatively independent, potential intellectual competencies: Linguistic, musical, logical-mathematical, spatial, bodily-kinesthetic, intrapersonal, interpersonal, and later naturalist. He proposed that each of the intelligences were based on particular, unique, “computational [capacities] or information-processing [devices]” and that through a combination of biological and environmental factors individuals develop different levels of strength for each intelligence (Gardner, 1983, p. 278). Gardner stated that all humans possess these intelligences and should develop them, but that certain individuals would demonstrate higher capacities for particular intelligences as compared to the other intelligences. While the construct cognitive ability focuses on individuals’ capacity or potential for success in particular areas, the construct of style focuses more on preference.

When discussing styles, tendencies or preferences, there are two major categories: cognitive style and learning style (Peterson et al., 2009). These fields have been criticized by many for the lack of clarity and overlapping nature of definitions. In an effort to establish a more cohesive framework for the Learning Style and Cognitive Style fields Peterson et al. (2009) surveyed 94 style researchers regarding definitions of learning and cognitive styles. Overall, cognitive styles tended to be described in terms of cognitive processing. They were seen as more stable, more innate, and more closely related to internal information processing mechanisms. Furthermore, most of the surveyed experts believed cognitive style was the “broader, more encompassing term”
than learning styles. The majority of the experts agreed on a definition of Cognitive Style by saying that,

Cognitive Styles are individual differences in processing that are integrally linked to a person’s cognitive system. More specifically, they are a person’s preferred way of processing (perceiving, organizing, and analyzing) information using cognitive brain-based mechanisms and structures. They are partly fixed, relatively stable, and possibly innate preferences. (Peterson et al., 2009, p. 520)

This is different from cognitive ability in that cognitive style has an element of preference whereas cognitive ability purely has to do with one’s capacity.

Learning Styles, on the other hand, tended to be described in terms of learning behaviors, seen as more variable and dependent on the learning environment. Where Cognitive Styles are often defined in terms of how an individual approaches cognitive tasks, Learning Styles tend to be defined in terms of how an individual approaches more specific learning tasks (Cassidy, 2004). According to the experts surveyed in Peterson et al.’s (2009) study, the majority of the experts agreed on a definition of Learning Style by saying that, “Learning styles are an individual’s preferred ways of responding (cognitively and behaviorally) to learning tasks which change depending on the environment or context. Therefore a person’s learning style is malleable” (Peterson et al., 2009, p. 520). Therefore, whereas Cognitive Style deals with a person’s preferred way of processing information through brain-based processes, Learning Style deals with a person’s preferred way of interacting with learning material.

In addition to the wide variety of Learning Style definitions, there are also numerous Learning Style theories, with over 71 identified theories in the UK alone (Coffield et al., 2004). With so many definitions and theories it is difficult to narrow down a concrete operationalized definition for a construct described in such a large
variety of ways. Of these theories, the two most influential Learning Style theorists are Kolb and Dunn (Desmedt & Valcke, 2004). In a citation analysis of the Learning Style literature, Kolb was cited at least once in 49% of all 349 documents from the Institute for Scientific Information’s (ISI) learning style file.

According to Kolb, learning is a continuous process based on experience, “Learning is the process whereby knowledge is created through the transformation of experience. Knowledge results from the combination of grasping experience and transforming it.” (Kolb, 1984 as cited in Coffield et al., 2004, p. 61). In his Experiential Learning Model (ELM), learning is broken down into a four-stage cycle of adaptive learning modes (Cassidy, 2004; Coffield et al., 2004; Loo, 2004). The cycle begins with Concrete Experiences, which allow for Reflective Observation by the learner. These observations combine to create Abstract Conceptualizations, which guide Active Experimentation. The relationship between the pairs of learning modes creates two independent dimensions (see Figure 1). The Concrete Experience and Abstract Conceptualization modes create the Perceiving Dimension whereas the Reflective Observation and Active Experimentation modes create the Processing Dimension. Kolb used these two dimensions to organize learners into four Learning Styles: The Converging Style, the Diverging Style, the Assimilating Style, and the Accommodating Style. Kolb viewed Learning Styles as “preferences for one mode of adaptation over the others; but these preferences do not operate to the exclusion of other adaptive modes and will vary from time to time and situation to situation” (Coffield et al., 2004, p. 63).
Figure 1. Kolb’s experiential learning model (ELM). The Experiential Learning Model identifies four learning modes, Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation. The relationship between the four learning modes creates two independent dimensions, Perceiving (Reflective Observation and Active Experimentation) and Processing (Concrete Experience and Abstract Conceptualization). Four Learning Styles emerge as a result of the two dimensions: The Accommodating Style, the Diverging Style, the Assimilating Style, and the Converging Style.

According to the Experimental Learning Model, individuals within the Converging Style prefer the use of the Abstract Conceptualization and Active Experimentation learning modes. Given this, they tend to be problem solvers and decision makers. They also tend to be good at the practical application of ideas, but struggle through interpersonal issues.
The Diverging Style combines the Concrete Experience and Reflective Observation learning modes. Therefore, individuals with a Diverging Learning Style tend to be imaginative and aware of value or meaning. These learners tend to view problems from a number of different perspectives and be more feeling-oriented.

The Assimilating Style is a combination of the Abstract Conceptualization and Reflective Observation modes. These individuals tend to use inductive reasoning to create theoretical models of ideas. Individuals with an Assimilating Learning Style tend to value the logical soundness more than the practical application of ideas.

Finally, individuals with an Accommodating Learning Style favor the Concrete Experience and Active Experimentation learning modes. These learners tend toward putting plans into action and are good at adapting to new experiences or changing circumstances. Individuals with an Accommodating Learning Style often solve problems using their intuition or “gut feelings” and trial-and-error techniques.

In identifying these different Learning Styles, Kolb also suggested learning methods that were best suited for particular learning styles. For example, he felt that projects or small-group discussions would be beneficial for Accommodating and Converging Style learners because they preferred Active Experimentation, however, lectures would not be beneficial for these individuals’ learning. Kolb, therefore, believed that instructors needed to individualize their instruction in accordance to their students’ learning styles in order to promote optimal learning within the classroom.

In Desmedt and Valcke’s (2004) citation analysis, Dunn was identified as the second most influential Learning Style theorist with citations in 22% of all 349 ISI Learning Style documents. According to this citation analysis, the Dunn and Dunn model
of Learning Styles is the most influential model that deals with perceptual Learning Styles: Visual, Auditory, and Kinesthetic (Cassidy, 2004; Coffield et al., 2004; Desmedt & Valcke, 2004; Dunn, 1984). These perceptual preferences are particularly popular within the education community as they offer relatively concrete categories as opposed to more abstract or conceptual categories as are seen in Kolb’s model (Scott, 2010). Specifically, Dunn and Dunn’s Learning Style Inventory (LSI) is the most widely used method for assessing student’s learning styles within elementary and secondary schools (Cassidy, 2004).

According to the Dunn and Dunn model, Learning Styles are defined as, “the way in which individuals begin to concentrate on, process, internalize, and retain new and difficult academic information.” (Dunn et al., 1995, p. 353). The Dunn and Dunn Learning Style Model focuses on the identification of individuals’ instructional environment, method, and resource preferences for receiving information and is based on a set of theoretical principles. For example, the Dunn and Dunn Model holds that Learning Styles are a biological and developmental set of characteristics that causes certain instructional environments, methods, or resources to be beneficial for some individuals and useless for others. Furthermore, according to the model accommodating learners’ preferences results in a measurable difference in learning performance especially when an individual has a particularly strong learning style or is academically unsuccessful. These benefits are reportedly applicable to students in elementary school, secondary school, and college.

The model identifies 21 different elements that influence student learning. These elements are grouped into five categories: Environmental, Emotional, Sociological,
Physical, and Psychological. In each of these categories there are different factors that contribute to the identification of an individual’s learning style (see Figure 2). In the

![Dunn and Dunn Learning Styles Model](image)

**Figure 2.** Dunn and Dunn learning styles model. Elements are grouped into five categories: Environmental, Emotional, Sociological, Physical, and Psychological. Each category contains the factors that contribute to an individual’s particular learning style.

Environmental category these factors include preferences for the level of sound, light, and temperature, as well as preferences for the furniture or seating design of the setting. In the Emotional category factors include one’s level of motivation, persistence, responsibility, and need for structure. For the purposes of this model, responsibility is defined as how well the individual in question is able to conform to the method of instruction. The Sociological category deals with elements including the learner’s preference for learning alone, in pairs, with peers, in a team, or with an instructor, as well as the learner’s preference to learn in the same social setting each time
or in a variety of arrangements. The Physical category is where perceptual modality preferences are located along with food and drink intake, time of day energy, and mobility while learning. Finally, in the Psychological category information processing elements are included. Specifically, global versus analytic processing, impulsivity versus reflection, and hemispherical differences are included. This category of dimensions was added at a later date in order to include an element of Cognitive Style in the model.

According to the Dunn and Dunn model, an individual’s learning style would be identified through the use of one of the many variations of Dunn and Dunn’s Learning Style Inventory (Dunn, 1984). The Dunn and Dunn Learning Style Inventory is the most widely used method for assessing students’ learning style in elementary and secondary schools (Cassidy, 2004). Each version of the measure is a self-report questionnaire requiring a 20-page manual for interpretation of the results (Coffield et al., 2004). The manual also provides suggestions regarding how best to accommodate the identified learning style.

Regardless of the theoretical model, all Learning Style theories agree on one major claim: Learning in accordance with one’s learning style allows for optimum learning outcomes, whereas not taking one’s learning style into account will result in ineffective or inefficient learning (Pashler et al., 2009). This notion has been aptly named the Learning Styles Hypothesis. The specific version of the Learning Styles Hypothesis that makes pedagogical implications, known as the Meshing Hypothesis, holds that classroom instruction should match the mode of an individual’s Learning Style. The Meshing Hypothesis is different from the Learning Styles Hypothesis in that the Learning Style Hypothesis makes a statement about how people learn or study on their own,
whereas the Meshing Hypothesis has to do with the implementation of teaching methods within the classroom that match students’ individual Learning Styles. This implication that instruction that matches a student’s learning style will promote learning, while instruction that is mismatched from an individual’s learning style will hinder learning, is an example of an attribution-treatment interaction. Given the incredible undertaking this would be for teachers, it is necessary to demonstrate strong empirical evidence supporting the hypothesis to warrant such a drastic change in teaching methods.

Therefore, in order to provide evidence in support of the Learning Styles Hypothesis, one would need to demonstrate that the instructional technique that resulted in optimum performance for one learning style is different from that which resulted in optimum performance for another learning style. For example, an aptitude-treatment interaction would be demonstrated if Visual learners experienced optimum performance when information was presented in a visual manner (through pictures, diagrams, text) but were negatively affected by material presented in an auditory format, and Auditory learners experienced optimum performance when information was presented in an auditory format (voice recording) but were negatively affected by material presented in a visual format. This style-by-method crossover interaction is what is necessary in order to demonstrate empirical evidence supporting the Learning Style Hypothesis (see Figure 3).

Despite the popularity of Learning Style theories however, there is no evidence of attribute-treatment interactions in the literature surrounding educational psychology, special education, or Learning Styles specifically (Kavale & Forness, 1987; Pashler et al., 2009; Snider, 1990). Even studies that Dunn and Dunn point to as support for their theory lack the proper evidence for supporting the Learning Style Hypothesis.
One such study by Douglass (1979) from *The American Biology Teacher* examined Learning Styles in terms of global and analytic students. A pretest-posttest control group design was used in which students were randomly assigned to one of three groups: Inductive, Deductive, or Control. Within the two experimental groups learning materials were sequenced in either an inductive or deductive manner. Initially, results indicated no significant interaction between students’ global/analytic learning style and inductive/deductive sequencing of course material. It was only after manipulating the data in such a way that the analysis only compared the “very global” and “very analytic” students that there was a significant interaction between analytic ability and achievement.
Specifically, the “very analytic” students scored better when material was sequenced deductively rather than inductively. However, for both groups the improvement in the scores was very small after comparing a small selection of the sampled population. Although there was a difference for the “very analytic” students—an increase of a couple of points for a highly selective group—this hardly seems convincing enough to make such drastic pedagogical changes as Learning Style theories would suggest, especially when even this laughable support is the exception rather than the norm. Even if the evidence provided by Douglass (1979) was more substantial, according to Pashler et al., (2009) it would still not be appropriate for demonstrating an attribution-treatment interaction as it does not demonstrate a detrimental effect for learners who received instruction in a mismatched mode.

Despite the lack of support for the theories, Learning Styles are still widely accepted (Coffield et al., 2004; Scott, 2010; Willingham, 2009). Specifically, Scott (2010) found 2,160,000 hits during an internet search for “Learning Styles.” Teachers are taught about Learning Styles and are encouraged to take them into consideration when teaching (Pashler et al., 2009; Willingham, 2005). However, learning styles are not new; even over 30 years ago 91% of surveyed teachers believed that modality should be a major consideration when teaching (Arter & Jenkins, 1977). Furthermore, these ideas are not limited to the classroom. Learning Style theories have been applied to a wide array of contexts including business, parenting, and even church sermons (Scott, 2010), which begs the question: Why, despite the lack of supporting evidence, do Learning Styles persist?
Learning Styles provide an easy way to think about and understand individual differences (Willingham, 2005). Learners have differences in their cognitive abilities in terms of processing speeds and capacity, as well as how successful they are in dealing with particular types of content (Willingham, 2009). Learning Style theories offer an easy and understandable bridge between innate cognitive abilities and their application to learning environments or behaviors. Furthermore, it provides instructors with a relatively simple, concrete solution for helping struggling students. Rather than accepting that a student may struggle in a particular area or that the instructor is not teaching the subject as clearly as possible, a Learning Style aficionado would claim it could just be because the material is presented in an auditory format when the student “needs” a visual format.

Another reason Learning Style theories persist may be a result of confirmation bias (Willingham, 2005). As instructors incorporate Learning Style theories into their teaching, it may seem as though students are improving, leading them to believe the incorporation of Learning Styles worked. However, the improvement could really be a result of the additional effort or a creative way of presenting material that benefited all students, not just those of a particular learning style. This confirmation bias, that stems from anecdotal evidence, however, feeds the common acceptance of Learning Style theories, which adds to the assumption that it must be a valid concept because it is so widely accepted (Scott, 2010; Willingham, 2005). The commercialization of Learning Styles is another contributing factor to both the persistence and widespread acceptance of these minimally supported theories (Scott, 2010). Learning Style inventories, teaching materials, and professional development training are all offered for a fee thus aiding in their acceptance as educational principles. This monetary motivation for keeping
Learning Styles alive is just one of the many sources of criticism for Learning Style theories.

Although the idea of matching teaching style to learning style provides a relatively simple and appealing solution for many classroom challenges, it is in opposition to what is known about memory and effective teaching practices (Scott, 2010). Learning Style theories point to the importance of the perceptual mode in which information is presented, yet the encoding process for new information is dependent upon the executive control system (Smith & Jonides, 1997; Willingham, 2009). This system involves regions in the frontal lobe and hippocampus where information is coded conceptually rather than perceptually, making the perceptual mode in which information is delivered insignificant. Therefore, heightened memory in a particular modality would not benefit the individual in terms of content memory. For example, a student who is an auditory learner might be better at remembering the inflection and tone of a speaker’s voice, however, it is unlikely that the test will be asking about those details. Instead, the individual would be tested on the content of what was spoken.

Furthermore, memory is enhanced through elaboration because it is consistent with the way in which memory is organized (Craik & Tulving, 1975). Therefore, teaching specifically in accordance to an individual’s learning style would limit the modes in which information is encoded into memory. Teaching to one modality ignores the importance of the other modalities, which can help provide further opportunities to interact with the material and therefore encode information in a more elaborate manner (Kavale & Forness, 1987).
The Dual Code Theory supports this line of reasoning as it holds that increased learning occurs when information is delivered and encoded in multiple modalities, specifically verbal and non-verbal (Paivio & Lambert, 1981). This benefit exists regardless of learning style (Paivio & Lambert, 1981; Moreno & Mayer, 1999). Specifically, Moreno and Mayer (1999) examined retention of materials in three conditions: Visual animation with auditory narration, visual animation with text narration, and visual animation with both auditory and text narration. Participants performed significantly better when visual and auditory narration were presented together regardless of the participants’ learning styles.

Similarly, when attempting to teach children mathematical concepts, experimenters coupled instruction with the requirement of the child to perform one of three behaviors: Mimic just the gestures, just the speech, or both gestures and speech of the experimenter (Cook, Mitchell, Goldin-Meadow, 2008). Using gestures or the combination of gestures and speech resulted in greater retention both immediately and after a four-week delay than those who mimicked speech alone. Therefore, what is known and widely accepted regarding cognition and memory is inconsistent with Learning Style theories and the Learning Styles Hypothesis.

Although critics attack the validity of Learning Styles due to the Learning Style Hypothesis, there is little dispute around the existence of individual differences in learning preferences as they are seen in both self-report and performance-based measures (Douglass, 1979; Dunn et al., 1995; Kratzig & Arbuthnott, 2006; Loo, 2004; Massa & Mayer, 2006; Pashler et al., 2009; Peterson et al., 2009; Snider, 1990; Willingham, 2005, 2009). Critics do, however, question the reliability and validity of Learning Style
measures used to identify these individual differences (Cassidy, 2004; Coffield, 2004; Curry, 1990; Snider, 1990; Scott, 2010). Like the variability that exists regarding Learning Style definitions, there is also a great deal of variability between Learning Style measures (Kratzig & Arbuthnott, 2006). Although all Learning Style measures attempt to reach the same construct, a factor analysis of multiple Learning Style instruments revealed that all of the questionnaires were clearly measuring different things (Ferrell, 1983).

Furthermore, in a study by Kratzig and Arbuthnott (2006), participants’ learning styles were identified using two separate self-report measures. Of the 65 participants only 29 (44.6%) were classified as the same type of learner by both measures. In fact, the two measures were not significantly correlated. In addition, there was no correlation between participants’ learning styles as identified by the self-report measures and their learning style as identified through a performance-based measure. They also found that when answering Learning Style questionnaires, participants tended to answer based on general heuristics about their learning preferences as opposed to critically evaluating methods in which material has been presented and their consequent performance. Based on this method of responding it is unknown whether the identified learning style is truly based on a specific style of learning or whether the identification is based on variable situational factors.

In addition to the criticisms of Learning Styles as a whole, there are also a number of criticisms against the Dunn and Dunn Learning Style Model specifically, which is the model most often referenced in education systems due to the inclusion of the perceptual modality dimension (Coffield et al., 2004; Scott, 2010). One such point of
criticism is that although Dunn and Dunn tout an abundance of supporting evidence for their theory (Dunn, 1984; Dunn et al., 1995; Dunn & Griggs, 2003; Dunn & Stevenson, 1997), with 879 supporting publications listed on their website (www.learningstyles.net), only 20% of these references are articles from scholarly, peer-reviewed journals (Coffield et al., 2004). Over a third of the material consists of doctoral dissertations, master’s theses, and unpublished conference papers. Moreover, like many others, their profitable Learning Style questionnaires are criticized for having poor reliability and validity (Coffield et al., 2004; Curry, 1990; Snider, 1990). However, all external criticisms against the Dunn and Dunn Model are disregarded by Dunn and Dunn because those criticisms regarding the model, its underlying theories, or its measures, are typically made by those who have not been trained and certified to use the Dunn and Dunn Model and are therefore considered “‘secondary’ or ‘biased’” by the Dunn and Dunn team (Coffield et al., 2004).

Much of the disregard for the criticism against Learning Styles, both on the part of Learning Style theorists and in the public eye, could be a result of critics suffering from the same lack of empirical support for their claims. Felder (2010) makes the point that a lack of support for Learning Styles does not mean it is an invalid construct, something that Dunn et al. (1995) have also pointed out. While it is true that a lack of support does not invalidate Learning Styles, it does raise some serious concerns about its scientific validity.

In other areas of scientific research, a method to find a phenomenon credibility has been to show a reliable consistency in an observed effect. For instance, for decades the phenomenon of synesthesia was not taken seriously. Only after synesthetic
associations were shown to be consistent over long-term intervals did it gain scientific momentum. Nowadays, the demonstration of consistent and valid synesthetic reports has become the “gold standard” for diagnosis (Baron-Cohen et al., 1987; Eagleman et al., 2007). Similarly, if Learning Styles are to be a legitimate scientific phenomenon, individuals should demonstrate consistent and valid learning style-based benefits.
CHAPTER III

METHOD

Participants

Undergraduate students from California State University, Chico were recruited by offering two hours of research participation, one hour for the first week’s session and one hour for the second week’s session. Students were able to turn in their research participation hours for extra credit in participating classes. Eighty students (28 males, 52 females; mean age = 22.9 years) representing a variety of majors volunteered to participate in both sessions. All participants were informed about the procedures, provided written consent for their participation, and were debriefed upon completion of the second session.

Materials

Learning was measured through verbatim recall tests for eight stories. One of these stories was taken from the Babcock Story Recall Test (Babcock & Levy, 1940). The story that was used for this recall test consisted of 21 memory units. The memory units varied in terms of length and number of words included. Correctly recalled memory units earned the participant a point. Points were added together to determine the overall recall score with a maximum of 21 points. The original form of this recall test was
conducted through interview; however, for the purposes of the current study, recall was assessed from the participants’ written responses.

We also used an adaptation of the Babcock Story Recall Test, known as the Portland Paragraph (Lezak, Howieson, & Loring, 1976). The development of the Portland Paragraph consisted of testing the new story to confirm that it was comparable to the original Babcock Story Recall Test. Therefore, both stories are broken into 21 memory units of comparable syntax and complexity.

In order to avoid practice effects from using the same story multiple times across the eight total conditions, six more stories were created. Each new story had similar content, structure, and complexity to both the Babcock and Portland stories. All eight stories were of comparable length, determined through word count, and consisted of 21 memory units. In a pilot study, we confirmed that participants received statistically similar recall scores on all eight stories (six newly created and two original) when presented in an auditory format.

Four different types of materials were created for each story according to the perceptual condition: Visual, Auditory, Kinesthetic, or Integrated. When the stories were presented in the Visual condition, participants received a laminated placard with the story presented as a news clipping containing the text, two related pictures, a graph, and a map. For the Auditory condition each story was recorded using the same narrator and made available as an unidentified track in iTunes on a computer. In the kinesthetic condition, participants received a placard with the story text and a bag of corresponding words and phrases from the story. During the condition, participants placed the word/phrase pieces onto the matching words/phrases on the placard. Finally, the Integrated condition
consisted of elements of all three conditions. Therefore, participants received three items: first, the aforementioned auditory recording, second a news-clipping containing the story text, two related pictures, a graph, and a map, and third, a bag of corresponding phrases and graphic pieces from the news-clipping.

After completion of the conditions, participants answered questions from three surveys, the Barsch, the VARK, and the DANQ. The Barsch Learning Style Inventory (BLSI) (Barsch, 1996; Kratzig & Arbuthnott, 2006) consists of 32 questions that explore the individual’s behavioral patterns as they relate to perceptual modalities. Participants answered the questions using a three-point Likert-type scale (often, sometimes, and seldom) to indicate how strongly they agree with the statement. An example of a question is, “I bear down extremely hard with a pen or pencil while writing” answered often, sometimes or seldom. The BLSI was scored according to its instructions.

The VARK Questionnaire (Version 7.1; Fleming, 2009) consists of 16 multiple choice questions each with four possible answer choices. Each question presents a hypothetical situation and the answer choices represent different perceptual modalities (visual, auditory, reading, and kinesthetic). The individual selects all the answers that describe what they would do in that situation, where multiple choices are allowed. An example of a question from the VARK is, “You are helping someone who wants to go to the airport, town centre, or railway station” with answer choices as “A. Go with her, B. Tell her the directions, C. Write down the directions, and D. Draw, or give her a map”. The VARK was scored according to the stepping stone instruction method of the 7.1 version.
The DANQ inventory was a two-item questionnaire created for the purposes of the current study. Specifically, it was designed to assess participants’ metacognitive abilities for estimating their personal recall performance and to identify individual preferences for the conditions within the current study. The first question asked participants to provide a rank order for their perceived performance in each of the four conditions. The second question provided pictorial representations of each condition and asked participants to identify which of the four conditions they most preferred.

Procedure

The current study utilized a within-subjects, experimental design with one independent variable, Sensory Modality, and four conditions: Visual, Auditory, Kinesthetic/Tactile, and Integrated. The dependent variable was story recall measured by the number of accurately recalled story units with a maximum score of 21. Participants were exposed to each condition twice over the course of two sessions, one week apart. In order to prevent practice effects and confounding variables, a Perl script (see Appendix B) was written to create the order in which participants experienced the four conditions and eight stories within each session. Through this process, the order of both the conditions and the stories were counterbalanced. In addition, the code equalized the number of times each story was represented within each condition.

During each session, participants were first presented with the story materials and were given 3 minutes and 30 seconds to study and learn each story. After the 3 minutes and 30 seconds ended, the story materials were collected and the participants recalled the story as accurately as possible on a provided form. After recalling the
information from the story, the participants received the materials for the next condition. Instructions for each condition varied. In the visual condition participants simply read and studied the material for the allotted time. In the Auditory condition the participants listened through the story once, they were then able to rewind and repeat sections at their discretion. For the Kinesthetic/Tactile condition, participants placed phrase-pieces directly on the matching words and phrases of the story text. Once they completed this matching process, participants read and studied the story until time was up. Finally, the integrated condition utilized each of the sensory modality variations’ materials in order to combine the modalities. Therefore, participants listened to a recording of the story, like in the auditory condition. After listening to the recording, they completed a story puzzle, similar to that in the kinesthetic condition. The integrated story card, however, was a news-clipping format similar to that of the visual condition, and included related pictures, map, and graph. After matching all the pieces with the words/phrases, and graphics on the card, participants then read the completed puzzle and finally recalled what they remembered when time was called (Figure 4).

After finishing each of the four conditions, participants completed the DANQ inventory as well as the Barsch Learning Style Inventory, the VARK Questionnaire, and demographic information questions. The order of the BLSI and the VARK Questionnaire was counterbalanced in order to prevent practice effects. The recall scores, the BLSI scores, and the VARK scores were then calculated and analyzed.

Recall scores were determined by counting the number of correctly recalled complete story units for each particular story. In order to be considered correct story units simply needed to be present; they did not have to be in the original order. In addition,
Figure 4. The four conditions in this experiment. Top left to bottom right: Visual, Kinesthetic, Integrated, and Auditory.

specifically selected alternate spellings for commonly confused words were counted as correct after determining that allowing the alternate spelling made a statistically significant difference. Similarly, story units from which specific words were omitted that made a significant difference were also counted as correct.
CHAPTER IV

RESULTS

Are Modality-Specific Recall Scores Consistent Over Time?

We performed four t-tests to compare participants’ recall scores within each condition across both sessions. We found significant changes in scores over time (Visual: $t(79) = 12.67, p < .0001$, Auditory: $t(79) = 11.3, p < .001$, Kinesthetic: $t(79) = 10.44, p < .001$, Integrated: $t(79) = 12.35, p < .001, \alpha = .0125$). Figure 5 shows these fluctuations. However, we would not expect participants to have the exact same scores in both sessions for a given presentation mode as these variations may have been mere random fluctuations.

If Learning Styles consistently result in better performance in a given condition, then the difference in recall scores between conditions should be considerable and consistent across the two sessions. In other words, if the Learning Style Hypothesis is correct, then the overall difference in an individual’s recall scores in each condition should be greater than the random fluctuations in scores within one condition from one week to the next (see Figure 6).

Between-modality variation and within-modality variation were compared using a paired-samples $t$-test. Within-modality variation was significantly greater than between-modality variation, $t(79) = 4.657, p < .001$, demonstrating that performance
Figure 5. Mean scores in each modality and session, and the average absolute difference between them. The comparisons between average within-modality scores do not reveal substantial variations, which is due to individual differences that cancel each other out. The averaged absolute differences, on the other hand, do reveal significant variations.

within a given modality changed more over time than the differences in performance between the four modalities (see Figure 7). In other words, participants’ ability to do well in each modality changed over time. This change was stronger than and overwhelmed the benefit, if any, gained from a particular modality.

Not only the consistency of recall scores but also the consistency of learning style categorizations can be used to assess the reliability of learning styles. Our data made
Figure 6. Predictions for recall performance stability across one week. If the Learning Styles Hypothesis is correct, Learning Styles would be consistent and there would be greater between-modality variation than within-modality variation (A). Conversely, if Learning Styles are not consistent, within-modality variation would be equal to or greater than between-modality variation (B).

Figure 7. Between-modality variation compared to within-modality variation in sessions one and two.
it possible to categorize learners based on performance, instead of subjectively reported preferences, which is how other researchers categorize learners.

Learning Style theories state that it is possible for a learner to be categorized under multiple perceptual modalities. Typically, surveys use cut-off criteria for identifying an individual’s learning style(s) that are poorly motivated or poorly specified. A systematic criterion should be based on an optimization process where a goal is specified and the parameters are determined that best meet that goal. In the current study, the goal is to investigate consistency of within-modality recall scores. Given this goal, we used an optimization process based on the ability to find consistent learning style categorizations between sessions. To begin, we standardized the recall scores to permit the computation of probability intervals between scores. Categorizing participants started by finding the modality in which they had the highest recall score. Including other modalities in their learning style categorization depended on the size of the probability interval between their highest score and their other scores. We thoroughly sampled all probability intervals between 0% and 100% in steps of 0.1%. At each level, we computed which modalities to include in their learning style categorization, separately for each session, and then compared the learning style categorizations between sessions to find consistency.

Figure 8 shows two important findings when looking at the number of participants with identical performance-based learning styles as a function of probability interval. First, at smaller probability intervals the criterion to include multiple modalities is naturally more strict and most participants were therefore categorized as single-modality learners. However, even in the best case, which occurred at a strict probability
interval of 0%, this still only led to consistent between-session categorizations for 20 out of 80 participants, or 25%. Since these categorizations only included a single modality, with the four modalities available in this study this is the same as would be predicted by chance. Second, as the probability interval increased, these matching categorizations first decreased and then created a lack in differentiation between modalities as the recall performance of participants in each modality was considered similar. In other words, participants were categorized as quadrimodal learners who were equally strong in all four presentation modes, which essentially suggests that learning styles do not matter.

Figure 8. Number of participants with matching learning style categorizations in both sessions as a function of the probability interval between recall scores in different modalities.
In sum, the process of finding an optimal criterion to categorize learners has demonstrated that consistent learning style categorizations are either based on chance or that learners can do equally well in multiple perceptual presentation modes.

Do Learning Style Surveys Predict Recall Performance?

The main purpose of this study was to examine the consistency of modality-specific recall scores. In addition, we can also use our data to test the Learning Styles Hypothesis in the traditional manner, namely by looking at an interaction between survey-based learning style categorizations and learning performance under different presentation modes.

We computed survey-identified learning styles using the highest scoring modality on the VARK and Barsch surveys, separately for each session. Both surveys add up points for each possible learning style, where the highest scoring modality is always part of the participant's learning style. Both surveys allow for participants to fall into multiple learning styles, although the criteria for including multiple learning styles are either seemingly arbitrary (Barsch) or proprietary (VARK). To avoid these criteria we decided to only include participants with a single maximum modality in this analysis. In order to begin analyzing the consistency of learning style identification using the BLSI and VARK questionnaire, contingency tables were created for each to see how many participants had identical learning style classifications across the two sessions. Using the BLSI 33 out of 80 total participants (41%) held the identical learning style classification across both sessions one week apart. Similarly, using the VARK Questionnaire 39 out of 80 total participants (49%) held the identical classification across both sessions.
Furthermore, to assess the attribution-by-treatment interaction four separate repeated-measures ANOVAs were performed, one for each session and survey, with survey-identified learning style as between-subject variable and our 4 modalities as within-subject variable. Because participants could not be assigned randomly to a survey-identified learning style this resulted in unequal n's in each group, which should be taken into consideration when interpreting the results. As Figure 9 shows, our results do not

Figure 9. Recall performance according to identified learning style in session one and session two, using either the VARK or Barsch inventory. Statistics in each graph report repeated-measures ANOVA results for the Presentation Mode x Learning Style interaction.
approximate what Pashler et al. (2008, Figure 1) considered acceptable evidence and
none of the interactions reached significance (VARK-Session 1: $F(9,186) = .976, p = .461$; VARK-Session 2: $F(9,198) = .761, p = .653$; Barsch-Session 1: $F(9,189) = 1.638, p = .107$; Barsch-Session 2: $F(9,186) = .709, p = .700$; observed power for these analyses was .48, .37, .75, and .35 respectively).

The problem of unequal number of participants in each group is the result of the process of categorizing participants. Additionally, categorizing participants based on the surveys loses information about their numerical score for each possible learning style. Instead, it is better to directly correlate survey scores with recall scores from the task. Pearson product-moment correlations between survey scores and recall scores were computed for both surveys with recall scores pooled across both sessions. According to Learning Style theories, corresponding scores should be correlated. However, results showed that recall performance either did not correlate significantly with corresponding modalities or correlated significantly with non-corresponding modalities (see Table 1). Therefore, whether participants are categorized into learning styles or whether their raw scores are correlated directly, in both cases the surveys used in this study have no meaningful relationship with actual memory performance.

Discussion

Our goal in this study was to investigate the validity of the Learning Styles Hypothesis as well as the Learning Styles construct as a whole. To do so we examined the consistency both of recall performance following different presentation modes and of performance-based learning style categorizations. To determine whether recall
Table 1

*Relationship Between Identified Learning Style and Recall Performance Pooled Across Both Sessions*

<table>
<thead>
<tr>
<th></th>
<th>VARK Visual</th>
<th>VARK Auditory</th>
<th>VARK Read/Write</th>
<th>VARK Kinesthetic</th>
<th>Barsch Visual</th>
<th>Barsch Auditory</th>
<th>Barsch Tactile</th>
<th>Barsch Kinesthetic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual</td>
<td>-0.018</td>
<td>-0.121</td>
<td>0.015</td>
<td>0.05</td>
<td>0.121</td>
<td>-0.348**</td>
<td>-0.115</td>
<td>-0.039</td>
</tr>
<tr>
<td>Auditory</td>
<td>-0.132</td>
<td>-0.056</td>
<td>-0.02</td>
<td>-0.065</td>
<td>0.056</td>
<td>-0.106</td>
<td>0.006</td>
<td>0.06</td>
</tr>
<tr>
<td>Kinesthetic</td>
<td>0.094</td>
<td>-0.068</td>
<td>0.155</td>
<td>0.151</td>
<td>0.107</td>
<td>-0.239**</td>
<td>-0.183*</td>
<td>-0.065</td>
</tr>
<tr>
<td>Integrated</td>
<td>-0.086</td>
<td>-0.015</td>
<td>-0.039</td>
<td>0.027</td>
<td>-0.023</td>
<td>-0.077</td>
<td>-0.167</td>
<td>0.009</td>
</tr>
</tbody>
</table>

*Note:* Green text would indicate significant correlations between corresponding modalities. Blue text indicates non-significant correlations between corresponding modalities. Red text indicates significant correlations between non-corresponding modalities. * Indicates significance at the .05 level ** Indicates significance at the .01 level.
performance was consistent over a one-week time period, we compared the variations between recall scores for each perceptual presentation mode (Visual, Auditory, Kinesthetic, and Integrated) in one session with the variations in recall scores within the same perceptual modality across two sessions, one-week apart.

We first examined the difference in recall scores between the four modalities (Visual, Auditory, Kinesthetic, and Integrated). This difference shows the degree of benefit an individual experiences from a given modality. If recall scores in one modality were higher than those from the other presentation modes, this would indicate a learning style in that perceptual mode. We also examined the difference in recall scores within each modality across the two sessions. This difference shows the degree of outside influence or random fluctuations between the two sessions. Given the one-week gap between the two sessions, some fluctuation between the scores was expected even if Learning Styles were valid. However, if Learning Styles are a valid construct, these differences should be less substantial than the differences between the four presentation modes.

Based on past research (Douglass, 1979; Kavale & Forness, 1987; Kratzig & Arbuthnott, 2006; Pashler et al., 2009), which has produced little to no support for Learning Styles, we expected to find greater within-variation than between-variation. This would demonstrate that random fluctuations are more influential in individuals’ recall scores than a preference for a particular presentation mode, thus providing data that contradict the Learning Styles Hypothesis.

Our results confirmed this prediction, demonstrating that the differences in recall scores between each of the presentation modes were less substantial than the
random fluctuations over time. In other words, in a one-week time period the learning benefits from specific modalities changed more than any differences that might exist between these modalities. This means that environmental factors or other outside influences had a greater impact on the benefits one gained from a particular presentation mode than did a particular style of approaching or responding to new information (Dunn et al., 1995; Peterson et al., 2009).

We also examined consistency by looking at participants’ performance-based learning style categorizations across the two sessions. Again, based on the past research mentioned above, we expected to find that the learning style categorizations would lack consistency from one session to the next. Our results indicated that even when using a systematic criterion based on the ability to find consistent learning style categorizations between sessions, only 25% of participants demonstrated a consistent modality preference across a one-week span. Given the current paradigm, 25% is equal to chance performance, clearly demonstrating a lack of consistency.

The lack of consistency that was demonstrated, both through recall scores and performance-based learning style categorizations across one week, suggests that extraneous factors play a larger role in determining which modality provides the best performance as opposed to any internal preferences for a particular presentation mode. These results were found despite using a verbatim recall task, which requires low-level, shallow processing (Craik & Lockhart, 1972). Given this, a verbatim task would provide the greatest chance of learning styles proving to be beneficial. A task requiring comprehension or application would involve higher levels of knowledge and would therefore require more conceptual encoding in addition to association-based storage
(Bloom, 1956; Halford, Wilson, & Phillips, 2010; Smith & Jonides, 1997; Willingham, 2009). Comprehension requires deeper levels of processing, therefore, if learning styles were inconsistent when using shallow processing it would be highly unlikely that they would be consistent during a more complicated processing task. Furthermore, comprehension is most often what is tested within an academic setting where the use of Learning Styles is often pushed, yet learning styles were inconsistent even at the most basic processing level. Given these considerations, we do not expect that a comprehension-based task will produce results with more consistent learning style-based benefits over time. However, we have received numerous comments and questions about the possible outcomes of this study had we used a comprehension task. The next step in this research process, therefore, is to perform a qualitative analysis of the written responses and perform our statistical analyses on these results as well to address these concerns.

In a review of the Learning Styles literature and evidence, Pashler et al. (2009) suggested that the methodologically correct approach for testing the learning styles hypothesis would be to identify individuals’ learning styles and assess whether they have significantly better performance in that modality and significantly poorer performance in other modalities. In light of testing for an attribution-treatment-interaction we compared participants’ survey-identified learning styles with their recall performances in corresponding conditions. Our results revealed unreliable survey scores and therefore unreliable survey-identified learning style categorizations. This was consistent with the reliability and validity criticisms of Learning Style measures found in the literature (Curry, 1990; Scott, 2010). The combination of inconsistency of learning
style identification as well as recall performance clearly demonstrated that no attribution-treatment-interaction was at play. This finding would only add to the lack of support for Learning Styles, which Felder (2010) claims is not enough to provide evidence against the validity of the construct. However, with our novel approach of investigating consistency, we found results that clearly contradict Learning Styles, providing evidence against the theories.

For a finding to be accepted as a genuine scientific phenomenon it must be replicable and consistent. An example of this can be seen in the area of synesthesia. The research on synesthesia only gained momentum after it had been shown that synesthetic associations are consistent across several months (Baron-Cohen et al., 1987). Consequently, consistency has become the “gold standard” for identifying genuine cases of synesthesia (Eagleman et al., 2007). For this reason, we examined the consistency of learning styles in the current study because if inconsistent, Learning Styles could not be a genuine scientific phenomenon. Our results demonstrated that Learning Styles, both in terms of recall performance and categorization, were inconsistent across only one week. This inconsistency suggests that Learning Styles are not a genuine scientific phenomenon and that “the theory is not right” (Willingham, 2009, p. 121). This conclusion is in line with the lack of attribution-treatment-interactions and the instability of Learning Style inventories found in past research (Curry, 1990; Scott, 2010). It can also explain why poor or no support was found in empirical tests in specific content domains from biology (Douglass, 1979) to kinesiology (Hsieh, Mache, & Knudson, 2012). If Learning Styles are not a genuine phenomenon, as our results suggest, then it would be impossible to have reliable, valid measures or to demonstrate an attribution-treatment-interaction.
This inconsistency of individuals’ learning styles, both in terms of self-reported preference and in performance-based ability, poses great difficulty for teachers attempting to apply the theory within the classroom. Inconsistent identification of learning styles would mean that instructors would need to spend time identifying students’ learning style on a continuous basis. In addition, given that information is best encoded conceptually, segregating the delivery of material based on modality could be a disservice to students as it limits the ways in which students receive material. Instead, Willingham (2005) suggests that teachers should think about modality in terms of how the specific information can best be conveyed. For example, when teaching algebra it is easier to demonstrate how to solve equations in a visual format than it would be to provide a purely auditory explanation. Scott (2010) also points out the potential harm that can be caused to learners through labeling. She warns that attempting to incorporate Learning Style theories in the classroom during which students are categorized as particular types of learners can promote the tendency to form expectations about students based on the label given them. Therefore, instead of working with what each student needs, students are generalized as certain types of learners thus requiring certain types of instruction. This is especially detrimental given what the current study has revealed about the inconsistency of these labels.

Furthermore, Scott (2010) points out that attempting to use these theories in the classroom can distract instructors from using techniques that do have empirical support. Therefore, instead of using valuable time and resources to identify and accommodate student learning styles, instructors should focus on using instructional techniques that have been empirically shown to improve learning and performance.
Examples of such techniques include retrieval practice (Karpicke & Blunt, 2011; Roediger & Karpicke, 2006), interteaching (Saville, Zinn, Neef, van Norman, & Ferreri, 2006), quality feedback (Hattie & Timperley, 2007), Dual Code theory (Moreno & Mayer, 1999), and student centered learning (Kuh, 2008).
REFERENCES


Stimulus Materials

INSTRUCTIONS TO PARTICIPANTS............................................................... 1
SIX ORIGINAL RECALL STORIES USED IN THE STUDY .......................... 3
STORIES FROM THE VISUAL CONDITION ............................................... 4
STORIES FROM THE KINESTHETIC CONDITION ...................................... 12
TEMPLATES FOR CUTTING OUT STORY UNIT PIECES FOR THE
KINESTHETIC CONDITION ........................................................................ 16
TEMPLATES FOR CUTTING OUT STORY UNIT PIECES FOR THE
INTEGRATED CONDITION ........................................................................ 20
**Instructions**

- In this condition you will be given a laminated card with text and pictures. The experimenter will indicate when you can turn over the card. You will then be given 3 minutes and 30 seconds to read the text, look at the pictures, and absorb the information on the card.

- After the allotted time is up, the experimenter will remove the card and you will be asked to write down the story exactly as it was presented on the card, word for word. When you are finished writing put down your pen and sit back to indicate you are finished.

- When you are finished reading these instructions please raise your hand to indicate you are ready to begin.

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**Instructions**

- In this condition you will be presented with an audio recording of a story. The experimenter will indicate when you can start the recording using the program on your screen. You will be given 3 minutes and 30 seconds to play the recording as many times as you would like in order to hear the story and absorb the information.

- The experimenter will indicate when time is up at which point you will be asked to write down the story exactly as it was presented in the recording word for word. When you are finished writing put down your pen and sit back to indicate you are finished.

- When you are finished reading these instructions please raise your hand to indicate you are ready to begin.
**Instructions**

- In this condition you will be given a laminated card with the text of a story. You will also be given a bag of puzzle pieces. The experimenter will indicate when you can turn over the card. You will then be given 3 minutes and 30 seconds to place the puzzle pieces directly on to the matching words and phrases on the card. Once finished, use the remaining time to read the story and absorb the information.

- After the allotted time is up, the experimenter will remove the card and pieces and you will be asked to write down the story exactly as it was presented on the card, word for word. When you are finished writing put down your pen and sit back to indicate you are finished.

- When you are finished reading these instructions please raise your hand to indicate you are ready to begin.

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**Instructions**

- In this condition you will be presented with an audio recording of a story as well as a laminated card with text and pictures and a bag of puzzle pieces. The experimenter will indicate when you can start the recording using the program on your screen. You will be given 3 minutes and 30 seconds to FIRST listen to the story using the program on your screen, SECOND to place the puzzle pieces directly on the matching words and phrases on the card. Once finished, use the remaining time to read the story and/or replay the recording as many times as you would like.

- The experimenter will indicate when time is up at which point the experimenter will remove the materials and you will be asked to write down the story exactly as it was presented in the recording and on the card, word for word. When you are finished writing put down your pen and sit back to indicate you are finished.

- When you are finished reading these instructions please raise your hand to indicate you are ready to begin.
Six Original Recall Stories Used In The Study

Eight stories were used in this study: the Babcock Recall Test (Babcock & Levy, 1940), the Portland Paragraph (Lezak & Howieson, 1976), and the six stories below.

Each story contains 21 units, separated by forward slash symbols (/). Recall scores were determined by counting the number of correctly recalled story units for each particular story. Combinations of words between parentheses represent alternative allowed spellings. Words between square brackets did not need to be included in the recall response to count as a correct unit. These flexibilities in the scoring were implemented after determining that doing so increased the number of correctly recalled story units.

- Last weekend/an avalanche/ covered /a ski slope/ 40 miles/ from Denver. /Snow covered a section of highway/ and flowed into the ski resort. /Nine people/ were killed/ and 350 others /were stuck/ in traffic overnight/ because of the amount of snow/ and debris/ on the road. /The resort/ /hopes/ /to clear the area/ and reopen/ before the end of the season.

- 4 /schools/ /sent students home/ /after a forest fire/ /entered/ /a residential area/ on the outskirts/ of (San Bernardino, San Bernadino). /Twelve people/ were killed/ and 200 others/ lost their homes/ as of this Thursday. /The fire/ /consumed/ /the suburban neighborhood/ and much of the forest area. /A well loved actor/ donated/ food and blankets/ for the victims.

- Last Wednesday /an earthquake/ struck/ 30 miles/ outside of Sherman. /8 people/ were killed/ and 130 people/ were injured/ when a damaged gas line/ caused a great fire/ in the area. /A woman/ was saved/ after being trapped/ under debris/ for 3 days. /Emergency shelters/ have been established for victims/ where they are provided/ food and water.

- 3 /news reporters/ were killed/ after a volcano blew/ near Tacoma/ last week. /Ash covered the streets/ and the heavy rains/ have created mudflows. /Nearby towns/ were evacuated/ however 11 people/ died/ and 240 others/ were buried/ while trying to escape. /The airspace/ in the area/ has been closed/ and the President/ has declared a national emergency.

- On Sunday/ a lightning storm/ in Lovington resulted/ in a (citywide, city wide, city-wide) /blackout, black out, black-out). /3 people/ died/ in a tragic accident/ after traffic signals/ stopped working/ and 700 others/ were sent home/ from work. /Many fires/ were started/ around the area/ and roads through the city/ were closed. /Workers/ are trying/ to get power back to the city.

- 6 /schools/ were closed after /a hurricane hit a residential area/ near the shore/ 10 miles/ from Gulfport. /As of Tuesday/ 3 people/ drowned from the high surf/ and the homes of 400 others/ were damaged. /Streets were flooded/ and filled with/ debris/ /branches/ flying off/ of trees. /Locals hope/ the storm/ will soon pass.
### December 6

Last week, a river overflowed because of the dampness and cold weather. In a small town ten miles from Albany, water covered the streets and entered the houses. Fourteen persons were drowned.

In saving a boy who was caught under a bridge, a man cut his hands.

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### Two semi-trailer trucks

Two semi-trailer trucks lay on their sides after a tornado blew a dozen trucks off the highway in West Springfield. In the Wednesday storm which hit an airport and a nearby residential area, one person was killed and 418 others were injured.

The governor will ask the President to declare the town a major disaster area.
Last weekend an avalanche covered a ski slope 40 miles from Denver. Snow covered a section of highway and flowed into the ski resort. Nine people were killed and 350 others were stuck in traffic overnight because of the amount of snow and debris on the road. The resort hopes to clear the area and reopen before the end of the season.

Four schools sent students home after a forest fire entered a residential area on the outskirts of San Bernardino. Twelve people were killed and 200 others lost their homes as of this Thursday. The fire consumed the suburban neighborhood and much of the forest area. A well loved actor donated food and blankets for the victims.
Last Wednesday

an earthquake struck 30 miles outside of Sherman. Eight people were killed and 130 people were injured when a damaged gas line caused a great fire in the area.

A woman was saved after being trapped under debris for three days. Emergency shelters have been established for victims where they are provided food and water.

Three news reporters were killed and 240 others were buried while trying to escape. The airspace in the area has been closed and the President has declared a national emergency.

Nearby towns were evacuated, however...
Six schools were closed after a hurricane hit a residential area near the shore ten miles from Gulfport. Streets were flooded and filled with debris from branches flying off of trees. As of Tuesday, three people drowned from the high surf and the homes of 400 others. Locals hope the storm will soon pass.

On Sunday, a lightning storm in Lovington resulted in a citywide blackout. Many fires were started around the area, and roads through the city were closed. Workers are trying to get power back to the city. Three people died in a tragic accident after traffic signals stopped working, and 700 others were sent home from work.
December 6. Last week a river overflowed in a small town ten miles from Albany. Water covered the streets and entered the houses.

Fourteen persons were drowned and 600 persons caught cold because of the dampness and cold weather. In saving a boy who was caught under a bridge, a man cut his hands.

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11 people died and 240 others were buried while trying to escape. The airspace in the area has been closed and the President has declared a national emergency.
Six schools were closed after a hurricane that hit a residential area near the shore ten miles from Gulfport. As of Tuesday, three people drowned from the high surf and the homes of 400 others were damaged. Streets were flooded and filled with debris from branches flying off of trees. Locals hope the storm will soon pass.

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APPENDIX B
PERLSCRIPT

#!/usr/bin/perl

sub fisher_yates_shuffle {
    my $array = shift;
    my @i;
    for ($i = @$array; --$i; ) {
        my $j = int rand ($i+1);
        next if $i == $j;
        @$array($i,$j) = @$array($j,$i);
    }
}

print "Content-type: text/html", "\n\n";

for ( $i=0; $i<24; $i++ ){
    for ( $j=0; $j<4; $j++ ){
        $conditions{ $i }{ $j } = 0;
    }
}

for ( $i=0; $i<24; $i++ ){
    for ( $j=0; $j<4; $j++ ){
        $stories[ $i ][ $j ] = 0;
    }
}

$row = 0;
for ( $i=1; $i<4; $i++ ){
    for ( $j=1; $j<4; $j++ ){
        for ( $k=1; $k<4; $k++ ){
            for ( $l=1; $l<4; $l++ ){
                if ( $i==$j and $i==$k and $i==$l and $j==$k and $j==$l and $k==$l ){
                    $conditions[ $row ][ 0 ] = $i;
                    $conditions[ $row ][ 1 ] = $j;
                    $conditions[ $row ][ 2 ] = $k;
                    $conditions[ $row ][ 3 ] = $l;
                    $row++;
                }
            }
        }
    }
}

#stories1 = (1,2,3,4,1,2,3,4,1,2,3,4,1,2,3,4,1,2,3,4,1,2,3,4);
fisher_yates_shuffle( \@stories1 );

#stories2 = (1,2,3,4,1,2,3,4,1,2,3,4,1,2,3,4,1,2,3,4,1,2,3,4);
$unhappy = 1;
while( $unhappy == 1 ){
    $unhappy = 0;
    fisher_yates_shuffle( \@stories2 );
    for ( $i=0; $i<24; $i++ ){
        if ( $stories1[ $i ] == $stories2[ $i ] ){
            $unhappy = 1;
        }
    }
}
$count = 0;
$possibilities = (1,1,1,1);
$storiesNum = (0,0,0,0);
for( $i=0; $i<24; $i++ ){
    $possibilities[ $stories1[ $i ] - 1 ] = 0;
    $possibilities[ $stories2[ $i ] - 1 ] = 0;
    for( $j=0; $j<4; $j++ ){n
        if( $storiesNum[ $j ] >= 6 ){n
            $possibilities[ $j ] = 0;
        }
    }
}$unhappy = 1;
while( $unhappy == 1 and $count<10000 ){n
    $try = int( rand(4) );
    #print $try . "<br>\n";
    if( $possibilities[ $try ] == 1 ){n
        $unhappy = 0;
    }
    $count++;
}$stories3[ $i ] = $try + 1;
$storiesNum[ $try ] += 1;
#push(@stories3, $try);
if( $count >10000 ){n
    print $count . "<br>\n";
}
$possibilities = (1,1,1,1);
$storiesNum = (0,0,0,0);
for( $i=0; $i<24; $i++ ){
    $possibilities[ $stories1[ $i ] - 1 ] = 0;
    $possibilities[ $stories2[ $i ] - 1 ] = 0;
    $possibilities[ $stories3[ $i ] - 1 ] = 0;
    for( $j=0; $j<4; $j++ ){n
        if( $storiesNum[ $j ] >= 6 ){n
            $possibilities[ $j ] = 0;
        }
    }
    for( $j=0; $j<4; $j++ ){n
        if( $possibilities[ $j ] == 1 ){n
            $stories4[ $i ] = $j + 1;
            $storiesNum[ $j ] += 1;
        }
    }
}
for( $i=0; $i<24; $i++ ){n
for( $i=0; $i<4; $i++ ){
    $stories[ $i ][ $j ] = $stories1[ $i ];
}

for( $i=0; $i<4; $i++ ){
    $storiesCount[ $i ][ $j ] = 0;
}

for( $i=0; $i<24; $i++ ){
    for( $j=0; $j<4; $j++ ){
        $storiesCount[ $i ][ $j ] = $stories[ $i ][ $j ] - 1
    }
}

for( $i=0; $i<4; $i++ ){
    for( $j=0; $j<4; $j++ ){
        print $storiesCount[ $i ][ $j ] . "", ";
    }
    print "<br>\n";
}

print "<table border="1" cellspacing="0" cellpadding="5">\n"
for( $i=0; $i<24; $i++ ){
    print "<tr>";
    for( $j=0; $j<4; $j++ ){
        print "<td">" . $conditions[ $i ][ $j ] . "</td>";
    }
    print "</td>&nbsp;</td>";
}
for( $j=0; $j<4; $j++ ){
    print "</td>" . $stories[ $i ][ $j ] . "</td>";
}
print "</tr>\n";
print "</table>\n";

# for( $i=0; $i<24; $i++ ){
#     print $stories1[ $i ] . "," . $stories2[ $i ] . "," . $stories3[ $i ] . "," . $stories4[ $i ] . "," . "<br>\n";
#}