UNIVERSITY OF CALIFORNIA, SAN DIEGO

SAN DIEGO STATE UNIVERSITY

Cultural Determinants of Category Learning

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in

Clinical Psychology

by

Xavier E. Cagigas

Committee in charge:

University of California, San Diego

Professor J. Vincent Filoteo, Chair
Professor Michael Cole, Co-Chair
Professor David P. Salmon

San Diego State University

Professor Hope Landrine
Professor Sarah N. Mattson
Professor Scott C. Roesch

2008

The dissertation of Xavier E. Cagigas is approved, and it

is acceptable in quality and form for publication

on microfilm:

____

____

____

____

____

Co-Chair

____

Chair

University of California, San Diego

San Diego State University

2008

DEDICATION

Dedico esta humilde obra a mis abuelos, Edmundo y Cruzita Cagigas, cuyas transiciones a la vida eterna marcaron el empiezo y el final de mis estudios graduados. Ellos simbolizan la raíz de mi familia que floreció en mi madre, Yolanda, quien ha sido y siempre será mi mejor maestra. Ellos me inspiraron a buscar el amor eterno que vivieron juntos y que encontré en mi esposa, Mayra. Por ellos, por mi familia y por mi raza he sembrado esta pequeña semilla que, con la ayuda de Dios, está por florecer…

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGEMENTS

I would first like to thank my mentor, Vince Filoteo, for journeying with me through the past seven years. His relentless encouragement and enthusiasm empowered me to embrace the current direction of my research and to strive toward becoming a better scientist. To my committee, I offer my most sincere thanks for their patience and guidance in bringing this work to fruition. I would also like to thank Michael Cole and the Laboratory for Comparative Human Cognition for kindly offering their laboratory space, and for welcoming me with open arms into their community of practice. To my research assistants, Robin, Ryan, and Shu, thank you for your tireless efforts on my behalf.

I have been extremely fortunate in always having good teachers throughout the evolution of my education. Though there are many professors to thank for the great impact they have had on my life, I would like to single out my undergraduate mentor and now friend, Steve Sabat. He is most certainly a giant upon whose shoulders I now see more clearly. I also wish to thank my classmates and colleagues who "grew up" with me; I am truly honored to call such bright souls my friends.

Finally, I would like to thank my family. My mother instilled in me a thirst for knowledge, a commitment to justice, and a love of humanity. I am who I am in large part because of who she is. To all of my *primos, tios*, and my Sasa – mil gracias! And finally, to my dearest wife, Mayra, who will journey with me wherever the road leads…gracias por existir.

VITA

Education

2008	Doctor of Philosophy in Clinical Psychology San Diego State University / University of California, San Diego Joint Doctoral Program in Clinical Psychology Specialization: Neuropsychology
2006	Master of Science in Clinical Psychology San Diego State University
1997	Bachelor of Arts in Psychology, Minor in Music Theory Georgetown University

Awards

NINDS/UCLA Postdoctoral Fellowship in Neurobehavioral Genetics

NIH Ruth L. Kirschstein National Research Service Award (NRSA-NIMH)

NSF Alliances for Graduate Education and the Professoriate (AGEP) Doctoral Scholar

Dorathe L. Frick Memorial Award for Outstanding Contribution by a Doctoral Student

University of California, San Diego Eugene Cota-Robles Fellowship

American Psychological Association Minority Undergraduate Student of Excellence

Publications

Cagigas, X.E., & Bilder, R.M. (in-press). Where culture meets neuroimaging: The intersection of Luria's method with modern neuroimaging and cognitive neuroscience research. In A.L. Christensen, D. Bougakov, E. Goldberg (Eds.), <u>Luria's Legacy in the 21st Century</u>.

Cole, M., & Cagigas, X.E. (in-press). Culture, Cognition, & Development. In M.H. Bornstein (Ed.), <u>Handbook of Cross-Cultural Developmental Science</u>.

Cagigas, X.E., Salmon, D.P. & Filoteo, J.V. (in-press). La Neuropsicología de la Demencia [Neuropsychology of Dementia]. In M. Perez-Garcia (Ed.), Manual de Neuropsicología Clínica. Madrid, Spain: Pirámide.

Cagigas, X.E., Filoteo, J.V., Stricker, J.L., Rilling, L.M., & Friedrich, F.J. (2007). Flanker effects in patients with Parkinson's disease: Impact of target onset delay and trial-by-trial changes in stimulus display. *Brain and Cognition 63:3*, 247-259.

Possin, K.L., Cagigas, X.E., Strayer, D.L., & Filoteo, J.V. (2006). Lack of impairment in patients with Parkinson's disease on an object-based negative priming task. *Perceptual and Motor Skills, 102*, 219-230.

Filoteo, J.V., Maddox, W.T., Simmons, A.N., Ing, A.D., Cagigas, X.E., Matthews, S., & Paulus, M.P. (2005). Cortical and subcortical brain regions involved in rule-based category learning. *NeuroReport, 16:2*, 111-115.

Sabat, S.R., & Cagigas, X.E. (1997). Extralinguistic communication compensates for the loss of verbal fluency: A case study of Alzheimer's disease. *Language and Communication, 17:4*, 341-351.

ABSTRACT OF THE DISSERTATION

Cultural Determinants of Category Learning

by

Xavier E. Cagigas

Doctor of Philosophy in Clinical Psychology

University of California, San Diego, 2008

San Diego State University, 2008

Professor J. Vincent Filoteo, Chair

Professor Michael Cole, Co-Chair

A review of the cultural psychology literature reveals that some ethnic groups consistently perform differently on even the most basic cognitive tasks. Specifically, Asians attend to more contextual information whereas Caucasians selectively attend to the most salient stimulus dimension. In order to determine if such processing differences in attention impact category learning, this dissertation investigated whether

Chinese, Caucasians, and Latinos performed differently on the perceptual categorization task.

Seventy-two Caucasian, 50 Chinese, and 47 Latino students matched in terms of years of education and gender represented a range of acculturation from foreign born bilingual immigrants to native born Americans whose only language is English. Participants learned to sort stimuli into one of two predetermined categories by receiving corrective feedback after each trial. In Experiment 1, participants learned a unidimensional rule requiring participants to attend selectively to a single stimulus dimension. In Experiment 2, participants learned a conjunctive rule requiring an *explicit* conjunction of two stimulus dimensions. In Experiment 3, participants learned an information-integration rule requiring that participants integrate information from two stimulus dimensions at an *implicit* level. In addition to examining potential differences in accuracy using repeated measures analysis of variance, mathematical models identified the types of categorization strategies participants actually used when learning one of the three categorization rules. Finally, a regression analysis further investigated the possible underpinnings of observed ethnic group differences in categorization accuracy.

No differences were observed between groups in Experiments 1 and 3, suggesting that category learning tasks that emphasize selective attention and implicit learning processes are not sensitive to the ethnic differences observed in previous studies. In Experiment 2, however, contrary to what would have been expected, Caucasians performed better than both Chinese and Latino participants when having to form an explicit sorting rule combining more than one stimulus dimension. Even after groups were equated based on the type of categorization strategies employed, these group differences persisted. Hierarchical regression further revealed that ethnicity did not predict accuracy after level of mainstream acculturation was taken into account. Secondary analysis of the acculturation subscales suggested that receptive language ability in English was the best predictor of overall accuracy in learning a conjunctive rule-based task over and above ethnic group membership. Overall, these results suggest that previously observed cultural differences are more likely related to factors other than ethnic group membership, and therefore warrant further study.

INTRODUCTION

The ability to categorize (i.e., place items into groups of similar items) is a fundamental cognitive process performed throughout our lives, and we are often required to learn new categories. Identifying whether cultural differences in category learning exist, therefore, is of critical importance given that this cognitive process is one of the most basic operations on which many higher-order processes are based. Over the last several decades, our understanding of the cognitive processes involved in categorization has grown to the point where formal models have been developed and tested. The influence of culture on category learning, on the other hand, has not been widely studied at this level of depth and yet may be a fundamental component of the categorization process itself. Past research has indeed found significant differences in how various ethnic groups categorize visual stimuli and also on the number and salience of stimulus attributes that they attend to, suggesting that cultural differences do indeed exist. Nevertheless, these past studies have been somewhat limited because (1) they did not control for important task variables that might also impact cultural differences in category learning, (2) they did not make any attempt to investigate the strategies or processes through which individuals actually make their categorizations, (3) they relied strictly on *ethnicity* or *race* to make group comparisons rather than attempting to measure the *cultural constructs* that might actually underlie any observed differences both between and within groups, and (4) few studies have been conducted *exclusively* within the United States to examine how acculturation to what has historically been considered the American mainstream might influence cultural differences in categorization.

The purpose of this dissertation is to examine whether self-identified ethnic group membership predicts category learning performance in three different experiments. In Experiment 1, participants learned a unidimensional rule in which optimal performance was based on learning to attend selectively to a single stimulus dimension while ignoring another dimension. In Experiment 2, participants learned a conjunctive rule in which optimal performance required learning a rule that was based on an explicit combination of two stimulus dimensions. In Experiment 3, participants learned an information-integration rule in which optimal performance was based on an implicit integration of the two relevant stimulus dimensions.

In addition to examining whether self-identified ethnic group membership predicts category learning performance in the three proposed experiments, this dissertation also addressed (1) whether differences in cognitive style directly affect category learning at the level of perception (i.e. field dependence/independence, FD/I) and/or beliefs about the self in relation to others and the environment (i.e. Individualism-Collectivism, IC); (2) whether a person's level of acculturation influences any of these differences; and (3) whether these differences become even more evident when the strategies individuals actually use to categorize stimuli are examined systematically. The following specific hypotheses attempted to address these research questions:

Hypothesis 1: <u>Measurable cultural differences exist when participants learn a unidimensional rule-based categorization task (Experiment 1)</u>.

Previous studies suggest that individuals from more independent or individualistic cultures (i.e. Caucasians) selectively attend to the most salient dimensions of a stimulus, while more collectivist or interdependent individuals (i.e. Asian and Latino) incorporate other contextual information to a greater extent. Based on these past observations, it was predicted that Caucasians (e.g. the typically more field-independent and individualistic group) would perform better than the other two more typically field-dependent and collectivist cultures in learning a *unidimensional rule-based* category learning task, in which optimal performance was based on attending selectively to a single stimulus dimension.

Hypothesis 2: Measurable cultural differences exist when participants learn a conjunctive rule-based categorization task (Experiment 2).

Again, if Caucasians as a group tend to attend more selectively to the most salient stimulus dimension of a stimulus display, whereas Asians and Latinos tend to incorporate more stimuli simultaneously, then it should be predicted that Asians and Latinos will perform relatively better than Caucasians in learning a conjunctive rule-based task, in which optimal performance is based on an *explicit* conjunction of multiple stimulus dimensions.

Hypothesis 3: Measurable cultural differences exist when participants learn a linear information-integration categorization task (Experiment 3).

If both Asians and Latinos *implicitly integrate* multiple stimulus dimensions when categorizing stimuli rather than making an explicit and verbalizable conjunction of stimulus dimensions, then they should both perform better than Caucasians on this task. If on the other hand, the proposed disposition toward incorporating multiple stimulus dimensions previously observed in more field-dependent and collectivist cultures is contingent upon their use of an explicit, hypothesis-driven approach (e.g., the conjunctive rule-based strategy that would result in optimal performance in Experiment 2), then they should both not show an advantage relative to Caucasians in learning a linear information-integration task. Nevertheless, it might also be the case that the bias toward integrating multiple stimulus dimensions observed in previous studies of more field-dependent and collectivist cultures represents an implicit process in Asians and an explicit process in Latinos or vice versa (i.e. Asians and Latinos might also be different from each other, and only one of these two ethnic groups may show an advantage in learning the information-integration task). The reasons why this might be the case will be examined in Hypothesis 5.

Hypothesis 4: <u>Cultural differences will also be observed when a more fine-grained examination of the category learning *strategies* a participant actually uses are modeled quantitatively</u>.

The application of quantitative models to the response pattern of research participants provided a more in-depth evaluation of any observed differences in terms of how various cultural groups might differ in the *strategies they actually use* when learning the aforementioned categories. As such, it was predicted that Caucasians would be more likely to apply a unidimensional rule in all three experimental conditions, whereas Asians and Latinos would be more likely to apply a conjunctive approach in Experiment 2 and an information-integration approach in Experiment 3.

Hypothesis 5: Separate quantifiable measures of (1) perceptual field-dependence/independence (FD/I), (2) individualistic and collectivist (IC) self-construal, and (3) level of acculturation better predict categorization strategy than self-identified ethnic group membership alone.

Although ethnicity has been used to explain group differences in most previous studies, other quantifiable constructs with better psychometric properties have also been shown to have equal or better explanatory power. If this is the case, then it follows that a greater degree of field-independence and individualism should be positively associated with performance on the unidimensional rule-based task and greater field-dependence and collectivism should be positively associated with performance on the conjunctive rule-based task, both between and within self-identified ethnic groups. It is important to note, however, that few cross-cultural studies have directly measured level of FD/I and IC self-construal separately within the same study, and so these two constructs have frequently been confounded by assuming that they measure similar yet distinct aspects of cognitive style. The unique contribution of the perceptual (i.e. FD/I) and belief-based (i.e. IC self-construal) aspects of cognitive style, however, may be particularly important in teasing apart differences in the analysis of the information-integration task which purportedly engages implicit learning processes (e.g. the comparison of Asians and Latinos in Hypothesis 3). Finally, it was also predicted that level of acculturation would also influence these relationships and, therefore, capture the dynamic nature of "ethnicity" which has historically been construed as a static, categorical variable.

In summary, the overall goal of this dissertation, therefore, was to begin to examine the possible role that quantifiable measures of perceptual style (i.e. FD/I) and cultural beliefs (i.e. IC) may play in explaining category learning differences within an ethnically diverse sample in the United States. Secondly, the proposed dissertation attempted to determine whether differences in FD/I, IC, or level of acculturation directly impact levels of categorization *accuracy* or whether they lead to *different strategies* in categorization, or both. Finally, rather than simply relying on a potentially heterogeneous grouping variable such as self-identified ethnicity, the predictive validity of empirical measures of FD/I, IC, and a two-factor acculturation scale (to be described later in this proposal) were put to the empirical test in accounting for any observed differences in both categorization accuracy and strategy.

WHY STUDY CULTURAL DIVERSITY IN THE UNITED STATES

The ever-increasing cultural diversity that makes up the United States of America has raised a series of issues in neurocognitive research and assessment that have not been adequately examined. The increased utilization of mental health services by historically underrepresented minority groups (U.S. Department of Health and Human Services, 2001), the failure of present diagnostic and treatment modalities with these populations (Snowden, 2003), and the relative lack of their participation (Sheikh, 2006) or inclusion (Wendler, et al., 2006) in neurocognitive research have led to the creation of various initiatives by the federal government to directly examine the role of cultural practices in mental health (Garber & Arnold, 2006; Yancey, et al., 2006). All of these factors combined have raised the possibility that perhaps present research methods do not adequately generalize to historically underrepresented populations both within the United States and globally. This problem is further compounded by the fact that most scientific investigators in neurocognition are not in the habit of reporting culturally relevant demographic information in their research reports (O'Bryant, et al., 2004). Those few studies that have reported such factors have done so under the rubric of ethnicity or even race and have attempted to explain observed differences without systematically investigating what may be driving these differences at the level of perception or belief systems within ethnic groups (Hunt, 2005). Furthermore, a historical overview of previous investigations involving race reveals that greater emphasis has been placed on bolstering a particular political ideology (i.e. the superiority of certain races over others) rather than impartially employing the scientific method to try to understand the evolving construct of race just like any other research variable (Gould, 1995). Nevertheless, cross-cultural research consistently continues to demonstrate that ethnic differences do indeed exist (see below for details), and that the amorphous constructs of race and ethnicity may be a proxy for other measurable dimensions of culture (Betancourt and Lopez, 1993; Helms, 1992; Phinney, 1996).

Despite any methodological shortcomings of past research programs that have attempted to examine cognitive differences in ethnicity or race, the fact of the matter is that the numbers of historically underrepresented minority groups in the U.S. are continuing to grow at exponential rates. It is estimated that Hispanic/Latinos in the U.S. represent 15% of the general population, and are projected to grow to at least 25% over the next 30 to 50 years (US Census, 2004). Furthermore, the heterogeneity of this ethnic group classification has led many researchers and policy makers to question whether Hispanic/Latino ethnicity, as a descriptive term, really means anything since there are at least an estimated 36 distinctly identifiable cultural groups within the umbrella heading of Hispanic/Latino, whose only commonality is the Spanish language (within which there are also significant differences at the level of dialect). The same has been said about Asian populations in the United States which are categorized as a different race rather than a different ethnicity relative to Caucasians. Asians in the U.S.A. represented roughly 4% of the general population in 2000 and are projected to double to 8% by 2050 (US Census, 2004). Again, it seems inaccurate to group people who, in this case, do not speak the same language (e.g. Japanese, Mandarin, Cantonese, Vietnamese, Taiwanese, Korean, etc.), do not share the same customs, and do not even come from the same parts of the world into the same group simply because of perceived similar physical characteristics (i.e. race) unless there is a scientifically-based reason to believe that they share something fundamental in common that justifies this aggregation. Yet this is precisely the practice adopted by the U.S. Census Bureau and most researchers of neurocognition and psychology without attempting to empirically measure a common denominator within the group.

In summary, the need for a better understanding of the bases of ethnic and cultural differences in cognition is highly important if an accurate understanding of human cognition is to be obtained. In addition, a better understanding of how culture impacts cognitive functions will help in the development of appropriate assessment tools in this ever diversifying and multicultural society.

PREVIOUS RESEARCH IN CROSS-CULTURAL AND CULTURAL PSYCHOLOGY

The emerging fields of cross-cultural and cultural psychology have posed a critical challenge to the idea that all cognitive processes are uniform across ethnic groups, and suggest that cognition is inseparable from the *cultural practices* of an individual (Cole, 1996; Markus & Kitayama, 1991; Nisbett, et al., 2001). In contrast to the wake left by the *cross-cultural* movement of the 1960s and 1970s, which provided an abundance of evidence suggesting that not all cultures perform the same across a wide range of cognitive tasks (Berry, et al., 1992), *cultural psychology* researchers have now gone a step further and hypothesized that even the most basic perceptual processes are completely constituted by the cultural practices in which an individual develops and participates (Cohen, 1994; D'Andrade, & Strauss, 1992; DiMaggio, 1997; Hong & Mallorie, 2004; Shore, 1996; Strauss & Quinn, 1997). In other words, rather than simply treating culture as an independent variable in the style of cross-cultural psychology, cultural psychology asserts that culture is not merely an influence upon cognition, but instead that cognition is by definition cultural (Greenfield, 2000). Cognition has a developmental history that takes shape within the context of a person's cultural practices, meaning that how a person thinks and experiences the world is a learned practice that is the product of interactions with other people and artifacts imbued with historical and cultural meaning (Cole, 1996; Cole & Means, 1981).

Although some have long suggested that language is the true reason for these differences (Bloom, 1981; Whorf, 1956), more recent evidence indicates that cultural differences in cognition clearly go beyond purely linguistic differences (Hunt & Agnoli, 1991; Ji, et al., 2004). In addition, recent scholarship has suggested that ethnicity and race are simply proxy variables for other potentially *measurable underlying constructs* that are shaped by the culture in which a person is raised, and do not necessarily represent fixed categories that travel with a person across time and multiple contexts (Lehman, Chiu, & Schaller, 2004). One of the most successful operationalized constructs for understanding cultural differences is the notion of cognitive or interactional style (Fernald & Morikawa, 1993).

Early work by Witkin and colleagues (1954) indeed supports the notion that some people are more perceptually "field dependent" than others, and therefore, that different cognitive styles exit. In other words, some people are more heavily influenced by the context in which stimuli are presented while others are less influenced. In this area of research, the construct of field-dependence was originally operationally defined and experimentally tested using the Rod and Frame Test (RFT), followed by the Embedded Figures Test (EFT), and finally the Group Embedded Figures Test (GEFT) which represents a more psychometrically stable and empirically supported improvement over the EFT (Witkin, 1971, 2002). The RFT was the first developed and is still one of the most widely used measures of FD/I. This test consists of a rod inside a frame, both of which are moveable, and the participant must adjust the rod to a true vertical position as the position of the frame is changed. Degree of error, or the number of degrees away from 90, is the measure used to score the test. The participant is considered field dependent or independent depending on the score on the test. The higher the score is, the more field-dependent the participant is considered; the lower the score, the more field-independent the participant is considered. The EFT was developed as an alternative to the RFT because of the cumbersome equipment required in administering the RFT, and the GEFT to improve upon the construct validity of the EFT (e.g. the EFT did not correlate as strongly with the RFT). The GEFT is also a standardized measure of cognitive style and analytical ability; however, it requires finding simple forms that are embedded in larger figures. The score is the average time in seconds to detect the simple forms, as well as the total number of correctly dis-embedded figures within a specified time. Thus, higher time scores reflect greater difficulty in analyzing a part separately from a wider pattern; or, alternatively, a greater tendency to perceive complete patterns rather than their separate components.

According to Witkin (1971; 2002), persons who are field-independent also experience *themselves* as separate and distinct entities from others, depend on internal referents, and are more autonomous in social relations. Field-dependent persons, on the other hand, have a less delineated "self" and rely primarily on external referents (including others) and tend to be limited in their personal autonomy. This extended understanding of FD/I (i.e. self-construal) led to the large literature of individualism and collectivism (e.g. independence/interdependence), which further suggested that the level of an individual's perceptual field-dependence emerges from the experience of the different cultural practices and beliefs which shape their self-construal during developmental ontogeny (Hofstede, 1991; Markus & Kitayama, 1991; Triandis, 1996). In other words, as a person matures in a particular cultural and historical context, they develop a different way of relating to others by either giving primacy to the group they are a part of (i.e., collectivist) or to themselves as individuals separate from the group (i.e., individualist). As a result, their self-construal (i.e. how they relate to self, others, and the environment) can either be individualistic and field-independent or collectivist and field-dependent. These dimensions of cognitive style have been extended by further research that proposed that specific ethnic groups, which engage in different cultural practices, are consistently more field-dependent than others (Berry & Annis, 1974; Eagle, et al, 1969; Witkin, et al, 1974; Witkin, et al, 1975; Witkin & Goodenough, 1977).

Nisbett and colleagues (2001) have since expounded upon the idea that differences in cognitive style can be readily observed by directly comparing the performance of Asian and Caucasian Americans in a variety of experiments that capitalize on this difference in self-construal or cognitive style. They found that it is relatively more difficult for Caucasians to detect changes in the background of scenes, suggesting that they are less field-dependent, whereas it is more difficult for Asians to detect changes within objects in the foreground of a scene, suggesting that they are more field-dependent. Simons and Levine (1997) have also demonstrated that Asians more accurately detect change in the environment or context while Caucasians selectively detect changes in objects in the foreground using the "change blindness" paradigm. When an object in the background was removed or added after a brief delay, Asians were aware of the change more often whereas Caucasians did not notice these changes in the background. Other research has attempted to explain these findings by suggesting that different cultures show different patterns of attention, with some incorporating more contextual information relative to others in their decision making processes (Masuda & Nisbett, 2001; Ji, et al, 2000). More specifically, Asians tend to focus their attention on the interrelationships between objects and the contexts in which they are embedded in visual space, whereas Caucasians attend primarily to the object in the foreground and its salient characteristics, echoing previous studies on differential level of perceptual field-dependency. Experimental evidence for this includes the fact that when objects are taken out of the original context in which they were presented, Caucasians have little difficulty identifying the object as familiar whether it is presented in isolation or with a new background, whereas Asians have greater difficulty identifying these same objects when they are presented with a novel background as opposed to in isolation (Masuda & Nisbett, 2001; Ji, et al., 2000). Other researchers, making no mention of the demographic makeup of their sample, have suggested that although semantic congruency between objects in the foreground and background increases accuracy, a bias toward processing objects in the foreground exists in the way humans perceive and categorize stimuli (Davenport, 2004). Nisbett and colleagues, nevertheless, contend that Asians do not simply fail to process the object in the foreground, but rather that they incorporate the spatial context and somehow bind it to their representation of the object.

For example, a recent study showed that patterns in eye movements correlate with observed differences in cognitive style (Chua, Boland, & Nisbett, 2005). Specifically, the eye movements of American (the ethnic make-up of this sample was not specified) and Chinese participants were measured while they viewed photographs of a focal object superimposed on a complex background. Examination using eye-tracking equipment revealed that American participants fixated more on focal objects and tended to fixate on the focal object more quickly after initial presentation of the photograph. Chinese participants, on the other hand, made more saccades to the background than did the Americans and took longer to direct their gaze specifically toward the focal object. Thus, cultural differences can be observed both at the behavioral level of performance, and also on a measurable physiological level.

Recent research also suggests that the cognitive differences observed between Asian and Caucasians, or between field-dependent and field-independent individuals, likely results from the use of different underlying neural systems when performing various cognitive tasks. For example, an ERP study by Goode, et al (2002) showed that more field-independent individuals recruited a different neurocognitive system during a serial-order recall task that stressed inhibition of “irrelevant” task variables relative to field-dependent individuals who incorporated these “irrelevant” stimuli and had to overcome their influence, suggesting that differences in cognitive style can be readily investigated on a direct and quantifiable physiological level as well. Specifically field-dependent participants were shown to exert more inhibition on irrelevant task variables, as indexed by greater P300 amplitude, necessary to change their usually global-perceptual attentional strategy and thereby increase attention to the salient characteristics of the stimuli needed for better recall performance. Field-independent participants, on the other hand, were able to engage in deeper working memory processing of relevant stimuli characteristics, as evidenced by a higher amplitude slow negative wave over the centro-parietal scalp and extending to the frontal scalp, since they did not have to actively inhibit irrelevant task variables (i.e. increased P300 in field-dependent group). Although this ERP study showed that differences in FD/I correlated with differences in the dynamics of the underlying neural correlates of the task, importantly, no difference was observed in the actual performance of the research participants. In other words, both groups performed at a comparable level on the task (i.e. level of recall), however, the way they went about it was different. Although this study did not directly compare cultural groups but rather focused on cognitive style (i.e., FD/I), one likely possibility is that, under these same experimental conditions, Caucasians would show a similar pattern of brain activity as field-independent participants, whereas Asians would show a similar pattern as field-dependent participants.

A recent fMRI study (Grön, et al., 2003) also showed that although *behavioral performance* (*i.e.* total recall and learning slope), was identical between Caucasians and Chinese on a visual learning task that required repetitive memorization of geometric patterns and repetitive active recall over five blocks, each group demonstrated a different pattern of neuronal activation during performance of the same task. Specifically, in the "what" and "where" framework of visuospatial processing (Ungerleider & Mishkin, 1982), initial learning (i.e. 1st learning block) within the Chinese group activated bilateral frontal and parietal areas (i.e. the dorsal stream for analysis of spatial features); whereas the Caucasian group recruited posterior ventral regions, especially the fusiform gyrus and hippocampal complex (i.e. the ventral stream for object identification). Interestingly, over time (between the 2nd and 3rd learning blocks) a crossover effect was observed such that Caucasian participants began to exhibit dorsal activation while Chinese participants began to exhibit ventral activation before returning to the initially observed baseline pattern (i.e. between the 4th and 5th blocks). The authors interpreted these results as demonstrating that differences in cultural upbringing likely influenced participants to initially approach stimuli in their default attentional style (i.e. trying to encode the geometric figures as whole objects for the Caucasians and trying to encode the visuospatial lay of the land in Chinese). The shift in processing strategy observed midway through the learning process likely represented an attempt to more fully consolidate the percept to be learned by engaging the complimentary analyzer (i.e. either the ventral or dorsal stream). Once the memorization of the figures had been stabilized in long term memory, participants returned to their default attentional style in the final blocks. Regardless of the interpretation of these results, however, the most important conclusion from this study is that there do indeed appear to be differences in how various cultural groups recruit neural systems when performing a given task.

In summary, based on past findings, it is clear that members of different cultures likely perform differently on some cognitive tasks and that there are also likely differences in how various members of different cultures recruit different neural systems when performing such tasks. Past research has also demonstrated that both level of FD/I and IC self-construal can be reliably quantified and that cultural differences in cognition are more clearly observed when taking into account these factors.

ETHNIC VS CULTURAL EXPLANATIONS OF COGNITIVE GROUP DIFFERENCES

As noted above, an important advancement in our scientific understanding of ethnic differences in cognition is the obvious notion that there is more to an individual than just an ethnic label. For example, in terms of findings with Asian groups, most cultural psychologists would agree that it is not a person's "Asian-ness" that drives any observed cultural differences. Evidence for the limitations of ethnicity as an explanatory construct and the need for further scientific investigation in this area has recently been well documented by other investigators (Helms, Jernigan, & Maryam, 2005; Smedley & Smedley, 2005), especially in the face of increased globalization and the concomitant increase in people who now self-identify as members of more than one ethnic group (Arnett, 2002). As noted in the previous section, a strong candidate for refining our scientific understanding of what “ethnicity” captures is the degree to which an individual’s perceptual patterns and beliefs can be placed along a continuum of FD/I or IC self-construal which might have a greater degree of explanatory power in understanding cognitive differences than just simply classifying a person as Asian or Caucasian. In fact, a growing literature suggests that the cultural practices within which a person develops during ontogeny may be responsible for determining the self-construal or level of perceptual FD/I in which cognition matures and operates throughout life (Lehman, Chiu, & Schaller, 2004; Cole and Means, 1981). Chua and colleagues (2005), for example, make the argument that cultural differences in the way objects are processed (i.e. level of FD/I as indexed by eye movement patterns) results from the emphasis that early cultural practices in development place on always looking for the *interrelationship* among things (i.e. collectivist self construal) rather than things in and of themselves (i.e. individualist self-construal: Chiu, 1972). Nisbett and colleagues have also made an equally compelling argument for different cultural physical environments playing a causal role in leading to different cognitive styles. For example, Asian street scenes are more complex to begin with relative to street scenes in non-Asian countries or parts of town and this complexity results in chronic patterns of attention allocation that incorporate multiple objects in the visual field (Miyamoto, Nisbett, & Masuda, 2006; Nisbett & Miyamoto, 2005). Thus, there is obviously more to the notion of "ethnicity" than just simply classifying an individual as being a member of one group or another, and it is highly likely that such underlying differences can help explain why classic observations among different ethnic groups exist in the first place. With regard to the current set of experiments, it was hypothesized that dispositional variables such as FD/I and IC self-construal might also help to understand the actual underlying differences among different cultural groups in terms of how they learn to categorize.

In addition to examining the underlying cultural factors that likely result in group cognitive differences, other variables can also be examined to determine if these factors play an important role in individual cognitive differences. One such factor is a person's degree of acculturation. However, traditional views of acculturation in the United States have been somewhat limited, at least in part, because of the long held belief in cultural assimilation which holds that this country is a "cultural melting pot". Recent scholarship in acculturation (Berry, 2004), however, has suggested that an increasing percentage of people with Asian or Latino cultural backgrounds do not simply assimilate, but rather become functionally bicultural (i.e. able to comfortably switch between indigenous and mainstream cultural practices) or marginalized (i.e. cling to their indigenous culture and do not adopt the cultural practices of the mainstream culture). This view is captured by Berry's two-factor model of acculturation that suggests it is important to examine both a person's identification with their own indigenous cultural practices (acculturation factor 1), and the degree to which an individual has adopted what has historically been considered mainstream American cultural practices (acculturation factor 2; Ferraro, et al., 2002; Fletcher-Janzen, Strickland, & Reynolds, 2000). It is possible that the degree to which an individual is either bicultural or marginalized (based on this two factor model of acculturation) impacts the degree to which an individual develops FD/I or IC self-construal approaches to perceptual/attentional processes or belief systems, respectively. As such, the degree of acculturation along these two factors might also impact the ability to learn different category structures that emphasize the attentional focus on an individual stimulus dimension (such as in Experiment 1), the explicit integration of two stimulus dimensions (such as in Experiment 2), or the implicit integration of two stimulus dimensions (such as in Experiment 3). The proposed dissertation, therefore, also examined the extent to which levels of acculturation influence perceptual and belief-based cultural influences on category learning.

CULTURE AND PERCEPTUAL CATEGORIZATION

As previously mentioned, categorization is one of the most basic cognitive processes upon which many higher-order cognitive processes are built. A more prominent role of culture in such a fundamental aspect of human cognition, therefore, could potentially have extensive repercussions. It is not surprising to find, then, that one of the domains of cognition in which cultural differences have often been observed is in the learning of categories. The rationale behind previous cultural studies of categorization follows quite simply from the fact that people learn to categorize "things" and it is generally accepted that the "things" people are exposed to and interact with in their daily lives vary from culture to culture. The majority of experiments that have attempted to study the interface of culture and categorization thus far, however, have focused almost exclusively on stimuli that have a large semantic component (Unsworth, et al., 2005; also see Medin & Atran, 2004 for a review). These studies include the categorization of living things, tools, the strength of arguments, and pictures of objects encountered in everyday life. Past studies have suggested that an individual's level of expertise or exposure to stimuli is what drives the differences often observed across cultures (Medin, 1987; Atran, 1990). However, as has been observed in other areas of cognition, another important factor hypothesized to impact differences in how cultures categorize is the degree to which different cultures allocate attention to either details or holistic aspects of information (i.e., the degree to which an individual is FD/I), which also is based on levels of experience or expertise.

This possibility was perhaps first addressed in research by Luria (Luria, 1931, 1976), in which individuals from rural areas categorized colors, geometrical shapes, and groups of objects, differently than individuals from more industrialized geographical regions (Luria, 1931, 1976). Specifically, Luria found that more rural, illiterate participants engaged in concrete-holistic thinking and focused more on the functional interrelationships between objects, as compared to the more urban participants, who tended to use more analytic and categorical rules to categorize these same stimuli. For example, participants were presented with a hammer, log, saw, and axe and asked to choose the three items that belonged to the same category. Whereas more urban and literate participants chose the hammer, saw, and axe as being representative of the category of "tools," Luria's more rural participants insisted that all the objects went together because a person actually uses all four items together to build a chair. Another experiment had participants extract common shapes from a stimulus array (i.e. shapes with straight lines from those with curved lines, triangles from circles, etc.), and once again, rural participants grouped them on their similarity to real objects not on abstract, categorical relationships. More urban participants, by contrast, employed a rule-based type of categorization strategy. These findings suggested the possibility that differences in cultural experiences (e.g. IC self-construal) could lead to differences in categorization and might be associated with different levels of "field dependency" or the nature in which attention is allocated to determine which characteristics of a stimulus are "relevant."

If one is to study cultural differences in categorization, therefore, it is important to take into account the likelihood of multiple category learning systems (see Ashby & Maddox, 2005; Smith, Patalano, Jonides, 1998; Maddox & Ashby, 2004). Different theories have been proposed to account for the different processes that underlie category learning. These proposed processes include exemplar/similarity, prototype, probabilistic, information-integration, and rule-based (Ashby & Maddox, 2005). Exemplar theories of category learning suggest that when a person encounters an unfamiliar stimulus its similarity is computed to a representation of each and every other previously seen exemplar from potentially related categories and it is assigned to a particular category based on the greatest sum of similarities between exemplars (Medin & Schaffer, 1978). In contrast, prototype theories assume that when a person encounters an unfamiliar stimulus, it is assigned to a particular category with the most similar prototype (Posner & Keele, 1968; Smith & Minda, 1998). Whereas most category learning theories are deterministic in that ultimately each stimulus is unambiguously a member of one category, in probabilistic theories some of the stimuli are probabilistically associated with the other category options, and learning takes place on an implicit level (Knowlton, et al., 1994).

Information-integration category rules are also learned on an implicit level because they require that participants use categorization rules that are not highly salient or verbalizable to integrate two or more stimulus components or dimensions, but unlike probabilistic rules, there is minimal overlap between categories. Rule-based theories, by contrast, are those where the rule defining the categories to be learned is highly salient and verbalizable and can often be based on a *single* stimulus dimension (Ashby, Alfonso-Reese, Turken, & Waldron, 1998). Considerable progress has been made in identifying the different neural and cognitive systems that subserve these different forms of category learning (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Elliott, Rees, & Dolan, 1999; Filoteo, Maddox, & Davis, 2001; Reber, Stark, & Squire, 1998).

The identification of these different categorization processes and systems might also have an important implication for understanding cultural differences in category learning. For example, Norenzayan, Smith, Kim, and Nisbett (2002) examined whether Asians and Caucasians differed in their use of rule-based (i.e. was a particular feature present or not) versus exemplar (i.e. comparing the target item with each individual item stored in memory) approaches when learning categories. Their first study was based on a variation of a well-developed paradigm in categorization research (Allen & Brooks, 1991; Regehr & Brooks, 1993; Smith, et al., 1998) in which participants viewed imaginary animals (e.g. "aliens") on a computer screen and were told that the aliens belonged to different categories. Participants were placed in a rule condition, which explicitly taught them a complex rule dictating how to classify animals, and in an exemplar-memory condition where participants were simply asked to observe the animals and make a guess as to which category they might belong. Feedback was given after each trial in both conditions. Results showed that Caucasians consistently applied rule-based strategies in both the rule and exemplar conditions of the task, whereas Asians adopted an exemplar strategy in both conditions.

A second experiment by Norenzayan and colleagues (2002) in the same study examined the hypothesis that Caucasians would categorize a target object as a member of one of two groups consisting of four similar objects solely on the basis of a *unidimensional rule* (i.e. selectively attending to a single salient stimulus dimension) rather than overall similarity to other objects in the groups, whereas the opposite was predicted for Asians. Participants were again placed in one of two conditions, a classification condition where they were asked to decide which group the target object belonged to, and a similarity judgment condition where participants were to judge which group the target object was most similar to. The same pattern of results was found, with Caucasians assigning group membership based on a unidimensional rule while Asians used an exemplar approach in both conditions.

Both these experiments together suggest that Asians and Caucasians perform differently on category learning tasks. Specifically, Caucasians selectively attend to a single stimulus dimension, which appears most salient to them, and use more rule-based categorization strategies, whereas Asians use more of an exemplar strategy by incorporating more stimulus dimensions from the field as a whole. Although the authors contend that the Asian group adopted more of an "intuitive" or implicit exemplar strategy rather than an explicit unidimensional rule-based strategy, it is difficult to rule out the possibility that the Asian group was not simply adopting a more complex or multidimensional strategy, which is still explicit, rule-based, and hypothesis-driven (i.e. conjunctive rule-based, see below). These results, therefore, suggest that the attentional differences observed on other cognitive tasks also appear to impact how different ethnic groups learn categories. Given the evidence that there are multiple systems of category learning, the above studies also make it reasonable to assume that cultural differences also emerge on different types of category learning tasks. In other words, an individual from a particular culture may show difficulty in one type of categorization task but not others, while a member of a different culture may show the opposite effect. In addition, the neurophysiological studies mentioned earlier suggest that even if no difference is observed in terms of performance accuracy between groups, the *underlying process, which often goes unobserved,* may be qualitatively different based on an individual's level of FD/I or IC.

A more formal experimental paradigm which has consistently demonstrated the dissociation of multiple category learning systems at the behavioral and physiological level and on which cultural differences may likely arise is that of the distinction between *rule-based* (R-B) and *information-integration* (I-I) category learning systems. As mentioned briefly above, R-B tasks are those where the rule defining the categories is highly salient and verbalizable (i.e. participants find it easy to describe the rule), and can often be based on a *single* stimulus feature (e.g., the stimulus goes into one category if it is a certain color and another category if it is a different color; Ashby, Alfonso-Reese, Turken, & Waldron, 1998). These tasks are often referred to as unidimensional rule-based tasks (UNI-RB). Conjunctive rule-based tasks (CON-RB), on the other hand, require the sequential integration of *two* stimulus dimensions, where optimal responding requires participants to first make a decision about one stimulus dimension and then combine that with a decision on the other dimension (e.g., respond A if the stimulus is small on dimension *x* and small on dimension *y*, otherwise respond B). It is important to point out that both UNI-RB and CON-RB tasks are explicit in nature, in that the participant is required to learn an explicit, verbalizable rule. In contrast, optimal performance on I-I tasks requires that participants use categorization rules that are not highly salient or verbalizable (i.e. participants are unable to describe the rule) and accuracy is maximized only if information from two or more stimulus components (or dimensions) is integrated at some implicit level (Ashby & Gott, 1988). I-I category structures often result because the stimulus features to be combined are in different physical units, making it difficult for participants to verbalize a combination of such features (Ashby et al., 1998; Ashby & Ell, 2001). As such, these rules are implicit in nature. For example, the stimuli to be used in the present experiments consist of Gabor patches (see *Figure 1* below) which can simultaneously vary in the spatial frequency and orientation of the gratings across trials, therefore making it difficult to explicitly formulate a decision rule.

Previous studies have provided considerable support for the distinction between these two types of category learning processes, and have largely been influenced by the Competition between Verbal and Implicit Systems (COVIS) model of category learning (Ashby, et al., 1998). This model assumes that learning R-B tasks requires an explicit, hypothesis testing system that employs executive attention and working memory, which are mediated mostly by the anterior cingulate, prefrontal cortex, and head of the caudate. The learning of I-I tasks, on the other hand, requires an implicit procedural-learning-based system that is mediated mostly by the tail of the caudate and does not involve cortical areas. Experimental evidence supporting the COVIS model includes the fact that the I-I learning but not R-B learning is negatively impacted by manipulations of the nature and timing of feedback (Ashby, Maddox, & Bohil, 2002; Maddox, Ashby, & Bohil, 2003; Maddox, Ashby, Ing, & Pickering, 2004) and by changes in the location of response keys (Ashby, Ell, & Waldron, 2003), whereas R-B learning but not I-I learning is negatively impacted by increasing demands on executive attention and working memory (Waldron & Ashby, 2001; Maddox, Filoteo, Hejl, & Ing, 2004). To date, however, no studies of culture-related influences such as FD/I or IC or even simple ethnic comparisons on category learning have formally distinguished between these two category learning systems.

The purpose of the present study is to examine cross-cultural differences in category learning using the perceptual categorization task (see below for details). The proposed project will test the hypothesis that (1) self-identified ethnic groups differ in learning these types of categorization tasks, and (2) that these observed self-identified ethnic group differences can be further explained by cultural differences in FD/I and IC (as measured by the GEFT and the Self Construal-Scale, S-CS). As previously described, the optimal learning of UNI-RB categories requires an individual to attend selectively to a relevant dimension while ignoring an irrelevant dimension Thus, it is predicted that if Caucasian participants truly attend selectively to the most salient stimulus properties, then they should demonstrate a greater ability in learning UNI-RB categories as compared to Asians and Latinos. In contrast, if Asians and Latinos are truly more field-dependent and collectivist, and therefore make more use of contextual information, it is predicted that they will perform better than Caucasians in the CON-RB condition, where optimal responding requires an explicit integration of the stimulus dimensions. If this predicted double-dissociation does not occur between Caucasians and the two more collectivist cultures on UNI-RB and CON-RB tasks, then it becomes especially important to examine the performance of the groups in the I-I condition. Although there is little in the literature specifically examining Latinos compared to the rather large literature on Asians, previous research does suggest that Latinos perform similarly to other collectivist cultures, such as Asians. The comparison between the Asian and Latino groups on the CON-RB and I-I conditions, therefore, is particularly important since it is hypothesized that collectivist groups incorporate multiple dimensions of stimuli during category learning, but one group may do so on a more implicit level relative to the other. For example, Norenzayan and colleagues (Norenzayan, et al., 2002) showed that Asians make intuitive categorizations based on similarity, but are not necessarily able to explain how they go about it, which suggests that this group uses an implicit approach when learning categories. If this is the case, then not demonstrating an advantage within the CON-RB condition, which requires an *explicit* conjunction between stimulus dimensions is to be expected, and a disproportionate advantage within the I-I condition, which emphasizes an *implicit* integration of multiple stimulus dimensions, may be more likely.

In addition to examining the effect of self-identified ethnicity on the learning of three different categorization rules using the PCT, this study also tried to tease apart whether any observed ethnic differences can be better explained by differences at the level of perceptual styles or cultural beliefs. Perceptual field-dependency was directly measured using Witkin's GEFT (1971; 2002). The Self-Construal Scale (S-CS: Singelis, et al., 1994) was also administered which measures various dimensions of cultural beliefs on which distinct cultural groups are known to differ (i.e. the relationship of the self to others and the environment: Hofestede, 1991; Hui & Yee, 1994; Matsumoto, et al., 1997; Schwartz, 1994; Triandis, 1996; Trompenaars, 1993). To assess likely differences in acculturation within ethnic groups, which may influence levels of FD/I or IC self-construal, the Abbreviated Multidimensional Acculturation Scale (AMAS) was also administered which was specifically designed to identify where a particular individual lies along a two-factor acculturation continuum (Berry, 2004; Chung, et al., 2004; Zea, et al., 2003). The two-factor model of acculturation, on which this scale is based, directly addresses not only the more common factor of whether categorization strategies used by minority individuals become more Caucasian-like (i.e. unidimensional acculturation) as they adopt more Caucasian cultural practices (i.e. individualistic self-construals and greater field-independence), but also examines the second factor of simultaneously retaining the cultural practices of their own indigenous culture (i.e. multidimensional acculturation). This second dimension is particularly important in light of research showing that even second-generation and later Asian and Latino individuals who are well acculturated to American culture simultaneously maintain their indigenous cultural practices (Ferraro, et al., 2002; Fletcher-Janzen, Strickland, & Reynolds, 2000).

<u>THE PERCEPTUAL CATEGORIZATION TASK</u>

The majority of the studies to date examining the differences between R-B and I-I category learning systems have used the perceptual categorization task (PCT; Ashby & Gott, 1988). Three separate experiments were conducted in this dissertation examining cultural differences in UNI-RB category learning, CON-RB category learning, and I-I category learning using the PCT. In each experiment, participants were shown simple perceptual stimuli consisting of a Gabor patch (see *Figure 1*) that varied from trial-to-trial in spatial frequency and orientation.

The PCT has several useful properties. First, because the experimenter defines the category distributions, a wide range of qualitatively different categorization rules can be specified precisely. Figures 2, 3, and 4 depict the distribution of stimuli that were used in the three experimental conditions. Because the categories are normally distributed, a unique experimenter-defined (optimal) categorization rule can be derived (i.e., the rule that maximizes long-run accuracy; e.g., Ashby, 1992b; Maddox & Ashby, 1993). The form of the rule is determined by the relationship between the two category distributions and thus, depends on the relationship between the two stimulus attributes. Because the stimuli are two-dimensional, they can each be denoted by a point in a two-dimensional space. In Figures 2, 3, and 4, each stimulus is represented by a single point in the two dimensional space. Black boxes represent individual Category A stimuli and open circles represent individual Category B stimuli. The x-axis represents the stimulus value on the spatial frequency dimension, and the y-axis represents the stimulus value on the orientation dimension. The optimal rule in each of these three conditions is depicted in Figures 2, 3, and 4 by either a solid line (for the UNI-RB and the I-I conditions) or two solid lines (for the conjunctive condition). Optimal responding in each of these conditions required the use of the optimal rule. For example, in the UNI-RB condition (Figure 2), optimal responding required that the participant learn to set a criterion on the spatial frequency dimension, ignore the orientation dimension, and categorize the stimuli as belonging to Category A if the frequencies were small, and Category B if the frequencies were large.

A second advantage of using the PCT is that the experimenter has a great deal of control over potentially important aspects of the categories. For example, the experimenter is able to control the maximum accuracy rate, the structure of the categories (e.g., the distributions), the number of categories, the number of stimuli sampled from each category, and the shape of the experimenter-defined categorization rule (e.g., linear or nonlinear), to name a few. Thus, any observed cultural differences in the three conditions could not be attributed to differences in the categorization task used. This has not been the case in previous studies examining the impact of culture on category learning. For example, the R-B and exemplar tasks in the Norenzayan study (2002) differed in the nature of the instructions given to participants, previous exposure to defining characteristics of category membership in the training phase, and the fact that some stimuli were more familiar than others (e.g. flowers vs. aliens) thus making it difficult to draw stronger conclusions regarding the nature of the observed cultural differences in this study.

A third advantage of using the PCT to study cultural differences in category learning is that this task can make use of very basic perceptual stimuli. As stated above, the proposed experiments used simple Gabor patches that varied in spatial frequency and orientation. The semantically laden nature of the stimuli in previous studies of culture in category learning places an undue emphasis on the stimuli themselves and how they activate different semantic representations and/or associations already within the individual. Thus, one could argue that these previous studies examined semantic aspects of categorization rather than the processes involved in category learning *per se*. The use of stimuli with less semantic representations (i.e. Gabor patches) minimizes the potential impact of culture-related semantic differences on category learning.

A final advantage of using the PCT is that researchers have developed quantitative models to examine performance in this task (for details see Ashby, 1992a; Filoteo & Maddox, 1999; Filoteo et al., 2001; Maddox & Ashby, 1993; Maddox & Filoteo, 2001; Maddox et al, 1996, 1998). Although quantitative modeling provides an excellent method to examine category learning in other contexts (e.g., examining the neurobiological bases of category learning; Filoteo, Maddox, & Davis, 2001; Maddox & Filoteo, 2001), to our knowledge it has not been applied to the study of culture and categorization. Thus, these models were applied in the proposed studies to help determine whether the participant was in fact using an optimal approach within a particular condition, something that cannot be determined by strictly examining accuracy rate alone. For example, it could be that the culture-related differences observed in previous studies come about because one group was better than another group at using a specific strategy, or because the two groups used entirely different strategies (e.g. Grön, et al., 2003) and the one group who performed better (in terms of accuracy) did so because that particular strategy was associated with better performance on that task (e.g. Goode, et al., 2002). The model-based approach that has been used with data provided by the PCT alleviates this problem because it allows one to determine what strategy a particular participant used and then (1) determine if groups differed in what strategy was used, and (2) determine if accuracy differences emerge between groups who used the same strategy. To date, this approach has not been taken in the study of cultural effects on category learning.

RESEARCH DESIGN AND METHODS

Participants

Participants in this study consisted of undergraduate students recruited from the University of California, San Diego through their psychology classes. All participants self-selected into the study on the UCSD Experimetrix website based on the inclusion/exclusion criteria described below. Participants were each given a short screen prior to their being accepted into the study and were excluded if they had a positive history for major neurological or psychiatric diagnoses, a significant substance use history, or a history of learning disability. Participants who met the inclusion criteria signed up online for available time slots, were consented, and then were randomly assigned to one of three separate categorization rule-learning conditions [i.e. UNI-RB (Experiment 1), CON-RB (Experiment 2), and I-I (Experiment 3)] such that a target number of 25 participants from each ethnic group was expected in each of the three conditions for a total estimated sample size of 225 participants. Examination of previous studies both looking at cultural differences in cognition and category learning suggested that this sample size was adequate for obtaining a reasonable effect size and power. Ethnicity was operationally defined by self-identification directly by participants in both an open-ended and forced-choice format. A total of 317 participants were recruited in this way. Of those 317, a total of seven participants were excluded from analysis because of lost data due to computer failure. Of the remaining 310 participants who self-identified as Asian (n=184), Caucasian (n=77), or Latino (n=49), only students who self-identified as Chinese within the Asian group were selected for inclusion in the analysis in order to test the proposed hypotheses. Previous studies comparing Caucasians and "Asians" were comprised of mostly Chinese participants, and so the Chinese group was selected for this reason and also because it represented a more homogenous group and was the largest of the Asian subgroups.

To minimize the amount of statistical noise in the sample, only participants who performed above chance (i.e. 57%) on the final block of trials for each experiment were included in the study. This approach also enabled a more accurate understanding of the model-based analyses (see below for details) because of the difficulty in interpreting the outcome of model applications that are applied to below-chance responding (see Filoteo & Maddox, 2004). Table 1 shows the number of participants in each group who performed above and below chance in each of the three experiments. Separate 3 (group: Chinese, Caucasian, Latino) X 2 (chance: above vs. below) χ^2 analyses were conducted within each of the three conditions to examine whether there were differences between the groups in the number of participants who performed above or below chance. None of these tests were significant at the $p<0.05$ level (UNI-RB: $\chi^2(2,n=64)=3.37$, $p=0.19$; CON-RB: $\chi^2(2,n=63)=0.79$, $p=0.96$; I-I: $\chi^2(2,n=58)=4.38$, $p=0.11$). All participants who performed below chance were excluded from all further analyses.

Table 1. Number of participants who performed above or below chance on Block 7 in Experiment 3

	Above Chance Performance			**Below Chance Performance**		
	Chinese	**Caucasian**	**Latino**	**Chinese**	**Caucasian**	**Latino**
Experiment 1	19	25	16	3	1	0
Experiment 2	20	24	16	1	1	1
Experiment 3	11	23	15	5	3	1

The final number of participants in each of the three ethnic groups and the demographics of age, gender, nativity, and years of education for all participants are summarized in Table 2 for each of the three experiments respectively. Given the between-subjects design of the study, ANOVA and Chi Square tests were used to assess the equivalence of the groups across the three experiments for age, gender, nativity, and years of education. A Tukey correction was used for all post hoc pairwise comparisons.

A 3 X 2 (group x condition) between-subjects factorial ANOVA was first conducted on age. There was a main effect for group, $F(2,160) = 3.14$, $p<0.05$. Posthoc comparisons revealed that Chinese were significantly younger than Caucasians but not Latinos, and the Caucasians did not differ from the Latinos. Neither the main effect for condition, $F(2,160) = 1.26$, $p=0.29$, nor the interaction of group and condition, $F(4,160) = 1.00$, $p=0.41$, were significant. This suggested that while the Chinese group was younger than the Caucasian group overall, this difference was constant across the three experiments.

A second 3 X 2 (group x condition) between-subjects factorial ANOVA was next conducted on number of years in college. The main effect of group was nonsignificant, $F(2,160) = 2.13$, $p = 0.12$, as were the main effect of condition, $F(2,160) = 1.83$, $p = 0.16$, and the group by condition interaction, $F(4,160) = 0.482$, $p = 0.75$. This suggested that the groups were equivalent across all conditions in terms of the years of education they had completed.

Chi Square analyses were conducted first within each ethnic group to test if the gender or nativity (e.g. whether participants were domestic or foreign born) frequency was different in each experiment, and then within each experiment to test if the gender and nativity frequency was different for each group. All Chi Square tests involving gender were nonsignificant at the $p < 0.05$ level indicating that although 68.6% of the entire sample was female, there was not a systematic difference in proportion either across experiments or groups. All tests involving nativity were nonsignificant at the 0.05 level, except for the 3 X 2 (group X nativity) Chi Square within Experiment 3, $\chi^2(2, n=49) = 11.03$, $p < 0.05$. Of the 10.2% of the sample in Experiment 3 who were foreign born, 80% were Chinese, 20% were Latino, and none were Caucasian. This was the only experiment in which a disproportionate number of Chinese were foreign-born relative to the other two groups.

Table 2. Sample demographics showing number of participants, means and standard deviations for age and years in college, and percentage of foreign born and female participants

		Age	**Years in College**	**Nativity (% foreign)**	**Gender (% female)**
Experiment 1	**Chinese (n=19)**	19.6 (1.3)	2.0 (1.3)	21.1	84.2
	Caucasian (n=25)	21.4 (3.0)	2.6 (1.2)	4.0	60.0
	Latino (n=16)	20.9 (2.4)	2.6 (1.6)	12.5	81.3
Experiment 2	**Chinese (n=20)**	19.8 (1.2)	2.0 (1.0)	15.0	60.0
	Caucasian (n=24)	21.2 (3.3)	2.5 (1.5)	4.2	70.8
	Latino (n=16)	20.6 (1.7)	3.0 (1.8)	12.5	62.5
Experiment 3	**Chinese (n=11)**	20.1 (1.5)	2.0 (1.1)	36.4	72.7
	Caucasian (n=23)	20.0 (1.1)	2.0 (1.1)	0	56.5
	Latino (n=15)	20.0 (1.2)	2.1 (1.3)	6.7	80.0

PCT

As previously mentioned, the PCT first developed by Ashby and Gott (1988) was used in each of three experiments. Sampling randomly from two bivariate normal distributions, 40 Category A and 40 Category B stimuli were generated. Each category distribution was specified by a mean and a variance on each dimension, and by a covariance between dimensions. Figures 2, 3, and 4 depict the relationship between the stimulus attributes in the three experiments along with the solid line(s) that represent the optimal rules.

Stimuli

The stimuli were computer generated and displayed on a 21" monitor with 1360 X 1024 resolution. In each of the three experiments, the stimuli consisted of a single Gabor patch (see Figure 1). Each of the stimuli varied in orientation and spatial frequency. Each Gabor patch was generated using MATLAB routines from Brainard's (1997) Psychophysics Toolbox. Each random sample (x_f, x_o) was then be converted to a stimulus by deriving the frequency, $f=.0025 + (x_f/5000)$ cycles per pixel, and orientation, $o = x_o(\pi/500) \times 180/\pi$ degrees. These scaling factors attempted to equate the salience of frequency and orientation. Each Gabor patch was 7 cm in diameter, which subtended a visual angle of about 8.8 degrees from a viewing distance of 45 cm.

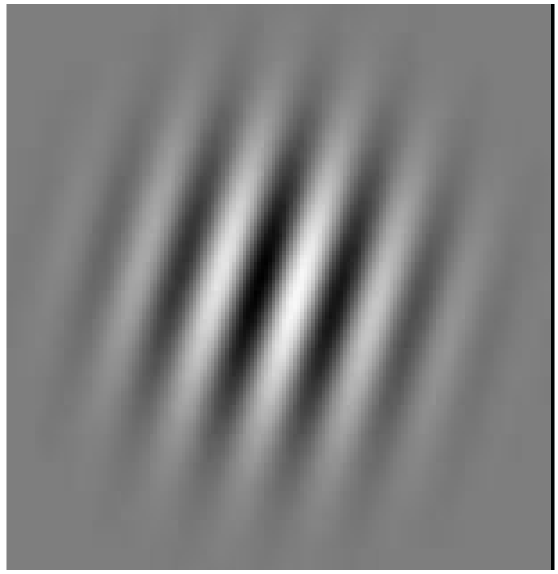

Figure 1. Sample stimuli for all experiments

General PCT Methods

Five hundred sixty trials were presented and broken down into 7 blocks of 80 trials apiece for each of the three experiments (UNI-RB, CON-RB, and I-I). At the start of each experiment, the participant was told that they would be involved in a study that examines their ability to categorize simple stimuli. Participants were told that a series of stimuli would be presented and that they would be asked to categorize each as a member of either Category A or Category B. They were also told that at the beginning of the experiment they might feel as though they were guessing, but as the experiment progressed, their accuracy would likely increase. Participants indicated their categorization responses by pressing one key for Category A stimuli and another key for Category B stimuli. For each trial, the stimulus was presented until the participant's categorization response was made, then immediately following their response, they were given feedback for 1 second that consisted of the word "wrong" if their response was incorrect or "correct" if their response was correct. Participants completed the GEFT, S-CS, and AMAS in a counterbalanced fashion either before or after completing one of the 3 experiments described below, and no ordering effects were observed. These paper and pencil assessments took approximately 40 minutes to complete and the PCT another 45 minutes for a total of approximately 90 minutes of participation time. Consistent with IRB approved guidelines, participants were then debriefed and given the opportunity to ask questions regarding the experiment's purpose.

Experiment 1

In Experiment 1 (UNI-RB task), participants were shown single stimuli that consisted of a Gabor patch (see Figure 1) that varied trial-by-trial in the orientation of the gratings and the spatial frequency of the gratings, and were asked to categorize it as a member of Category A or Category B. Correct responding required that the participant set an appropriate criterion on the spatial frequency dimension and ignore the orientation dimension (see Figure 2). Importantly, although the orientation of the stimuli did not provide any information as to the correct category of the stimuli, this dimension also varied from trial-to-trial, thus good performance on this task required participants to selectively attend only to the spatial frequency dimension.

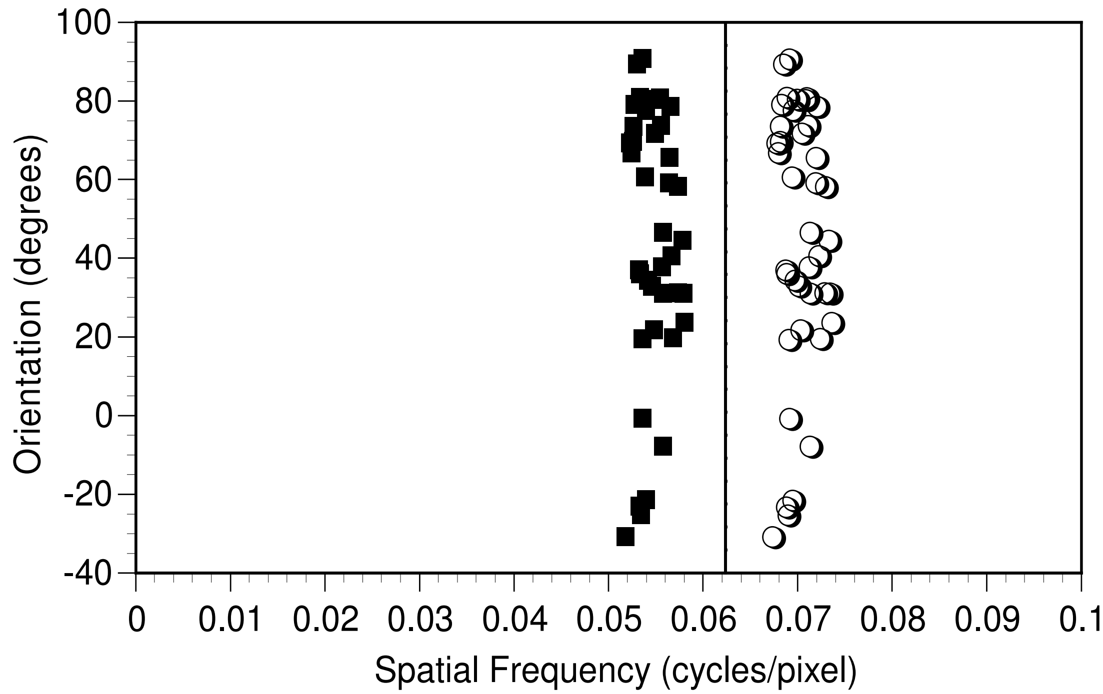

Figure 2. Stimulus distributions for the Unidimensional Rule-based experimental condition. Filled squares represent stimuli from Category A and open circles represent stimuli from Category B. The line separating the 2 categories represents the optimal rule for this condition.

Experiment 2

In Experiment 2 (CON-RB task), participants were administered a version of the PCT in which correct categorization required participants to base their response on a post-decisional combination of the features. Specifically, for optimal responding, the participant was required to use one of two approaches to solve the task. First, they could set a criterion on the orientation of the stimulus and if it was more vertical *and* had a larger spatial frequency, the participant would respond A, if not, they would respond B (see Figure 3). Alternatively, the participant could first set a criterion on spatial frequency and if it was large *and* the orientation was more vertical the participant would respond A, if not, they would respond B. Note that either approach represents a post-decisional combination of the two features and both rules are highly verbalizable, and as such, this task is considered to be rule-based.

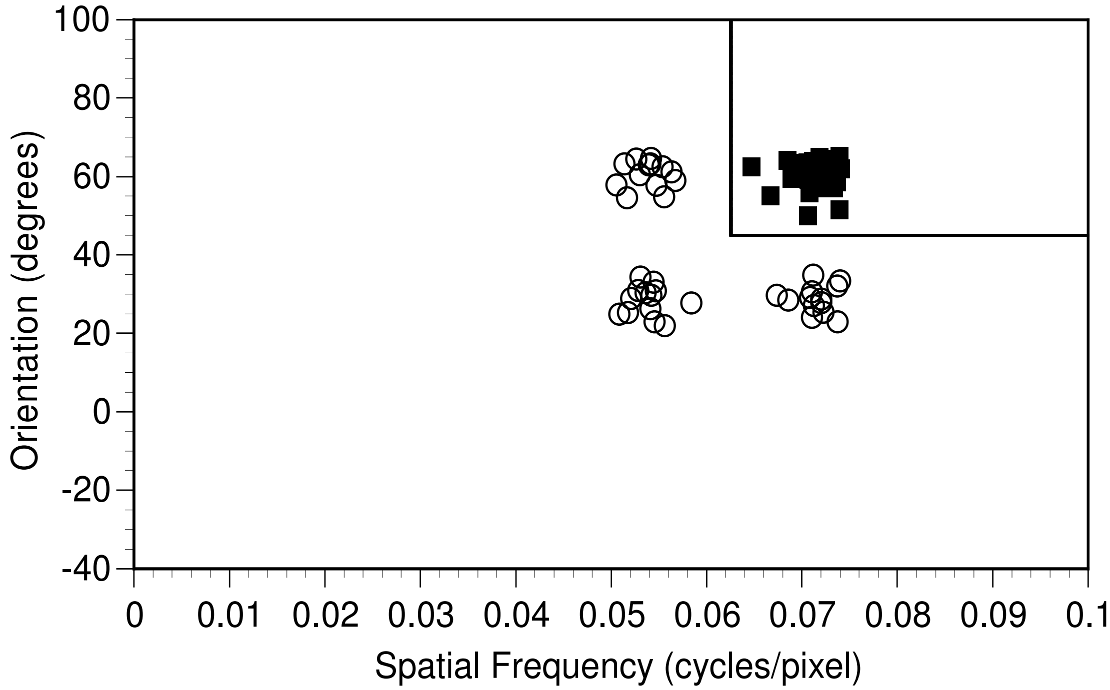

Figure 3. Stimulus distributions for the Conjunctive Rule-based experimental condition. Filled squares represent stimuli from Category A and open circles represent stimuli from Category B. The lines separating the 2 categories represent the optimal rule for this condition.

Experiment 3

Finally, in Experiment 3 (I-I condition), participants were administered a version of the PCT in which correct responding required a pre-decisional, linear integration of the spatial frequency and orientation dimensions. Specifically, optimal responding required participants to simultaneously integrate both the spatial frequency and orientation of the stimuli when making their categorization (see Figure 4).

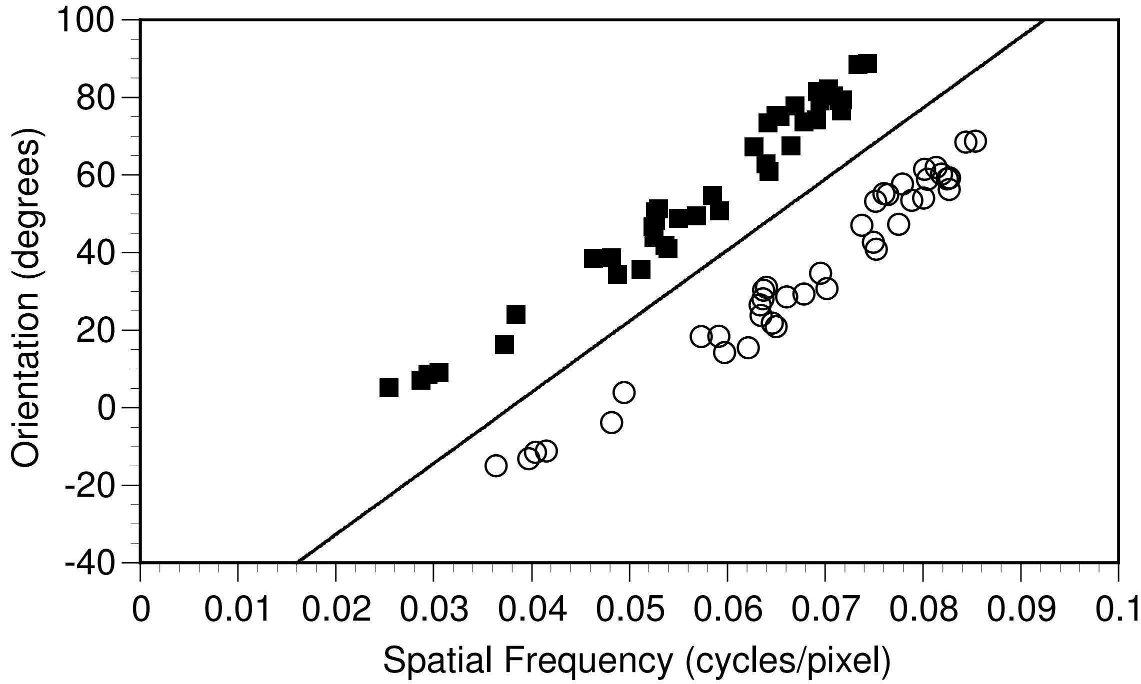

Figure 4. Stimulus distributions for the Information-Integration experimental condition. Filled squares represent stimuli from Category A and open circles represent stimuli from Category B. The line separating the 2 categories represent the optimal rule for this condition.

Model-Based Approach

An important advantage of using the PCT is that a number of formal mathematical models have been developed to analyze data obtained in this task (Ashby, 1992; Ashby & Maddox, 1993; Maddox & Ashby, 1993). These models have proven invaluable when attempting to determine the type of processes actually used by a participant when learning categories. Therefore, an important question that was also addressed is whether the self-identified ethnic groups differ in their categorization strategies. It may be, for example, that the groups do not differ within each experiment in terms of overall accuracy, but that they do differ in the categorization strategies they employ. In order to address this issue, quantitative models were applied to each participant's data in the three experiments to further delineate the possible underlying processes that drive UNI-RB, CON-RB, and I-I categorization strategies.

The details of the models have been described elsewhere (for details see Ashby, 1992; Maddox & Ashby, 1993; Maddox et al., 1996), but briefly they are derived from general recognition theory (GRT; Ashby & Townsend, 1986), which is a multivariate generalization of signal detection theory (e.g., Green & Swets, 1966). Each of the models was fit separately to the data for each block of trials within each experiment. The model parameters were estimated using maximum likelihood (Ashby, 1992; Wickens, 1982) and the goodness of fit index, -lnL (negative log likelihood). The smaller the value of this fit index, the better the model fits the data. However, in order to directly compare the different models and identify the one that provided the most parsimonious accounting of the data, the following goodness-of-fit statistic was used: [$AIC = 2r - 2lnL$], where r is the number of free parameters and L is the likelihood of the model given the data (Akaike, 1974; Takane & Shibayama, 1992). The *AIC* statistic penalizes a model for each free parameter by increasing the AIC value by a factor of two. In this way, the smaller the AIC, the closer a model is to the "true model," regardless of the number of free parameters. Thus, to find the best model among a given set of competitors, one simply computes an AIC value for each model, and chooses the model associated with the smallest AIC value. Two basic classes of models were examined in each of the three experiments, R-B and I-I models. The R-B models consist of UNI-RB and CON-RB models while the I-I models consisted of optimal and suboptimal I-I models (see below for details).

In Experiment 1, within which participants learned a UNI-RB version of the PCT, selective attention to the relevant dimension was required. The first model assumes that the participant adopts the optimal rule (depicted as the solid line separating the 2 categories in Figure 2). In the *optimal unidimensional model*, the participant ignores the irrelevant orientation dimension and sets a criterion of 299.5 units (or .0624 in cycles/pixel units) on the spatial frequency dimension that is used to partition Category A and Category B responses. This model has one free parameter that denotes the trial-by-trial variability in the perceptual and criterial noise. The second model, the *sub-optimal unidimensional model*, assumes that the participant also attends selectively to the relevant spatial frequency dimension, but that the participant does not use the optimal criterion of 299.5 units, but rather estimates the criterion based on the participant's responses. This model has two free parameters, one for the trial-by-trial variability in perceptual and criterial noise, and one for the estimate of the participant's criterion used to separate the two categories. The third model, the *sub-optimal* I-I *model* (aka, general linear classifier, or GLC), assumes that the participant's decision on each trial is based on information from both dimensions (perceived spatial frequency and orientation), although the weighting given to the two dimensions may be unequal. The model also assumes that the integration is linear, and estimates three parameters from the data, including the trial-by-trial variability in perceptual and criterial noise, the decision bound slope, and the decision bound intercept. The optimal model for each condition will depend on stimulus distributions within that condition. For example, in the UNI-RB condition, since only one stimulus dimension is relevant, I-I is sub-optimal because the decision bound is not orthogonal to the relevant dimension.

In Experiment 2, which uses the CON-RB version of the PCT, 5 models were applied to participants' data. The optimal model assumes that participants make one decision about the spatial frequency of the lines (i.e. narrow or wide), a separate decision about the orientation of the lines (i.e. shallow or steep), and then integrate this information post-decisionally. The *optimal CON-RB model*, however, can take two forms that differ only in how information is integrated to generate a categorization response. The conjunctive(1) model assumes that the participant uses the following rule: Respond A if the spatial frequency is narrow and orientation is steep, otherwise respond B. The conjunctive(2) model assumes that the participant uses the following rule: Respond B if the spatial frequency is wide and the orientation is shallow, otherwise respond A. The conjunctive(1) and conjunctive(2) models contain 3 parameters (length criterion, orientation criterion, and noise variance). There are two suboptimal UNI-RB models in Experiment 2, the *suboptimal spatial frequency model*, which assumes the participant attends selectively to the spatial frequency dimension and then makes an explicit decision about the stimulus on this dimension, and the *suboptimal orientation model*, which assumes that the participant sets a criterion on the orientation dimension and responds based on this single dimension. Finally, there is also the *suboptimal I-I model*, as described in Experiment 1.

In Experiment 3, the linear I-I categorization task, 5 different models were applied to the data. The *optimal I-I model* assumes that the participant uses the optimal decision bound (see Figure 4) and contains a single noise parameter. The GLC (above) assumes that the participant uses a suboptimal linear decision bound and contains three parameters (the slope and intercept of the decision bound and the noise variance). The minimum distance classifier (MDC) assumes that the participant constructs two decision bounds to separate the A and B categories such that there are four quadrants in the spatial frequency-orientation space (similar to the CON-RB model). Finally, two *suboptimal unidimensional models* will be applied, one assumes the participant sets a criterion on the spatial frequency dimension and the other one assumes a criterion is set on the orientation dimension.

The basic approach to analysis consisted of first conducting a general comparison among the ethnic groups (Asian, Caucasian, and Latino) in terms of whether there were differences in the application of R-B versus I-I approaches. In other words, each participant was classified as a R-B or I-I user based on which model provided the best fit of the data (based on the methods described above) and then frequency comparisons were carried out among the cultural groups using a 2 (group: Caucasians vs. Chinese) X 2 (best fitting model: R-B vs. I-I) χ^2 analysis. It was hypothesize that if Caucasians (supposedly field-independent individualists) attend more selectively to a single stimulus dimension, which they find most salient, then they would show a preference for UNI-RB strategies. If Chinese participants (supposedly field-dependent collectivists), on the other hand, are more prone to incorporating multiple stimulus dimensions due to attention to the whole field, they would likely adopt more I-I strategies.

Measurement of Cognitive Style and Acculturation

All research participants completed three paper and pencil assessment measures: *GEFT* (Witkin, 2002), *S-CS* (Singelis, 1994), and *AMAS (*Zea, et al., 2003; Chung et al., 2004). Most previous studies provide evidence that Asian and Caucasian participants differ significantly on the GEFT, and S-CS. Research involving Latinos, however, has been more limited and not as replicable. More importantly, the bulk of the experimental research examining the underlying constructs of these measures (i.e. field dependence and self-construal), which has demonstrated cultural differences, primarily involved the comparison of Asians with Caucasians. In order to preserve statistical power and test the primary hypothesis that these two groups are different, primary analyses were conducted first on these two groups (Caucasian vs. Chinese) with secondary analyses then examining how Latino participants, the less well understood group, performed.

The GEFT is a timed 25-item paper and pencil test in which a participant's task on each trial is to trace the outline of a predetermined figure within a more complex figure which has been organized so as to obscure or embed the sought-after simple figure within this more complex figure. Participants are given one block of seven practice items followed by two blocks of nine test items each. Both number of correct items completed and time to completion are reported as outcome measures. The GEFT is perhaps one of the most widely studied measures of cognitive style and has received substantive empirical support for its strong psychometric properties (Thompson & Melacon, 1987).

The S-CS is a 24-item, 7-point likert scale adopted from various individualism-collectivism questionnaires (Oyserman, et al., 2002) that has demonstrated both good reliability and validity in the study of minority populations (including mostly Asians and some Hispanic/Latinos) within the United States (Coon & Kemmelmeier, 2001). Higher scores are associated with greater levels of collectivism whereas lower scores are associated with greater levels of individualism. The AMAS has been shown to be a good measure of acculturation in both Asian (Chung, et al., 2004) and Hispanic/Latino samples (Zea, et al., 2003). This 42-item, 2-factor, 4-point likert scale assesses both the level of a person's adoption of mainstream American culture (factor 1; 21 items) and the maintenance of their indigenous culture (factor 2; 21 items). Each of the two factors can be further subdivided into 4 subscales: 1) cultural identity, 2) cultural knowledge, 3) receptive language, and 4) expressive language.

HYPOTHESES AND DATA ANALYSES

Accuracy

As previously mentioned, the primary analyses focused on potential differences between Caucasian and Chinese participants since most studies that have found ethnic group differences in the past have used these groups. Secondary analyses were then conducted examining potential differences involving the Latino participants since little justification for a priori predictions are found in the literature. In each of the 3 experiments, initial performance was examined by contrasting participants' accuracy (percent correct) across the entire 560 trials in 7 blocks of 80 trials each using a 2 (group: Caucasian vs. Asian) X 7 (blocks 1-7) mixed-design ANOVA with group as a between-subjects factor and number of trial blocks as a repeated measure.

Hypothesis 1: Measurable cultural differences exist when participants learn a unidimensional rule-based categorization task (Experiment 1).

Previous studies have suggested that individuals from more independent or individualistic cultures (i.e. Caucasians) selectively attend to the most salient dimensions of a stimulus, while more collectivist or interdependent individuals (i.e. Asian and possibly Latino) incorporate other contextual information to a greater extent. Based on these past observations, it was predicted that Caucasians (e.g. the typically more field-independent and individualistic group) would perform better than the Chinese, the more typically field-dependent and collectivist cultures in learning a

UNI-RB category learning task, in which optimal performance is based on attending selectively to a single stimulus dimension. Specifically, it was predicted that Caucasians would achieve higher levels of accuracy and demonstrate an incrementally faster learning curve when compared to the Chinese group.

Hypothesis 2: <u>Measurable cultural differences exist when participants learn a conjunctive rule-based categorization task (Experiment 2)</u>.

Again, if Caucasians as a group truly tend to attend more selectively to the most salient stimulus dimension of a stimulus display, whereas Chinese tend to incorporate more stimuli simultaneously, then Chinese should perform relatively better than Caucasians in learning a conjunctive rule-based task, in which optimal performance is based on an *explicit* conjunction of multiple stimulus dimensions. It was specifically predicted that Chinese would achieve higher levels of accuracy compared to Caucasians and demonstrate a faster rate of learning. This would be consistent with the hypothesis proposed by previous research that Chinese incorporate more stimulus dimensions when making categorizations while Caucasians focus more on the single most salient stimulus dimension.

Hypothesis 3: <u>Measurable cultural differences exist when participants learn a linear information-integration categorization task (Experiment 3)</u>.

If previous observed differences are driven by Chinese *implicitly integrating* multiple stimulus dimensions when categorizing stimuli rather than making an explicit and verbalizable conjunction of stimulus dimensions, then they should perform better than Caucasians on this task. If on the other hand, the proposed disposition toward incorporating multiple stimulus dimensions previously observed in more field-dependent and collectivist cultures is contingent upon their use of an explicit, hypothesis-driven approach (e.g., the conjunctive rule-based strategy that would result in optimal performance in Experiment 2), then they should not show an advantage relative to Caucasians in learning a linear information-integration task.

Hypothesis 4: <u>Cultural differences will also be observed when a more fine-grained examination of the category learning *strategies* a participant actually uses are modeled quantitatively</u>.

It was predicted that the application of quantitative models to the response pattern of research participants would provide a more in-depth evaluation of any observed differences in terms of how various cultural groups might differ in the *strategies they actually use* when learning the aforementioned categories. As such, it was predicted that Caucasians would be more likely to apply a unidimensional rule in all three experimental conditions, whereas Asians and Latinos would be more likely to apply a conjunctive approach in Experiment 2 and/or an information-integration approach in Experiment 3.

Hypothesis 5: Separate quantifiable measures of (1) perceptual field-dependence/ independence (FD/I), (2) individualistic and collectivist (IC) self-construal, and (3) level of acculturation better predict categorization strategy than self-identified ethnic group membership alone.

Although ethnicity as a categorical variable has been used to explain group differences in most previous studies, an examination of other quantifiable constructs that are more conceptually grounded and have greater explanatory power has the potential to greatly increase our understanding of what may underlie these differences. In order to further understand the group differences observed, a regression analysis was implemented to test the hypothesis that a greater degree of field-independence and individualism should be positively associated with performance on the UNI-RB task and greater field-dependence and collectivism should be positively associated with performance on the CON-RB task, both between and within self-identified ethnic groups. Although an empirical question, one would not necessarily expect that these constructs would be associated with performance on the I-I task since it purportedly taps on implicit learning, which may be less influenced by these factors. It is important to note, however, that few cross-cultural studies have directly measured level of FD/I and IC self-construal separately within the same study, and so these two constructs have frequently been confounded by assuming that they measure similar yet distinct aspects of cognitive style. Finally, it was also predicted that level of acculturation would possibly influence these relationships and, therefore, capture the dynamic nature of “ethnicity” which has historically been construed as a static, categorical variable.

RESULTS

Experiment 1

The data for all groups across blocks are presented in Figure 5. A 2 (group: Caucasian vs. Chinese) X 7 (blocks 1-7) mixed-design ANOVA was run to test the hypothesis that Chinese and Caucasians participants were different in terms of their overall accuracy across blocks when learning a UNI-RB task. The model was significant for violation of sphericity and so a Huyhn-Feldt correction was used when appropriate in all subsequent analyses. There was a nonsignificant between-subjects main effect of group, $F(1, 42) = 1.36$, $p = 0.25$ and a highly significant within-subjects main effect of block, $F(1.663, 69.840) = 50.57$, $p<0.0001$. The interaction, however, was nonsignificant, $F(1.663, 69.840) = 0.68$, $p=0.48$.

A secondary analysis was conducted to see whether the Latino group, which is purportedly also more collectivist, but has not been formally studied in previous studies, was more similar to the Caucasian or Chinese group. Independent sample t-tests were run examining the potential difference between Latinos and both Caucasians and Chinese separately on each of the seven blocks. All of these analyses, however, were nonsignificant at the $p<0.05$ level. In summary, no group differences were detected in either the primary or secondary analyses.

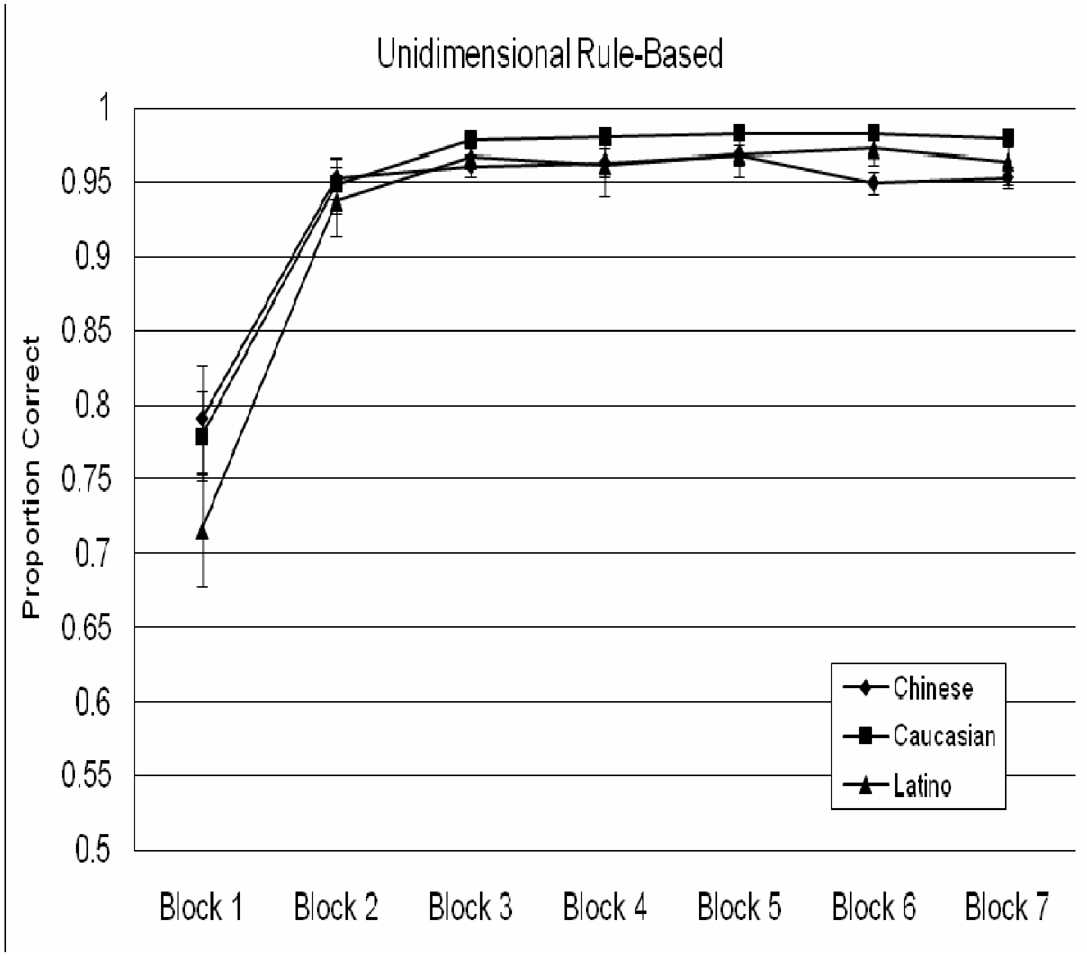

Figure 5. Mean proportion correct across the seven experimental blocks. Error bars represent standard error of the mean

As previously mentioned, in order to examine the strategies that participants were actually using while learning the UNI-RB task, participants were classified into either RB or I-I users (see Table 3). All participants across the groups used not only a rule-based strategy, but specifically a unidimensional rule-based strategy, and so the data were not analyzed further for this experiment.

Table 3. Percentage of participants in each group employing a rule-based or information-integration categorization strategy in Experiment 1

Experiment 1	**Group**		
	Chinese (n=19)	**Caucasian (n=25)**	**Latino (n=16)**
Rule-based	100%	100%	100%
Information-Integration	0%	0%	0%

Experiment 2

The data for all groups across blocks are presented in Figure 6. A (group: Caucasian vs. Chinese) X 7 (blocks 1-7) mixed-design ANOVA was run to test the hypothesis that Chinese and Caucasians participants were different in terms of their overall accuracy across blocks when learning a CON-RB task. There was a significant between-subjects main effect of group, $F\ (1, 42) = 5.32$, $p<0.05$, indicating that Caucasian participants performed more accurately than Chinese participants, and a highly significant within-subjects main effect of block, $F\ (4.076, 171.174) = 38.18$, $p<0.0001$, indicating that accuracy improved across the 7 blocks. The interaction, however, was nonsignificant, $F\ (4.076, 171.174) = 0.92$, $p=0.46$.

Once again, a secondary analysis was conducted to see whether the Latino group was more similar to the Caucasian or Chinese group. Independent sample t-tests were run examining the potential difference between Latinos and both Caucasians and Chinese separately on each of the seven blocks. No significant differences were found between Latinos and Chinese at the $p<0.05$ level. Significant differences were, however, found between Latino and Caucasian participants in blocks 1, 3, and 7, t (40) = 2.20, 2.09, and 2.13, respectively (all p's <0.05), and marginally significant differences in blocks 2, 5, and 6, t(40) = 1.81, 1.95, 1.71 respectively (all p's <0.10). The difference in block 4 was nonsignificant, t (40) = 1.40, p=0.17. In summary, the general trend across these tests was for Caucasians to perform better than Latinos across all blocks of the CON-RB task, and Latinos did not differ significantly from Chinese participants.

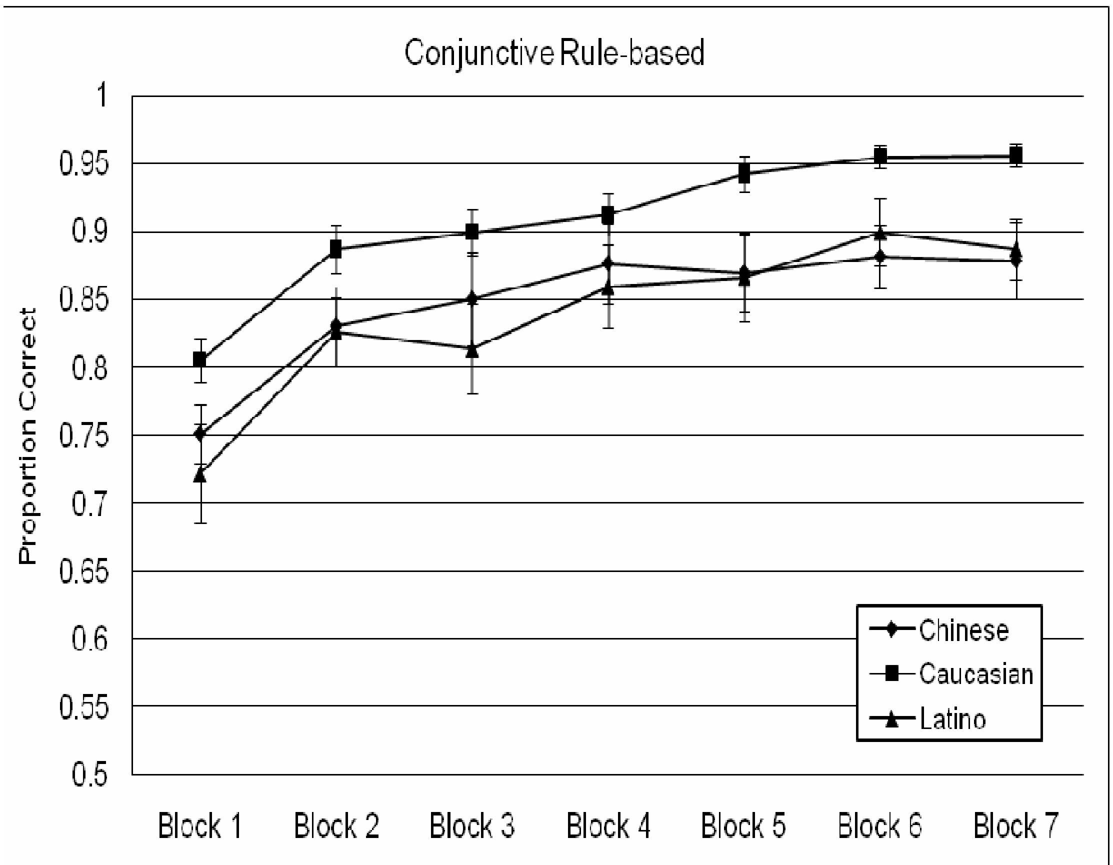

Figure 6. Mean proportion correct across the seven experimental blocks. Error bars represent standard error of the mean

The results for the model-based analysis are summarized in Table 4. A 2 (cultural group: Caucasian vs. Chinese) X 2 (best fitting model: RB vs. I-I) χ^2 analysis yielded a nonsignificant result, $\chi^2(1, n=44) = 0.10$, $p= 0.76$ with 72.7% of the Caucasian/Chinese sample preferring a rule-based strategy within the conjunctive rule-based task. Secondary chi-square analyses examining the Latinos also demonstrated that although there was a tendency for fewer participants in this group to use a rule-based approach, no significant difference were observed when compared to both Caucasians, $\chi^2(1, n=40) =0.90$, $p= 0.34$, and Chinese, $\chi^2(1, n=36) = 1.41$, $p= 0.24$.

Table 4. Percentage of participants in each group employing a rule-based or information-integration categorization strategy in Experiment 2

Experiment 2	**Group**		
	Chinese (n=20)	**Caucasian (n=24)**	**Latino (n=16)**
Rule-based	75.0%	70.8%	56.3%
Information-Integration	25.0%	29.2%	43.8%

To provide a more stringent test of the previously reported group differences in accuracy, a second examination of the accuracy rates for this condition was made, but this time, only in participants who actually employed the type of approach they were supposed to within a given experiment. Specifically, groups of participants whose data were best fit by a rule-based model in the CON-RB condition were compared, and those participants whose data were best fit by an information-integration model were excluded from the analyses.

The data for all groups who used a rule-based strategy across blocks are presented in Figure 7. A 2 (group: Caucasian vs Chinese) X 7 (blocks 1-7) mixed-design ANOVA was run to test the hypothesis that Chinese and Caucasians participants who used a rule-based strategy were different in terms of their overall accuracy across blocks when learning a CON-RB task. There was now only a marginally significant between-subjects main effect of group, $F(1,30) = 3.02$, $p<0.10$, indicating that there was a trend for Caucasian participants to still perform more accurately than Chinese participants. However, despite there no longer being a main effect of group based on this ANOVA, t-tests did indicate that the groups differed in block 6, $t(30) = -2.66$, $p<0.05$, and block 7, $t(30) = -2.37$, $p<0.05$, with Caucasians still out performing Chinese. The ANOVA also revealed a highly significant within-subjects main effect of block, $F(3.69, 110.67) = 28.64$, $p<0.0001$, indicating that accuracy improved across the 7 blocks. The interaction, however, was nonsignificant, $F(3.69, 110.67) = 0.95$, $p=0.43$. Planned independent sample t-tests were used in order to assess whether Latino participants, who also used a rule-based strategy, continued to differ from Caucasians in terms of accuracy. Only the mean difference for Block 7 between Caucasians and Latinos was significant, $t(24)= 2.378$, $p<0.05$, with marginal effects in block 3, $t(24) = 2.05$, $p<0.01$, and block 6, $t(24) = 1.91$, $p<0.10$, suggesting that Caucasians continued to achieve higher levels of accuracy relative to Latinos. As before, the Latinos were not different from the Chinese in any of the blocks including block 7, $t(22) = -0.49$, $p=0.63$.

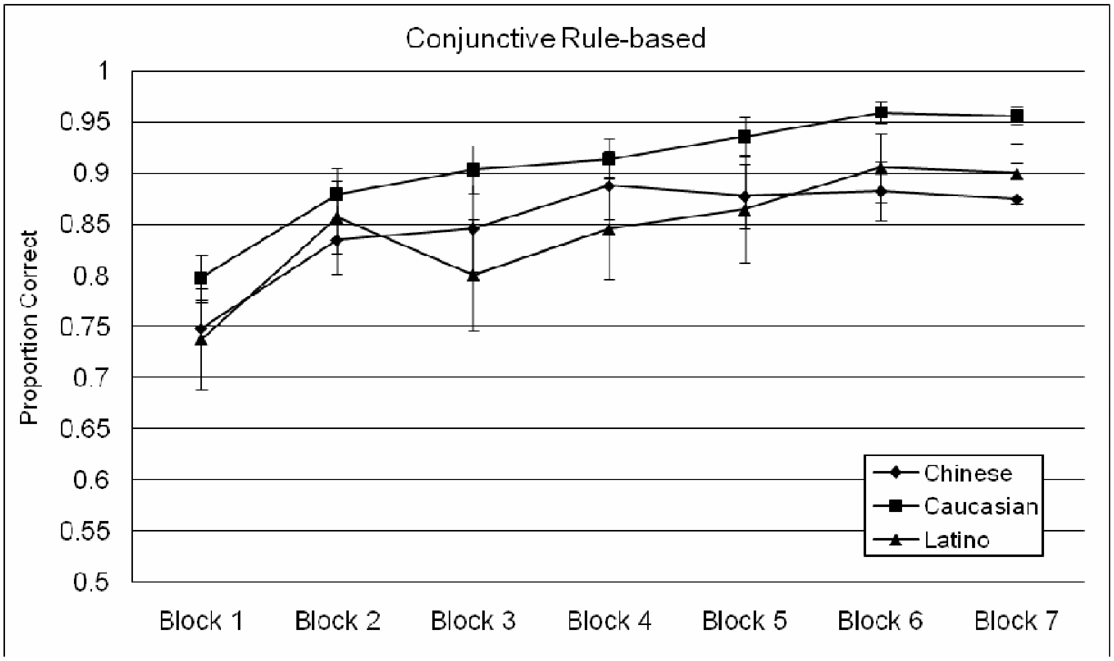

Figure 7. Mean proportion correct across the seven experimental blocks for those participants who used a R-B approach. Error bars represent standard error of the mean

<u>Experiment 3</u>

The data for all groups across blocks are presented in Figure 8. A 2 (group: Caucasian vs. Chinese) X 7 (Blocks 1-7) mixed-design ANOVA was run to test the hypothesis that Chinese and Caucasian participants were different in terms of their overall accuracy across blocks when learning an I-I task. There was a nonsignificant between-subjects main effect of group, $F(1, 32) = 0.13$, $p = 0.72$, but a highly significant within-subjects main effect of block, $F(4.464, 142.838) = 48.53$, $p < 0.0001$. The interaction, however, was nonsignificant, $F(4.464, 142.838) = 1.24$, $p = 0.29$.

A secondary analysis was conducted to see whether the Latino group was more similar to the Caucasian or Chinese group. Independent sample t-tests were run examining the potential difference between Latinos and both Caucasians and Chinese separately on each of the seven blocks. All tests were nonsignificant at the $p<0.05$ level.

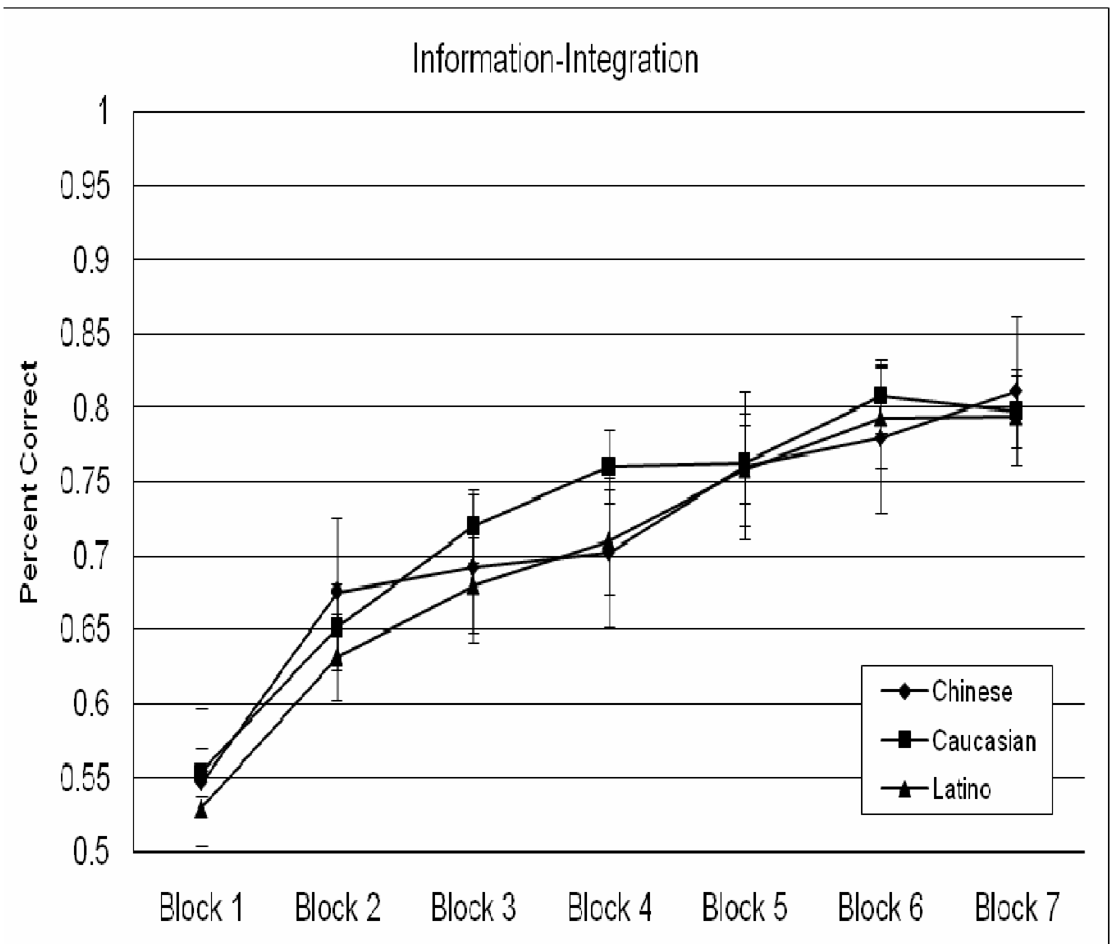

Figure 8. Mean proportion correct across the seven experimental blocks. Error bars represent standard error of the mean.

Model-based analyses for the I-I condition are summarized in Table 5. A 2 (group: Caucasian vs. Chinese) X 2 (best fitting model: RB vs. I-I) χ^2 analysis yielded a nonsignificant result, $\chi^2(1, n=34) = 0.024$, p= 0.88 with 61.8% of the sample across the Caucasian/Chinese group preferring an information-integration strategy within the information-integration condition.

Table 5. Percentage of participants in each group employing a rule-based or information-integration categorization strategy in Experiment 3

Experiment 3	**Group**		
	Chinese (n=11)	**Caucasian (n=23)**	**Latino (n=15)**
Rule-based	36.4%	39.1%	33.3%
Information-integration	63.6%	60.9%	66.7%

A second examination of the accuracy rates for this condition was made, but this time, only taking into account participants who actually employed an information-integration strategy. A 2 (group: Caucasian vs Chinese) X 7 (blocks 1-7) mixed-design ANOVA was run to test the hypothesis that Chinese and Caucasians participants who used an information-integration strategy were different in terms of their overall accuracy across blocks when learning an I-I task. There was a nonsignificant main effect of group, $F(1,19) = 1.00$, $p=0.329$, a highly significant effect of block, $F(4.94, 93.77) = 44.61$, $p<0.001$, and no interaction, $F(4.94, 93.77) = 0.51$, $p=0.48$. Planned independent sample t-tests were used in order to assess whether Latino participants, who also used an information-integration strategy, achieved different levels of accuracy than the Caucasians or Chinese across blocks. All of these were nonsignificant at the $p<0.05$ level.

Cognitive Style and Acculturation Differences

Before attempting to examine the possible underpinnings of the relationship of self-identified ethnicity and category learning accuracy, it was important to know whether the self-identified ethnic groups differed on the GEFT, S-CS, and AMAS across the three experiments. For example, if ethnicity were simply a proxy variable for the cultural constructs of FD/I and self-construal, then it might be expected that the three self-identified ethnic groups would differ on the GEFT and S-CS. Separate 3 (group: Caucasian, Chinese, Latino) X 3 (UNI-RB, CON-RB, I-I) ANOVAs were run to examine the possible differences between all participants on the GEFT, S-CS, and AMAS (all continuous variables) separately across the 3 experiments.

GEFT

Mean total items correct (0 to 18) and standard deviations for all groups in each condition are presented in Table 6. The ANOVA for items completed on the GEFT elicited a main effect of group, $F(2, 159) = 7.43$, $p<0.01$, but no main effect of condition, $F(2,159) = 1.24$, $p=0.29$, and no interaction, $F(4,160) = 0.51$, $p=0.73$. Posthoc pairwise comparisons[1] revealed that both Caucasians and Chinese completed more items on the GEFT than Latinos, but Caucasians and Chinese were not different from each other.

[1] Tukey protection was employed for all posthoc pairwise comparisons.

Table 6. Mean items correct with standard deviations on the Group Embedded Figures Test

	Total Correct Items			**Total Correct Items (Extended Time)**		
	Chinese	**Caucasian**	**Latino**	**Chinese**	**Caucasian**	**Latino**
Experiment 1	16.1 (3.8)	15.7 (2.9)	13.2 (4.6)	16.9 (2.8)	17.2 (2.0)	16.0 (3.4)
Experiment 2	16.5 (2.4)	15.7 (2.4)	14.8 (2.9)	17.7 (0.9)	17.5 (1.0)	16.1 (3.4)
Experiment 3	16.8 (1.2)	15.9 (2.4)	14.2 (3.8)	17.8 (0.4)	17.1 (2.2)	16.0 (4.2)

This same pattern was also observed for time to completion on the GEFT with a significant main effect of group, $F(2, 160) = 9.50$, $p<0.001$ and no effect for condition, $F(2, 160) = 0.08$, $p=0.92$, or the interaction, $F(4, 160) = 0.80$, $p=0.53$. Posthoc pairwise comparisons revealed that both Caucasian and Chinese participants were faster in completing the items on the GEFT relative to Latino participants, and further that there was a trend for Chinese participants to be faster than Caucasian participants. The mean total time to completion and respective standard deviations for all groups in each condition are presented in Table 7.

Overall, these results suggest that Latinos are more field dependent than both Caucasian and Chinese participants, and that Caucasian and Chinese participants are not significantly different from one another.

Table 7. Mean total time in seconds and standard deviations on the Group Embedded Figures Test

	Experiment 1	**Experiment 2**	**Experiment 3**
Caucasian	643.9 (185.8)	665.5 (187.4)	666.9 (159.5)
Chinese	564.8 (204.1)	559.7 (171.2)	617.4 (136.5)
Latino	786.6 (147.4)	746.0 (187.1)	706.2 (201.7)

S-CS

Mean scores and standard deviations for all groups in each experiment are presented in Table 8. The ANOVA for the S-CS elicited a significant main effect of group, $F(2, 160) = 3.76$, $p<0.05$, a marginal main effect of condition, $F(2,160) = 1.91$, $p=0.15$, and no interaction, $F(4,160) = 1.12$, $p=0.35$. Post hoc pairwise comparisons revealed that Chinese participants endorsed higher degrees of collectivism when compared to Caucasians, but not Latinos. Latinos, however, were not significantly different from Caucasians or Chinese at the $p<0.05$ level.

Table 8. Mean scores and standard deviation on the Self Construal Scale (higher scores represent a higher degree of collectivism)

	Chinese	**Caucasian**	**Latino**
Experiment 1	3.99 (0.45)	3.75 (0.53)	3.89 (0.45)
Experiment 2	4.17 (0.37)	3.79 (0.42)	3.96 (0.52)
Experiment 3	4.09 (0.27)	4.06 (0.33)	3.94 (0.22)

AMAS

Mean scores and standard deviations for all groups in each condition are reported in Table 9. Separate ANOVAs were run for each of the two factors that comprise the AMAS (i.e. mainstream and indigenous acculturation). There was not a statistically significant difference on the AMAS between the groups in terms of their mainstream acculturation, $F\ (2,160) = 0.16$, $p=0.85$; however, there was a significant difference between experiments, $F\ (2,160) = 3.41$, $p<01$, but no interaction of group with experiment, $F\ (4,160) = 1.83$, $p=0.13$. Posthoc pairwise comparisons demonstrated that there was a trend for the participants in Experiment 1 (i.e. UNI-RB) to be less acculturated to the mainstream than those participants in Experiment 2 (i.e. CON-RB), but no different than those in Experiment 3 (i.e. I-I).

On the other hand, there was a highly significant difference in the degree to which the different groups maintain the practices of an indigenous culture, $F\ (2, 160) = 310.179$, $p<0.0001$, and no main effect suggesting differences between the experiments, $F\ (2, 160) = 0.48$, $p=0.62$. However, both these effects on indigenous acculturation were qualified by a significant group by experiment interaction, F (4, 160) = 3.61, p<0.01. In order to better understand this interaction, separate one-way ANOVAS were carried out examining the effect of experiment on indigenous acculturation within each group. Within the Chinese group, there was a difference between the three experiments, F (2, 49) = 3.41, p<0.05. Posthoc pairwise comparisons revealed a difference between Experiments 2 and 3 with greater adherence to an indigenous culture in Experiment 3. Within the Caucasian group, there was also a significant difference between experiments, F (2, 69) = 3.52, p<0.05. Posthoc pairwise comparisons revealed a difference between Experiments 1 and 2 with greater adherence to an indigenous culture in Experiment 2. Within the Latino group, there was no significant difference between experiments, F (2, 44) = 1.11, p=0.34.

Table 9. Mean scores and standard deviations on the Abbreviated Multidimensional Acculturation Scale (AMAS)

	Mainstream			**Indigenous**		
	Chinese	**Caucasian**	**Latino**	**Chinese**	**Caucasian**	**Latino**
Experiment 1	63.5 (5.1)	63.2 (3.2)	60.9 (5.4)	45.8 (9.0)	8.6 (8.1)	51.8 (8.5)
Experiment 2	63.2 (5.3)	64.5 (3.3)	66.4 (6.9)	43.6 (9.3)	15.8 (11.7)	51.5 (9.5)
Experiment 3	62.5 (5.1)	62.8 (2.5)	63.3 (6.1)	52.5 (9.0)	10.8 (9.0)	47.2 (10.4)

Relationship Between Categorization Performances, Cognitive Style and Acculturation

Rather than relying solely on self-identified ethnic membership as the grouping factor for all analyses, the relationship between performance in the various experiments and cognitive style/acculturation was examined by determining the association between participants' accuracy performance in the various experiments and their scores on the well-established measures of FD/I, IC, and acculturation (i.e. GEFT, S-CS, & AMAS respectively). Although previous studies have suggested that these variables readily explain some of the variance accounted for by ethnicity, to our knowledge, they have never been simultaneously measured and compared in a single study, and no study has attempted to determine whether these variables are associated with cognitive performance in specific ways.

To identify which of these measures might explain a significant proportion of the variance in accuracy for Block 7 in all three experiments, and the order of these associations, stepwise multiple linear regressions were carried out to empirically make this determination. Block 7 performance was used as the dependent measure because this represents the most stable point in learning. Total time to completion on the GEFT[2], average level of collectivism on the S-CS, and both factors of the AMAS (e.g. mainstream and indigenous acculturation) were entered simultaneously into a stepwise regression together with ethnicity dummy coded for Chinese and Caucasian. Including all of these variables together with ethnicity in a single block served the purpose of testing the hypothesis that some or all of these continuous variables could

[2] Total time to completion was more sensitive in detecting differences than total items completed on the GEFT between Caucasians and Chinese, and so was included in the regression analysis to maximize the potential for explaining any possible group differences.

better account for the data than ethnic group membership alone. Multicollinearity was assessed by examination of tolerance and VIF statistics. Interaction terms of each continuous variable with ethnicity were also included to test whether the effect of the continuous variables on accuracy in Block 7 for each experiment differed as a function of ethnic group membership.

Experiment 1

The results of the multiple regression described above indicated that the overall model was significant, $F(5,38) = 2.53$, $p<0.05$, and accounted for 15% of the total variance in Block 7 accuracy. Only one of the beta coefficients, however, approached significance (mainstream acculturation $t(43) = -1.77$, $p=0.09$) suggesting the possibility that the model may have been over-specified. Inspection of the collinearity diagnostic statistics further revealed that two of the variables, self-identified ethnicity and indigenous acculturation, had poor tolerance/VIF, 0.17/5.99 and 0.17/6.00 respectively. These two variables were also highly correlated ($r = 0.912$, $p<0.001$).

Since the aim of this analysis was to try to explain which variables other than self-identified ethnicity may be related to accuracy on the PCT, a hierarchical regression was run with stepwise selection of all variables except self-identified ethnicity in block 1 followed by the inclusion of ethnicity in block 2. This had the effect of selecting those aspects of cognitive style and acculturation that might be related to Block 7 accuracy prior to including self-identified ethnicity as a predictor, and thereby maximizes the probability that the model was not over-specified. The most parsimonious solution for block 1 of the hierarchical regression again accounted for 15% of the variance in Block 7 accuracy, $F(2,41) = 4.81$, $p<0.05$, and consisted of indigenous acculturation, $\beta = -0.001$, $t(41) = -2.20$, $R^2 = 0.096$, $p<0.05$, and mainstream acculturation, $\beta = -0.003$, $t(41) = -2.20$, $R^2\Delta = 0.094$, $p<0.05$. The addition of ethnicity in block 2 did not produce a significant improvement in the model, $\beta = -0.038$, $t(40) = -1.60$, $R^2\Delta = 0.049$, $p= 0.118$. The hierarchical regression was then run again with ethnicity in the first block and the two acculturation factors in block 2. This time, ethnicity accounted for approximately 13% of the variance on its own, $\beta = -0.027$, $t(42) = -2.68$, $R^2 = 0.146$, $p<0.05$, and only mainstream acculturation added significantly to the model, $\beta = -0.003$, $t(41) = -2.15$, $R^2\Delta = 0.087$, $p<0.05$, but not indigenous acculturation. These results suggest that mainstream acculturation has an effect over and beyond that of ethnicity, and that indigenous and mainstream acculturation together help to explain the variance accounted for by ethnicity.

A secondary analysis geared toward understanding which aspects of both acculturation factors might be driving the observed effect was also undertaken. The two-factors of the acculturation scale (i.e. indigenous and mainstream) both are comprised of four subscales which assess: 1) cultural identity, 2) cultural knowledge, 3) receptive language, and 4) expressive language. These four factors for both indigenous and mainstream acculturation were put into a second stepwise regression to examine if any one factor accounted for a majority of the variance explained. This more specific model was also significant, $F(2, 41) = 5.495$, $p<0.008$, and accounted for 17% of the total variance in Block 7 accuracy. The strongest predictors that comprised this model were indigenous receptive language, $\beta = -0.003$, $t(41) = -2.87$,

$R^2 = 0.127$, $p<0.01$, and mainstream cultural knowledge, $\beta = -0.003$, $t(41) = -2.01$, $R^2\Delta = 0.085$, $p<0.05$.

Experiment 2

The same analysis procedure was carried out as in Experiment 1. Collinearity diagnostic statistics were unremarkable (e.g., all tolerance >0.20 and VIF < 4). The initial model with all factors entered in a single step yielded a significant model, $F(5,38) = 3.68$, $p<0.01$, which accounted for 24% of the total variance in Block 7 accuracy. Only mainstream acculturation had a strong predictive relationship with accuracy, $\beta = 0.007$, $t(38) = 2.37$, $p<0.001$. Of note, self-identified ethnicity did not emerge as a significant predictor. Stepwise regression resulted once again in both acculturation factors comprising the most parsimonious model, which accounted for 25% of the total variance in accuracy; indigenous, $\beta = -0.002$, $t(41) = -2.84$, $R^2 = 0.184$, $p<0.01$, and mainstream, $\beta = 0.007$, $t(41) = -2.45$, $R^2\Delta = 0.104$, $p<0.05$. Self-identified ethnicity did not account for any of the variance after these two variables were in the model. Once again, the hierarchical regression was run with ethnicity in the first block and the two acculturation factors in block 2. This time, ethnicity accounted for approximately 14% of the variance on its own, $\beta = -0.078$, $t(42) = -2.83$, $R^2 = 0.160$, $p<0.05$, and only mainstream acculturation added significantly to the model, $\beta = 0.008$, $t(41) = 2.45$, $R^2\Delta = 0.107$, $p<0.05$, but not indigenous acculturation. These results again suggest that mainstream acculturation has an effect over and beyond that of ethnicity, and that indigenous and mainstream acculturation together help to explain the variance accounted for by ethnicity.

As before, a secondary analysis geared toward understanding which specific aspects (i.e. subscales of the AMAS) of both acculturation factors might be driving the observed effect was also undertaken. This more specific model was also significant, $F(1, 42) = 24.31$, $p<0.001$, and accounted for 35% of the total variance in Block 7 accuracy. The only predictor in this model was mainstream receptive language, $\beta = 0.04$, $t(42) = 4.93$, $R^2 = 0.367$, $p<0.001$.

Experiment 3

All factors inputted into both the simple and stepwise regressions failed to explain a significant proportion of the variance in the I-I condition, $F(6, 26) = 0.94$, $p=0.48$, adjusted $R^2 = -0.011$. This suggests that neither ethnicity nor the various indicators of cognitive style or acculturation were related to accuracy in learning the I-I categorization rule.

DISCUSSION

Although a great deal of evidence has begun to emerge demonstrating the effects of culture on various cognitive processes, including categorization (Norenzayan, 2002), the possible reasons for these differences are not yet well understood. Recently, some researchers have proposed that aspects of cognitive style such as field dependency and/or degree of individualism and collectivism (i.e. self-construal) may be causally related to observed differences between cultural groups (Masuda & Nisbett, 2001; Ji, et al, 2000). Much of the support for this theory has come from observations of Chinese research participants performing worse relative to Caucasians on tasks of selective attention, but better than Caucasians when having to integrate multiple stimulus attributes to form a categorization rule. A complicating factor in all these studies, however, is the frequency with which these proposed indicators of cognitive style (e.g. field dependence and self-construal) are assumed rather than empirically measured. In addition, some studies have all together failed to empirically capture differences in field dependence and self-construal between ethnic groups while others have succeeded (Oyserman & Lee, 2008).

Another possible approach to understanding cultural differences in categorization, which has only begun to be undertaken, is the examination of the actual *process* of category learning. In other words, studies of *categorization* examine the *application* of previously formed categories that people already possess and then use to classify or sort stimuli into groups based on these pre-existing categories; *category learning*, on the other hand, examines the *acquisition* of a predetermined category, which a person may or may not be familiar with prior to beginning the task of learning this category structure. Cultural differences in *categorization,* therefore, highlight the already learned, fixed categorization rules that people bring with them to a task. The experimenter determines the stimuli, and the categorization rule a subject uses to sort the stimuli is the variable of interest. For example, categorization studies have examined whether a subject categorizes stimuli based on either a specific stimulus attribute or how similar a particular stimulus is to those that have come before it. By contrast, in category learning paradigms, both the stimuli and the categorization rule are fixed by the examiner and the subject's ability to learn or acquire the categorization rule is the variable of interest. Cultural differences in *category learning*, therefore, address the degree to which a person can learn a categorization rule, which may be similar or different to other categorization rules already in that person's repertoire.

The present set of experiments attempted first to examine whether some of the ethnic differences that have been observed cross-culturally in categorization also become apparent within a category learning paradigm using the PCT (Ashby & Gott, 1988). In addition, these experiments sought to provide a more fine-grained analysis of possible differences between Caucasian, Chinese, and Latino participants on the PCT by examining some of the constructs that other studies in categorization have suggested may be driving cultural differences. These included both measures of field dependency and self-construal along with level of acculturation for each participant to examine whether these constructs actually manifest the theoretical relationships in a diverse sample of college students, which other researchers have found and attribute to self-identified ethnicity.

The PCT was chosen for a variety of reasons; however, perhaps the most prominent being the high degree of control the examiner has over all aspects of the stimuli and design of the experiment. Having been widely studied in category learning research, the properties of the PCT are well understood and allow for the application of mathematical models that enable a deeper understanding of the type of categorization task a participant is asked to undertake and also the strategy that a participant employs during the task. This increase in experimental control, however, strips away the semantic layer of most stimuli, which some researchers have argued may actually drive cultural differences in categorization (Medin, et al., 1987). The stimuli used in the PCT are elementary and devoid of any semantic component and, therefore, provide an opportunity to determine whether there are differences across cultural groups when such semantics are removed.

Category Learning Differences Across Ethnic Groups

Experiment 1 was designed to examine the extent to which participants could learn a highly verbalizable categorization rule that required selective attention to a single stimulus dimension. Previous studies had demonstrated that Caucasian participants tend to excel in tasks which require selective attention and do not require the incorporation of multiple stimulus dimensions simultaneously, whereas Chinese participants tend to automatically incorporate multiple stimulus dimensions into their decision making process (Norenzayan, 2002). This pattern of results in previous studies has been interpreted as Caucasian and Chinese participants demonstrating different cognitive styles, which purportedly guide and color their performance across a variety of cognitive tasks. The present results, however, did not find a significant difference between these two groups on the PCT in Experiment 1. This may have been due to the fact that learning a unidimensional rule is a relatively transparent or highly face-valid task made highly explicit, if not obvious, by the corrective feedback which was presented after each trial. Both groups also learned the rule rather quickly achieving accuracy rates of 70% or higher in the first block of trials and upwards of 90% by the second block. Despite the fact that the ceiling on this task was so low, the notion that Caucasians always perform a certain way and Chinese another is perhaps overly simplistic and naive. Regardless, performance on this simple rule supported the notion that Chinese participants are indeed *capable* of learning a unidimensional rule-based task. This argument is made stronger when the model-based analysis is also taken into account, which demonstrates that not only were accuracy rates comparable across the three groups, but also that all groups used a unidimensional rule-based strategy to achieve these high levels of accuracy.

Experiment 2 attempted to test the converse hypothesis of Experiment 1; namely that Chinese participants would perform better than Caucasians when having to integrate two stimulus dimensions to learn a more complex categorization rule. Again, the results were surprising in that Caucasians performed better than Chinese, specifically in the later trial blocks of the study. This finding would not have been predicted based on observations made in previous studies that Chinese are more field dependent and demonstrate a bias for incorporating multiple dimensions of stimuli in their categorization judgments whereas Caucasians tend to zero in on what they perceive to be the most salient stimulus attribute.

One question which Experiment 2 was able to clarify, however, was that Chinese participants are *capable* of using explicit rule-based strategies, and also that Caucasian participants are capable of incorporating multiple dimensions of stimuli. Even after equating both groups in terms of the strategy used to learn the task (i.e. rule-based strategy); Caucasians continued to perform better than Chinese on the task. The fact that Experiment 2 found a cultural difference that was in the opposite direction from what would have been predicted by previous studies suggests that either something other than attentional biases or a perceptual difference in cognitive style was responsible or that the sample was somehow different from that in other studies.

A re-examination of Norenzayan's studies (2002), in which participants had to either consistently apply a rule which they were taught or use their own idiosyncratic rule to classify stimuli provides some insight into what may have been driving the direction of findings in Experiment 2. In Norenzayan's studies, Caucasians identified a single rule that determined category membership based on a single trait that all stimuli shared and *consistently* applied that rule regardless of the changing relationships among the other stimuli; whereas Chinese did not consistently apply the same rule, but rather adopted more of an exemplar approach incorporating multiple characteristics of the stimuli in categorizing the same group of objects. Given the experimental design, however, the possibility that the Chinese participants were also using a more elaborate rule-based strategy could not be ruled out. Furthermore, the stimuli for these experiments were human or animal-like aliens and groups of flowers which are objects that, at least in theory, are similar to objects encountered in everyday life.

Unlike Norenzayan's studies and most categorization studies that can be explained by differing degrees of expertise with the stimuli presented, the PCT does not present "meaningful" or semantically laden stimuli on which different ethnic groups might be expected to differ *a priori* to the experimental test. For example, it is possible that both the "aliens" and groups of flowers may have primed other related category structures, which have differential meaning for the two contrasting cultural groups (e.g. interpersonal and/or group relations). This then may have gone on to influence the type of categorization strategy that was selected for the task. In other words, the nature of the stimuli themselves may have activated different categorization rules or strategies already present within the individuals participating in the experiment, the nature of which was fundamentally different in both groups (Hong, et al., 2003). In the case of the Chinese, similarity among the stimulus objects took precedence, reflecting a more holistic problem solving approach, while the Caucasians instead chose to consistently apply a hypothesis-driven, rule-based approach reflecting a more analytic problem solving approach (Nisbett, et al., 2001). By contrast, in the PCT, the stimulus dimensions are such that they do not have meaning outside of the experimental task itself (e.g., gabor patches that vary in their spatial frequency and/or orientation do not mean much outside of the context of the PCT), and so one might expect that if differences emerge, that they are not based on priming of already established categories, but rather are exemplary of how different cultures might approach objects with which they have had no previous experience or contact. Though both are studies of category learning, the present set of experiments and Norenzayan's studies are fundamentally different in that success on the PCT requires a greater degree of selective attention to the specific stimulus set presented and an inhibition of previously learned categorization strategies.

Whereas some previous studies demonstrate that Chinese perform differently than Caucasians and attribute these findings to differences in attention allocation and perceptual patterns (Masuda & Nisbett, 2001), Norenzayan's experiments perhaps suggest that rather than being perceptual per se, these differences may be contingent upon the stimuli themselves activating culture-specific scripts for behaving in a certain way (i.e. adopting an analytic, rule-based, hypothesis-driven approach or focusing instead on similarity, which is a more holistic approach based on real-life experience). In other words, the same stimuli may be understood differently based on the person's self-construal which then influences the perception of the stimuli themselves. In contrast, the PCT forces participants to focus on particular, experiment-specific stimulus dimensions if they are going to increase their accuracy by integrating corrective feedback into their responses, which also forces participants to adopt a logical, hypothesis-driven, rule-based approach. It does not allow participants to draw on personal experience outside of the testing environment (i.e. habitual ways of constructing meaningful relationships) if they are going to increase their accuracy. It may, therefore, be the case that the Caucasian group performed better than the Chinese group on Experiment 2 because they were able to more efficiently limit their attentional focus to the task at hand without allowing previous experiences outside of the testing situation to influence their problem solving. This would be more in line with Witkin's original formulation of field dependence (Witkin, 1971; 2002), which extends beyond mere perception into how a person understands the self and negotiates with the environment. The Caucasian group's field independence, therefore, may be more related to the fact that they do not bring experiences outside of the testing environment to bear on the experimental task, such that when higher degrees of accuracy are based on maintaining attention to task-specific variables and applying a consistent rule derived from these task specific variables, they excel. Whereas Chinese may be more dependent on the field of their previous experiences, Caucasians may be more inclined to focus solely on the present object of study without drawing upon previous experiences. This reformulation of field dependency to reflect the degree to which a person can partition their attention to focus exclusively on a task may better reflect and explain both the present and previous findings, and demonstrates a return to Witkin's original theory.

The combination of experiments 1 and 2, therefore, suggests that the different cultural groups are capable of using both cognitive style orientations (i.e. selectively attending to a single stimulus dimension and combining multiple stimulus dimensions). The reversal in effect for Experiment 2, from what would have been expected, further suggests that the differential preference for one over the other style demonstrated in previous studies may perhaps be a function of a broader preference for analytic versus holistic styles of reasoning, which may be primed by the stimuli themselves (Nisbett, et al., 2001), and becomes more apparent when task demands become more complex.

In contrast to Experiments 1 and 2, Experiment 3 examined the question of whether cultural differences exist at an implicit level. In other words, if Chinese participants truly incorporate multiple stimulus attributes automatically in a reflexive manner, then they should have performed extremely well on this condition relative to Caucasians because it requires an implicit integration of multiple stimulus attributes. The fact that there were no differences whatsoever among the groups suggests that perhaps implicit learning processes may be immune to cultural influence. In other words, on a task such as the PCT which strips away the semantic nature of stimuli and focuses more on signal detection of basic stimuli (e.g. gabor patch), the further need to learn an implicit, nonverbalizable task, may also bypass the influence of culture because the task at hand draws less on previous semantic and culture-specific practices shaped by explicit awareness or conscious experience. Nevertheless, cultural differences were still observed on Experiment 2 possibly because of differences in the form of verbal explicit reasoning and the need to limit attentional focus to the task variables at hand.

As previously mentioned, most studies of categorization in the real world tend to focus on a person's level of expertise with a particular stimulus set as the factor that explains cultural differences (Medin, 1987; Atran, 1990). Cultural consensus models (Romney, et al., 1996; 1986), for example, show that certain stimuli are more meaningful for some cultural groups relative to others due to specific experiences that a particular culture shares which those outside the culture do not. Indeed previous studies have demonstrated that people's ability to carry out certain cognitive abilities is contingent upon their using materials that are familiar to them (Mishra & Tripathi, 1996; Serpell, 1979; Sonke, et al., 1999). In other words, all cultures are *capable* of learning any type of categorization rule, however, an experimenter's ability to observe this may be contingent upon the stimulus set that is used and the relevance that it has to a particular cultural group. However, the results in Experiment 3 clearly go beyond this and suggest that cultural differences may not even exist on this level of category learning at all.

The distinction between R-B and I-I category learning systems has been well established by previous research studies. These two category learning systems have been dissociated both in terms of behavioral studies, as well as, studies that examine the underlying neural architecture of these systems. Specifically, learning R-B tasks requires an explicit, hypothesis testing system that employs executive attention and working memory, which are mediated mostly by the anterior cingulate, dorsolateral prefrontal cortex, and head of the caudate. The learning of I-I tasks, on the other hand, requires an implicit procedural-learning-based system that is mediated mostly by the tail of the caudate and does not involve cortical areas (Filoteo, et al., 2005; Nomura, et al., 2007). In essence, the learning of an I-I rule, such as that in Experiment 3, is believed to rely to a less extent on cortical areas and instead selectively tap procedural learning systems in the basal ganglia. The fact that there were no differences in Experiment 3 but there were differences in Experiment 2 suggests that, just as different types of category learning systems have been found to have different neural underpinnings, perhaps cultural differences may be selectively operating in one category learning system (R-B) but not another (I-I). Although this would require replication, and a different set of experiments to further isolate this effect, the results of the current set of experiments suggest that the impact of cultural differences may occur within different learning systems.

Ethnic Differences in Cognitive Style

Interestingly, there were no differences between the Chinese and Caucasian groups on the GEFT. The finding that Chinese and Caucasians were not different from one another on the GEFT is not typical of what has been observed in other studies (Thompson & Melancon, 1987); however, it is not unheard of either (Kuhnen, 2001). In fact, Bagley and colleagues (1983) found that Asian children were actually more field independent than American children, and DeVos (1980) found the same result with adults. Despite the recent outpouring of studies that might suggest Chinese are more field-dependent as a group, there are a small number of studies consistent with the present findings that do not replicate this result (Heine & Norenzayan, 2006).

Importantly, a wide range in degree of field-dependence has specifically been found in Chinese research participants both domestically and abroad with some evidence to suggest that Chinese nationals may actually demonstrate less field dependence on the GEFT because of their everyday exposure to Chinese written characters while still demonstrating field dependence on the RFT, which reportedly does not tap the skill set acquired through character reading (Chen, et al., 1989). The fact that a subset of Chinese have been found to excel on the GEFT has further led to the creation of a revised GEFT that raises the ceiling in the instrument by adding more complicated items and thereby making the GEFT more capable of capturing the extended range of ability in some Chinese participants. However, this revised adaptation of the GEFT for a subset of Chinese nationals has resulted in an inability to directly compare Chinese with other cultural groups due to a lack of equivalence in instruments. This methodological difference highlights the fact that the ability to reify simple shapes within more complex patterns is tied to specific cultural practices (i.e. reading Chinese characters). Nevertheless, a large number of researchers continue to assume that the construct of field dependence is valid without submitting it to the same scientific rigors of reliable and valid measurement necessary to examine true equivalence cross-culturally (Matsumoto & Yoo, 2006).

This evidence suggests that in the present set of experiments, the possible lower ceiling of the GEFT for Chinese and other stimulus related variables may have been driving the lack of difference in field dependence both between and within subjects, and that greater attention should be paid to trying to identify which Chinese participants test as field dependent and under what conditions. In addition, it may still be the case that because the Chinese participants in the present study were so highly acculturated, they did not demonstrate the expected effect on the GEFT, but that they would have on another measure of field-dependence (i.e. RFT).

Interestingly, the Latino participants did test as more field dependent on the GEFT. However, in this case, the construct of field dependence may have been confounded with the importance that time itself may have upon a culture's performance level. Examination of the data dealing with the GEFT, for example, reveals that although the Latino group's total items completed was significantly lower than the other two groups, when given extended time, their scores fell within the overall average range across groups. Furthermore, the Latinos spent more time overall on the task than the other two groups suggesting that perhaps their observed field dependence may be an artifact of a different set of cultural values associated with speed and accuracy trade-offs (Llorente, 2008). It is difficult to argue, therefore, that the construct of field dependence was adequately measured in our sample using the GEFT. And still more difficult, to say that field dependence and self-construal are related in the way described by previous studies that did not actually measure these constructs empirically, but rather assumed them based on self-identified ethnicity.

Despite not performing as more field dependent on the GEFT, Chinese subjects, did however, tests as more collectivist on the S-CS. By contrast, Latinos did perform as more field dependent on the GEFT, but less collectivist on the S-CS. It may seem as though perhaps the GEFT and SC-S were correlated somehow, and that this may be the reason for why they do not appear significant simultaneously, but this was not the case in our sample either across or within groups. Although many researchers believe that degree of field dependence predicts the direction and degree of a person's self-construal (i.e. greater degrees of field dependence are related to greater degrees of collectivism), this was not the case in the present study. To our knowledge only one other study has attempted to measure field dependency and cognitive style side by side, and it too failed to demonstrate the frequently assumed relationship between these two constructs (Zhang, 2004). Again this highlights the need to empirically measure these constructs, and the fact that degree of field dependence and collectivist practices may not necessarily share a common denominator. On the other hand, it may be that field dependence and self-construal are measuring different manifest aspects of the same latent construct proposed by Witkin which has yet to be adequately measured.

Leaders in the field of cultural psychology have recently suggested that perhaps it is time to move beyond the early phases of research in cultural psychology geared toward demonstrating cross-cultural differences toward adopting what they call, "linkage studies" (Matsumoto & Yoo, 2006; Heine & Norenzayan, 2006). This shift in emphasis attempts to link the measurement of theoretical explanatory constructs (i.e. self-construal, field dependence) with observed behavioral differences (i.e. preferences for selective attention to objects and field-dependent examination of the whole display). This new proposed framework is certainly consistent with the present set of findings. Whereas differences between groups continue to be found under specific conditions but not others, the question of what is driving these differences needs to be empirically tested. The proposed theories attempting to explain these differences are now at a stage where direct empirical tests are necessary lest unreliable stereotyped group differences continue to yield mixed results.

The explanatory power of acculturation

In terms of trying to understand the group differences that were observed in Experiment 2, not surprisingly, the GEFT and SC-S did little to "unpack" these differences attributed to self-identified ethnicity. It was only a person's level of acculturation as measured by the AMAS that predicted performance in learning the conjunctive rule-based task. These findings indicate that individuals who were more acculturated to the mainstream tended to perform better on the task. In Experiment 1, no differences between groups were found, however, regression analyses revealed that levels of both mainstream and indigenous acculturation positively predicted increased accuracy on a unidimensional rule-based task. In Experiment 2, levels of acculturation also better predicted the differences that were observed, and a more in depth analysis revealed that specifically, the receptive language aspects of acculturation were driving this effect. The fact that acculturation helped to explain performance both when self-identified ethnicity did and did not suggests that perhaps this may be what is driving differences to begin with.

The question of why a person's receptive language ability in English on the AMAS would be so highly predictive of accuracy in the final block of Experiment 2 is complex and potentially very informative. The final model in the regression analysis suggested that the better a person's receptive language in English, the better they performed on the CON-RB condition of the PCT. What appeared at first to simply be an ethnic group difference, turned out to be related to how proficient a person is in understanding English within the mainstream culture. Unlike ethnicity, a categorical variable, receptive language ability seems more amenable both to empirical measurement and meaningful interpretation along a continuum. Its ability to dynamically model a person's level of linguistic proficiency better maps on to why cultural differences have been at times elusive and at others replicated in previous studies.

The questions on the AMAS related to the receptive language subscale specifically ask, "how well do you understand English…on television or in movies…in newspapers and magazines…words in songs…and in general?"

Assuming that a person has achieved enough receptive language proficiency to understand these things, it is then not difficult to also suggest that they are now more heavily influenced by these same variables, which they now have access to because of linguistic competence. If a person can more readily understand the language of the mainstream culture and can begin to participate in its cultural practices more fully, then perhaps they can also assimilate its cultural practices to a greater extent. However, there is no data at present to suggest that receptive language ability is any better able to predict degree or speed of assimilation than the other three factors in the AMAS or other indicators of acculturative status for that matter. The findings in the present study, however, do suggest that perhaps degree of receptive language proficiency in the mainstream culture does play a unique role in achieving higher accuracy rates in Experiment 2, and therefore warrants further study.

The question of what may be driving the correlation between learning an explicit and verbalizable conjunctive rule and receptive language ability in English is quite intriguing. Given the high demand on working memory for this task, one may be tempted to hypothesize that perhaps the degree of bilingualism in the Chinese group is somehow related to the observed effect. In fact, a growing literature suggests that bilinguals have greater working memory and executive cognitive set switching abilities than monolinguals (Bialystok, 2007). However, given the present results, this would also presuppose that monolingual Caucasians somehow have better working memory ability overall since they still outperformed the bilingual Chinese. Since working memory was not specifically assessed and there is no strong theoretical reason to suggest that Caucasians would have stronger working memory ability, this hypothesis loses some of its luster.

Another possibility is that mastering the conjunctive rule on the PCT required participants to think in a linear, hypothesis driven way that isolated the two relative dimensions and then set a criterion on each dimension before making categorization decisions based on this deciphered rule. The modeling analysis further allowed us to state with a degree of confidence that most participants were following a rule-based approach. Perhaps what these results suggest then, using Nisbett's terminology, is a broader, more analytic style of thought characteristic of Western societies, acquired through participation in the dominant language of the culture, of which field independence and individualist self-construal are only select subcomponents. Such an analytic style of thought can be defined as involving:

> detachment of the object from its context, a tendency to focus on attributes of the object in order to assign it to categories, and a preference for using rules about categories to explain and predict the object's behavior. Inferences rest in part on the practice of decontextualizing structure from content, the use of formal logic, and avoidance of contradiction (Nisbett, et al., 2001 p.293)

as opposed to a more holistic system of thought characteristic of Eastern societies which can be defined as involving:

> an orientation to the context or field as a whole, including attention to relationships between a focal object and the field, and a preference for explaining and predicting events on the basis of such relationships. Holistic approaches rely on experience-based knowledge…and are dialectical (Nisbett, et al., 2001, p. 15)

Receptive language ability in English within the mainstream culture may, therefore, be a proxy for increased participation in mainstream cultural practices that lead to a more analytic style of thought; however, this remains to be borne out by future studies. It is important to note, however, that the methodology of the PCT forces participants to adopt this style of thinking or processing information via the selective corrective feedback provided in the task. The degree to which a person is able to adopt this cognitive style, therefore, predicts the degree of success they will demonstrate on the task. The learning of this particular rule-based strategy, which is highly analytic, would therefore be easier for persons who already habitually use this type of hypothesis-drive strategy. Thus, Caucasians may have outperformed Chinese specifically for this reason.

If this is the case, it is interesting that the other subscales of the AMAS do not seem to tap into the degree to which someone is willing or able to engage in more analytic thought. One might think that general knowledge about the mainstream culture or a greater personal identification with mainstream culture might be more directly associated with being influenced by a certain style or type of reasoning. Or perhaps that expressive language is a better indicator of having adopted a particular cognitive style because expressive language requires deeper processing of linguistic information than receptive listening. However, it may be inferred from the present results that the key issue here is not one of mastery or assimilation, but one of simply having access to the potential for being influenced by the mainstream culture through language. This degree of specificity implied by the present results, however, requires further study in order to draw stronger conclusions, especially since none of the previously observed patterns in self-construal and field-dependency were replicated in the sample recruited for this set of experiments. Still, the potential importance of none of the field dependence, self-construal, and acculturation variables correlating with performance and no group differences emerging on Experiment 3 cannot be minimized.

Neurobiological Considerations

Although the behavioral data collected across the three experiments speaks for itself, a burgeoning perspective in the recent literature suggests that in cross-cultural research, and most studies of neurocognition for that matter, this is no longer enough to draw accurate inferences regarding neurocognition. A greater amount of attention is now being paid to what the possible underlying neural correlates of cognition may be, which can also help to inform the nature of the cognitive process under study. This is certainly the case in the present set of experiments with the finding that R-B category learning tasks are capable of demonstrating cultural differences whereas I-I learning tasks are not. As already mentioned, previous studies provide strong evidence for why underlying neural differences might be expected between R-B and I-I conditions, and the current results suggest that dimensions of culture may also lead to further underlying neural differences due to the behavioral differences observed. However, even observations of equivalent behavioral performance have demonstrated that different cultural groups may recruit distinct neurocognitive systems in the brain to perform the same behavioral task in some cases, while other studies have demonstrated the recruitment of different neurocognitive systems that discretely map on to differences observed behaviorally.

For example, as previously reviewed, Grön and colleagues (2003) demonstrated equivalent performance at the behavioral level on a visual learning task, but found that Asians recruited more dorsal visual processing areas whereas Caucasians recruited more ventral visual processing areas on the same task within an fMRI paradigm. They further demonstrated that each group was capable of using both visual processing streams, but that they seemed to have a preference for one over the other at different stages of learning. In essence, this suggests that just because one observes equivalence at the level of behavioral performance does not guarantee that the underlying neural systems that are tapped by the experimental task are also equivalent.

Gutchess and colleagues (2004) on the other hand, demonstrated that consistent with behavioral research which has shown that Westerners focus more on objects, whereas East Asians attend more to relationships and contexts, concomitant differential patterns of activation were also observed in an event-related fMRI study. Specifically, Asian and Caucasian participants incidentally encoded pictures of either a target object alone, a background scene with no discernable target object, or a distinct target object against a meaningful background. Caucasians tended to activate more regions implicated in object processing when compared to Asians while few differences emerged within brain regions implicated in the processing of background scenes. Here, behavioral differences are correlated with differences at the level of functional organization in the brain. However, it is interesting that functional neural differences were observed only in the processing of objects with Caucasians demonstrating greater levels of activation.

Most recently, Hedden and colleagues (2008) assessed fMRI responses during performance of a simple visuospatial task in which participants made absolute judgments requiring selective attention or relative judgments requiring incorporation of the visual context. A paradigm developed by Kitayama and colleagues (2003) was used in which subjects were assigned into one of two tasks in which they viewed a vertical line inside a box. In the relative-instruction task, participants judged whether a box and line combination of each stimulus matched the proportional scaling of the preceding combination, and in the absolute-instruction task, participants judged whether the current line matched the previous line, regardless of the size of the accompanying box. Caucasians have been shown to typically respond based on the absolute length of the line whereas Asians respond based on the relative proportion of the line to the box.

Activation in frontal and parietal brain regions known to be associated with attentional control was greater for Caucasians when having to selectively attend to the absolute size of the line and for Asians when having to incorporate the proportional size of the line to the box. Activation differences in these regions also correlated strongly with scores on questionnaires measuring either degree of individualism in Caucasians and level of acculturation in Asians. The cultural background of an individual and the degree to which the individual endorsed cultural values, therefore, seemed to moderate activation in the same brain networks engaged during the same task. The same neural systems, therefore, were recruited by both groups but to different degrees based on the relation between task demands and degree of field dependence. The fact that activation was observed in frontal-parietal regions, rather than early visual regions, further suggested that the processes most affected by cultural experience are primarily related to “high-level” attention mediated by association areas, rather than to early-stage encoding mediated by primary perceptual areas. In summary, the authors interpreted their results as showing how experience in and identification with particular cultural practices may shape brain responses associated with attentional control. This finding is highly consistent with the fact that groups did not differ in Experiment 3 and that self-construal and field dependency were unrelated to the learning of an implicit I-I rule suggesting that "lower level" learning is more immune to cultural influence.

These examples highlight what seems to be a surge by cultural psychologists engaging in what Poldrack refers to as "reverse inference" techniques using neuroimaging (Poldrack, 2006). In other words, when a poorly specified task is used in a functional imaging paradigm and then inferences are drawn about the activation patterns that are observed, there is potential for misinterpretation because one does not really understand what this activation pattern means. Part of the problem with prematurely conducting behavioral research while simultaneously collecting neurobehavioral data in paradigms such as fMRI, then, is that most experimental tasks have not demonstrated the necessary reliability and validity in measuring the construct of interest to then relate performance to correlated active neurophysiology. To borrow a phrase from Poldrack and colleagues, we lack a "cognitive ontology" onto which we can then map positive imaging findings (Poldrack, 2006). The use of the PCT, however, helps to remedy this problem because the paradigm itself has been studied extensively and there are theoretical reasons and empirical findings to suggest that aspects of the task itself recruit different neural systems to begin with. Nevertheless, it may still be the case that different cultural groups are using different neural systems other than those that would be predicted by the task itself during the PCT; however, this is truly an empirical question requiring further study.

Research in pharmacogenomics and ethnopsychopharmacology has also begun to seriously examine the possibility of cross-cultural differences at the level of neuroreceptors and availability of neurotransmitters secondary to the effects of behavioral cultural practices (i.e. diet, environmental exposure, stress coping skills, and other lifestyle choices) as well as interactions of these variable with genetic influences (Pi and Simpson, 2005). Though a “purely genetic” basis for the differences which have been observed cross-culturally has almost completely been dismissed, a shift has occurred which focuses instead on cultural practices, such as diet, which lead for example, to the availability of specific enzymes which modulate the metabolism of neurotransmitters and transporter systems (Ruiz, 2000). Given that the present set of studies demonstrated differences in two neurobiologically dissociable category learning systems (i.e. RB and I-I) that are heavily dependent on dopamine, the fact that Asians have been shown to have different rates of metabolism and reuptake in this system begs the question of whether differences in the dopamine system, which may be indirectly modulated by cultural practices might also map onto the differences observed. Though highly speculative at this point, such questions represent a new area of research that attempts to tease apart cultural differences that have neurobiological consequences which may ultimately lead to different neurocognitive systems being engaged (Lim & Poland, 1995).

Limitations of the present study

It is important to note that the present study has many limitations that qualify the interpretations made above. For example, the differences in field dependence and self-construal typically found in other studies were not replicated. Although an argument was made that these inconsistent findings are more frequent than some researchers would like to acknowledge, it may also be the case that the recruited convenience sample did not adequately represent a sufficient range of ability to observe these differences. The unequal sample size across the three experiments that resulted due to a deviation from the original sampling strategy (i.e. only including Chinese participants from the Asian sample) led to an unequal distribution of cases in the different cells of the experimental design, and may have also created unnecessary noise in the sample and minimized the probability of observing other potential differences between groups. All of the subjects in these experiments were also highly acculturated compared to some of the past studies that have examined participants from different countries. The fact that category learning was examined rather than categorization also makes it difficult to draw direct comparisons between past studies and the current set of experiments. In order to truly make the case that the PCT is a more “culturally neutral” paradigm, a study that demonstrates the ethnic differences within the same sample in the expected directions on the semantic-based categorization tasks but not on the PCT tasks would be need to be implemented. Despite these and other methodological shortcomings, however, the present set of experiments raises more questions to be deciphered in future research studies using the PCT, and adds to a slowly emerging literature attempting to examine cultural differences with greater specificity.

Conclusions

The results from this dissertation suggest that the elements of cognitive style that researchers now take for granted based on self-identified ethnicity should be empirically measured to ensure that false attributions are not made and progress in future studies is not hampered by incorrect assumptions. Second, these results also suggest that the nature of the stimuli employed in cross-cultural studies may partially determine whether cross-cultural effects are observed or not. Third, the three cultural groups studied provided evidence of being able to learn both unidimensional rule-based and information integration tasks suggesting that all three groups are capable of both learning to selectively attend to a single stimulus dimension and implicitly combining multiple stimulus dimensions when learning categorization rules. Fourth, the observed cross-cultural differences in learning a conjunctive categorization rule may be more readily explained by level of acculturation than by self-identified ethnicity. Specifically, assessment of receptive language ability in the mainstream culture of interest is a strong predictor of accuracy.

Perhaps the most significant conclusion that can be drawn from this set of experiments, however, has to do with the lack of any observed effects in Experiment 3. Not finding cultural differences within a task that primarily engages subcortical systems in the context of finding cultural differences in a parallel task that engages both subcortical and cortical regions begs more questions than it answers. Nevertheless, the fact that no group differences were observed coupled with the lack of association between performance and the cultural and perceptual variables that previous studies have consistently replicated makes the present set of findings not only interesting, but also highly provocative. Though the possibility that an atypical sample may be driving the current findings exists, it may also be the case that learning an I-I task using the PCT demonstrates a more universal learning system while more cortically based systems more strongly bear the imprint of engaging in specific cultural practices.

Luria and Vygotsky had long argued that "higher cortical functions," such as category learning, developed within a larger cultural historical context that provided an extracortical organization to these learned neurocognitive abilities (Luria, 1976). In other words, those more complex forms of reasoning had their origin in the cultural practices within which the developing brain participated during ontogeny. The fact that no cultural differences were observed in implicit learning within the I-I condition that supposedly occurs in a phylogenetically older brain system whereas differences were observed in the learning of the CON-RB task and engaged frontal cortical systems that require working memory and language, points the way toward where cultural differences in category learning may be observed in the brain, and where the imprint of culture may be more readily observed. Although few true developmental studies of cultural differences have emerged attempting to link the development of specific constructs with observed behavioral differences throughout the lifespan, there is enough evidence to suggest that cultural practices manifest differences at different points throughout development (Park & Gutchess, 2006; Li, 2003). This "hierarchical organization" is consistent with what would be predicted from the perspective of Luria, perhaps the first true cultural neuropsychologist, and points the way toward helping to determine the possible cultural determinants of category learning.

APPENDIX A

The Abbreviated Multidimensional Acculturation Scale (Zea, et al., 2003; Chung et al., 2004)

Instructions: The following section contains questions about your *culture of origin* and your *native language*. By *culture of origin* we are referring to the culture of the country either you or your parents came from (e.g., Puerto Rico, Cuba, China). By *native language* we refer to the language of that country, spoken by you or your parents in that country (e.g., Spanish, Quechua, Mandarin). If you come from a multicultural family, please choose the culture you relate to the most: ______________________________.

Please mark the number from the scale that best corresponds to your answer.

1	2	3	4
Strongly disagree	Disagree somewhat	Agree somewhat	Strongly agree

1. I think of myself as being U.S. American.
2. I feel good about being U.S. American.
3. Being U.S. American plays an important part in my life.
4. I feel that I am part of U.S. American culture.
5. I have a strong sense of being U.S. American.
6. I am proud of being U.S. American.
7. I think of myself as being (a member of my culture of origin).
8. I feel good about being (a member of my culture of origin).
9. Being (a member of my culture of origin) plays an important part in my life.
10. I feel that I am part of culture (culture of origin).
11. I have a strong sense of being (culture of origin).
12. I am proud of being (culture of origin).

Please answer the questions below using the following responses:

1	2	3	4
Not at all	A little	Pretty well	Extremely well

How well do you speak English:

13. at school or work
14. with American friends
15. on the phone

16. with strangers
17. in general

How well do you understand English:
18. on television or in movies
19. in newspapers and magazines
20. words in songs
21. in general

Please answer the questions below using the following responses:

1	2	3	4
Not at all	A little	Pretty well	Extremely well

How well do you speak your native language:
22. with family
23. with friends from the same country as you
24. on the phone
25. with strangers
26. in general

How well do you understand your native language:
27. on television or in movies
28. in newspapers and magazines
29. words in songs
30. in general

How well do you know:
31. American national heroes
32. popular American television shows
33. popular American newspapers and magazines
34. popular American actors and actresses
35. American history
36. American political leaders

How well do you know:
37. national heroes from your native culture
38. popular television shows in your native language
39. popular newspapers and magazines in your native language
40. popular actors and actresses from your native culture
41. history of your native culture
42. political leaders from your native culture

APPENDIX B

Self-Construal Scale
(S-CS; Singelis, 1994)

<u>Interdependent Items</u>

1. I have respect for the authority figures with whom I interact.
2. It is important for me to maintain harmony within my group.
3. My happiness depends on the happiness of those around me.
4. I would offer my seat in a bus to my professor.
5. I respect people who are modest about themselves.
6. I will sacrifice my self-interest for the benefit of the group I am in.
7. I often have the feeling that my relationships with others are more important than my own accomplishments.
8. I should take into consideration my parent's advice when making education/career plans.
9. It is important to me to respect decisions made by the group.
10. I will stay in a group if they need me, even when I'm not happy with the group.
11. If my brother or sister fails, I feel responsible.
12. Even when I strongly disagree with group members, I avoid an argument.

<u>Independent Items</u>

13. I'd rather say "No" directly, than risk being misunderstood.
14. Speaking up during class is not a problem for me.
15. Having a lively imagination is important to me.
16. I am comfortable with being singled out for praise or rewards.
17. I am the same person at home that I am at school.
18. Being able to take care of myself is a primary concern for me.
19. I act the same way no matter who I am with.
20. I feel comfortable using someone's first name soon after I meet them, even when they are much older than I am.
21. I prefer to be direct and forthright when dealing with people I've just met.
22. I enjoy being unique and different from others in many respects.
23. My personal identity independent of others, is very important to me.
24. I value being in good health above everything.

REFERENCES

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control* 19:6, 716–723.

Allen, S.W., & Brooks, L.R. (1991). Specializing the operation of an explicit rule. *Journal of Experimental Psychology: General, 120*, 3-19.

Arnett, Jeffrey Jensen. (2002). The Psychology of Globalization. *American Psychologist, 57:10*, 774-783.

Ashby, F.G. (1992a). Multidimensional models of categorization. In F.G. Ashby (Ed.). *Multidimensional Models of Perception and Cognition*. Hillsdale, NJ: Erlbaum.

Ashby, F. G. (1992b). Multivariate probability distributions. In F.G. Ashby (Ed.), *Multidimensional models of perception and cognition* (pp. 1-34). Hillsdale, NJ: Erlbaum.

Ashby, F.G., Alfonso-Reese, L.A., Turken, U., & Waldron, E.M. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological Review, 105*, 442-481.

Ashby, F.G., & Ell, S.W. (2001). The neurobiology of human category learning. *Trends in Cognitive Sciences, 5:5*, 204-210.

Ashby, F.G., Ell, S.W., & Waldron, E.M. (2003). Procedural learning in perceptual categorization. *Memory & Cognition, 31*, 1114-1125.

Ashby, F.G., & Gott, R. (1988). Decision rules in the perception and categorization of multidimensional stimuli. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 14,* 33-53.

Ashby, F.G., & Maddox, W.T. (1990). Integrating information from separable psychological dimensions. *Journal of Experimental Psychology: Human Perception and Performance, 16*, 598- 612.

Ashby, F.G., & Maddox, W.T. (1992). Complex decision rules in categorization: Contrasting novice and experienced performance. *Journal of Experimental Psychology: Human Perception and Performance, 18*, 50-71.

Ashby, F.G., & Maddox, W.T. (1993). Relations between prototype, exemplar, and decision bound models of categorization. *Journal of Mathematical Psychology, 37:3*, 372-400.

Ashby, F.G., & Maddox, W.T. (1994). A response time theory of separability and integrality in speeded classification, *Journal of Mathematical Psychology, 33*, 423-466.

Ashby, F.G., & Maddox, W.T. (1998). Stimulus categorization. In M.H. Birnbaum (Ed.) *Measurement, Judgment, and Decision Making*. Academic Press: San Diego.

Ashby, F.G., & Maddox, W.T. (2005). Human category learning. *Annual Review of Psychology, 56,* 149-178.

Ashby, F.G., Maddox, W.T., & Bohil, C.J. (2002). Observational versus feedback training in rule-based and information-integration category learning. *Memory and Cognition, 30:5*, 666-677.

Ashby, F.G., & Townsend, J.T. (1986). Varieties of perceptual independence. *Psychological Review, 93:2*, 154-179.

Atran, S. (1990). *Cognitive foundations of natural history: Toward an anthropology of science*. New York, NY: Cambridge University Press.

Bagley, C., Iwawaki, S.,&Young, L. (1983). Japanese children: Group-oriented but not field-dependent? In C. Bagley & G. Verma (Eds.), *Multi-cultural childhood: Education, ethnicity and cognitive styles* (pp. 27-37). Aldershot, UK: Gower Press.

Berry, J.W. (2004). Psychology of group relations: cultural and social dimensions. *Aviation, Space, and Environmental Medicine, 75:7C*, 52-57.

Berry, J.W., & Annis, R.C. (1974). Ecology, culture, and psychological differentiation. *International Journal of Psychology, 9:3*, 173-193.

Berry, J.W., Poortinga, Y.H., Segall, M., & Dasen, P.R. (1992). *Cross-cultural Psychology: Research and Applications*. New York: Cambridge University Press.

Betancourt, H., & Lopez, S.R. (1993). The study of culture, ethnicity, and race in American psychology. *American Psychologist, 48:6*, 629-637.

Bhatia, S., & Ram, A. (2004). Culture, hybridity, and the dialogical self: Cases from the South Asian Diaspora. *Mind, Culture, and Activity, 11:3,* 224-240.

Bialystok, E. (2007). Language acquisition and bilingualism: Consequences for a multilingual society. *Applied Psycholinguistics, 28:3*, 393-397.

Bloom, A.H. (1981). *The linguistic shaping of thought: A study in the impact of language on thinking in China and the west.* Hillsdale, NJ: Erlbaum.

Cantlon, J.F., & Brannon, E.M. (2006). Adding up the effects of cultural experience on the brain. *Trends in Cognitive Sciences, 11:1*, 1-4.

Chalfonte, B.L., & Johnson, M.K. (1996). Feature memory and binding in younger and older adults. *Memory and Cognition, 24*, 403-416.

Chen, S.Y., Yang, B.M., & Gao, Y.P. (1989). *The group embedded figures test (Chinese version).* Beijing University Press: Beijing, PR China.

Chirkov, V.I., Lynch, M., & Niwa, S. (2005). Application of the scenario questionnaire of horizontal and vertical individualism and collectivism to the assessment of cultural distance and cultural fit. International *Journal of Intercultural Relations, 29*, 469-490.

Chiu, L.-H. (1972). A cross-cultural comparison of cognitive styles in Chinese and American children. *International Journal of Psychology, 7*, 235-242.

Choi, I., & Nisbett, R.E. (2000). The cultural psychology of surprise: Holistic theories and recognition of contradiction. *Journal of Personality and Social Psychology, 79*, 890-905.

Choi, I., Nisbett, R.E., & Smith, E.E. (1997). Culture, categorization, and inductive reasoning. *Cognition, 65*, 15-32.

Chua, H.F., Boland, J.E., & Nisbett, R.E. (2005). Cultural variation in eye movements during scene perception. *Proceedings of the National Academy of Sciences of the United States of America, 102:35*, 12629-12633.

Chung, R.H.G., Kim, B.S.K., & Abreu, J.M (2004). Asian American Multidimensional Acculturation Scale: Development, Factor Analysis, Reliability, and Validity. *Cultural Diversity and Ethnic Minority Psychology, 10:1*, 66-80.

Cohen, A.P. (1994). *Self-consciousness: An alternative anthropology of identity*. London: Routledge.

Cohen, R. (1969). Conceptual styles, culture conflict, and nonverbal tests of intelligence. *American Anthropologist, 71:5*, 825-856.

Cole, M. (1996). *Cultural psychology: A once and future discipline*. Cambridge: Harvard University Press.

Cole, M., & Means, B. (1981). *Comparative studies of how people think: An introduction*. Cambridge, MA, US: Harvard University Press.

Coon, H.M., & Kemmelmeier, M. (2001). Cultural orientations in the United States (re)examining differences among ethnic groups. *Journal of Cross-Cultural Psychology, 32:3*, 348-364.

D'Andrade, R., & Strauss, C. (1992). *Human motives and cultural models*. Cambridge: Cambridge University Press.

Davenport, J.L., & Potter, M.C. (2004). Scene consistency in object and background perception. *Psychological Science, 15:8*, 559-564.

DeVos, G.A. (1980). Ethnic adaptation and minority status. *Journal of Cross-Cultural Psychology, 11:1*, 101-124.

DiMaggio, P. (1997). Culture and cognition. *Annual Review of Sociology, 23*, 263-287.

Doyle, J.M. (2006). What race and ethnicity measure in pharmacologic research. *Journal of Clinical Pharmacology, 46*, 401-404.

Eagle, M., Goldberger, L., & Breitman, M. (1969). Field dependence and memory for social versus neutral and relevant versus irrelevant incidental stimuli. *Perceptual and Motor Skills, 29*, 903-910.

Elliott, R., Rees, G., & Dolan, R. J. (1999). Ventromedial prefrontal cortex mediates guessing. *Neuropsychologia, 37*, 403-411.

Fernald, A., & Morikawa, Hiromi. (1993). Common themes and cultural variations in Japanese and American Mother's Speech. *Child Development, 64*, 637-656.

Ferraro, F. Richard (ED.). (2002). *Minority and cross-cultural aspects of neuropsychological assessment:* Lisse, Netherlands: Swets & Zeitlinger.

Ferraro, F.R., & McDonald, L.R. (2005). More culturally sensitive neuropsychological tests (and normative data) needed. *Alzheimer's Disease and Associated Disorders, 19:2,* 53-54.

Filoteo, J.V., & Maddox, W.T. (2004). A quantitative model-based approach to examining aging effects on information-integration category learning. *Psychology and Aging, 19:1*, 171-182.

Filoteo, J.V. & Maddox, W.T. (1999). Quantitative modeling of visual attention processes in patients with Parkinson's disease: Effects of stimulus integrality on selective attention and dimensional integration. *Neuropsychology, 13*, 206-222.

Filoteo, J.V., Maddox, W.T., & Davis, J.D. (2001). Quantitative modeling of category learning in patients with amnesia. *Journal of the International Neuropsychological Society 7*, 1-19.

Filoteo, J.V., Maddox, W.T., Simmons, A.N., Ing, A.D., Cagigas, X.E., Mathews, S., & Paulus, M.P. (2005). Cortical and subcortical brain regions involved in rule-based category learning. *Neuroreport, 16:2*, 111-115.

Fletcher-Janzen, Elaine (ED.), Strickland, Tony L. (ED.), & Reynolds, Cecil R. (ED.). (2000). *Handbook of Cross-Cultural Neuropsychology*. New York, NY: Kluwer Academic/Plenum Publishers.

Garber, M., & Arnold, R.M. (2006). Promoting participation of minorities in research. American Journal of Bioethics, 6:3, 14-20.

Goh, J.O.S., Siong, S.C., Park, D., Gutchess, A., Hebrank, A., & Chee, M.W.L. (2004). Cortical areas involved in object, background, and object-background processing revealed with functional magnetic resonance adaptation. *The Journal of Neuroscience, 24:45*, 10223-10228.

Goode, P.E., Goddard, P.H., & Pascual-Leone, J. (2002). Event-related potentials index cognitive style differences during a serial-order recall task. International *Journal of Psychophysiology, 43*, 123-140.

Gould, S. J. 1995, *The mismeasure of man*. New York: W.W. Norton and Company.

Green, D.M., & Swets, J.A. (1966). *Signal detection theory and psychophysics.* Oxford, England: Wiley.

Greenfield, P.M. (2000). Three approaches to the psychology of culture: Where do they come from? Where can they go? *Asian Journal of Social Psychology, 3*, 223-240.

Grön, G., Schul, D., Bretschneider, V., Wunderlich, A.P., & Riepe, M.W. (2003). Alike performance during nonverbal episodic learning from diversely imprinted neural networks. *European Journal of Neuroscience, 18*, 3112-3120.

Gutchess, A.H., Welsch, R.C., Boduroglu, A., & Park, D. (2006). Cultural differences in neural function associated with object processing. *Cognitive, Affective, & Behavioral Neuroscience, 6:2*, 102-109.

Harty, L., Johnson, K., & Power, A. (2006). Race and ethnicity in the era of emerging pharmacogenomics. *Journal of Clinical Pharmacology, 46*, 405-407.

Hedden, T., Ketay, S., Aron, A., Markus, H.R., Gabrieli, J.D. (2008). Cultural influences on neural substrates of attention control. *Psychological Science, 19:1*, 12-17.

Heine, S.J., & Norenzayan, A. (2006). Toward a psychological science for cultural species. *Perspectives on Psychological Science, 1:3,* 251-269.

Helms, J.E. (1992). Why is there no study of cultural equivalence in standardized cognitive ability testing? *American Psychologist, 47*, 1083-1101.

Helms, J.E., Jernigan, M., & Mascher, J. (2005). The meaning of race in psychology and how to change it: A methodological perspective. *American Psychologist, 60:1*, 27-36.

Hofstede, G. (1991). *Cultures and organizations*. London: McGraw-Hill.

Hong, Y.-y., Benet-Martinez, V., Chiu, C.-y., & Morris, M.W. (2003). Boundaries of cultural influence: Construct activation as a mechanism for cultural differences in social perception. *Journal of Cross-cultural Psychology, 34:4*, 453-464.

Hong, Y.-y., & Mallorie, L.A.M. (2004). A dynamic constructivist approach to culture: Lessons learned from personality psychology. *Journal of Research in Personality, 38:1*, 59-67.

Hong, Y.-y., Chiu, C.-y., & Kung, T. (1997). Bringing culture out in front: Effects of cultural meaning system activation on social cognition. In K. Leung, Y. Kashima, U. Kim, & S. Yamaguchi (Eds.), *Progress in Asian Social Psychology* (Vol. 1, pp. 135-146). Singapore: Wiley.

Hui, C.H., & Yee, C. (1994). The shortened individualism-collectivism scale: Its relationship to demographic and work-related variables. *Journal of Research in Personality, 28,* 409-424.

Hunt, E., & Agnoli, F. (1991). The Whorfian hypothesis: A cognitive psychology perspective. *Psychological Review, 98:3*, 337-389.

Hunt, L.M. (2005). Health research: what's culture got to do with it? *The Lancet, 366*, 617-618.

Ji, L., Zhang, Z., & Nisbett, R.E. (2004). Is It Culture or Is It Language? Examination of Language Effects in Cross-Cultural Research on Categorization. *Journal of Personality & Social Psychology. 87*, 57-65

Ji, L., Peng, K., & Nisbett, R.E. (2000). Culture, control, and perception of relationships in the environment. Journal of Personality and Social Psychology, 78, 943-955.

Knowlton, B.J., Squire, L.R., & Gluck, M.A. (1994). Probabilistic classification learning in amnesia. *Learning and. Memory. 1*, 106–20.

Kozhevnikov, M., Kosslyn, S., & Shephard, J. (2005). Spatial versus object visualizers: a new characterization of visual cognitive style. *Memory and Cognition, 33:4*, 710-726.

Kühnen, U., Hannover, B., Röder, U., Schubert, B., Shah, A.A., & Zakaria, S. (2001). Cross-cultural variations in identifying embedded figures: Comparison of U.S., Germany, Russia, Malaysia. *Journal of Cross-cultural Psychology, 32:3*, 365-371.

Kühnen, U., & Oyserman, D. (2002). Thinking about the self influences thinking in general: cognitive consequences of salient self-concept. *Journal of Experimental Social Psychology, 38:5*, 492-499.

Lehman, D.R., Chiu, C-Y., & Schaller, M. (2004). Psychology and Culture. *Annual Review of Psychology, 55*, 689-714.

Li, S.C. (2003). Biocultural orchestration of developmental plasticity across levels: The interplay of biology and culture in shaping mind and behavior across the life span. *Psychological Bulletin, 129*, 171-194.

Lin, K.M., & Poland, R.E. (1995). Ethnicity, culture and psychopharmacology. In: F.E. Bloom, & D.J. Kupfer DJ (Eds.) *Psychopharmacology: the fourth generation of progress.* Raven Press, New York, pp 1907–1917

Llorente, A.M., Ponton, M.O., Taussig, I.M., & Satz, P. (1999). Patterns of American immigration and their influence on the acquisition of neuropsychological norms for Hispanics. *Archives of Clinical Neuropsychology, 14:7*, 603-614.

Llorente, A.M. (Ed.). *Principles of neuropsychological assessment with Hispanics: Theoretical foundations and clinical practice. Issues in diversity in clinical neuropsychology.* New York, NY: Springer Science.

Luria, A.R. (1931). Psychological expedition to Central Asia. *Science, 74*, 383-384.

Luria, A.R. (1976). *Cognitive development: Its cultural and social foundations*. Cambridge: Harvard University Press.

Maddox, W.T. (1992). Perceptual and decisional separability. In F. G. Ashby (Ed.), *Multidimensional models of perception and cognition* (pp. 147-180). Hillsdale, NJ: Erlbaum.

Maddox, W.T. (1995). Baserate effects in multidimensional perceptual categorization. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 21*, 288-301.

Maddox, W.T., & Ashby, F.G. (1993). Comparing decision bound and exemplar models of categorization. *Perception & Psychophysics, 53*, 49-70.

Maddox, W.T., & Ashby, F.G. (2004). Dissociating explicit and procedural-learning based systems of perceptual category learning. *Behavioural Processes, 66:3*, 309-332.

Maddox, W.T., Ashby, F.G., & Bohil, C.J. (2003). Delayed feedback effects on rule-based and information-integration category learning. *Journal of Experimental Psychology. Learning, memory and cognition, 29:4*, 650-662.

Maddox, W.T., Ashby, F.G., & Gottlob, L.R. (1998). Response time distributions in multidimensional perceptual categorization. *Perception & Psychophysics, 60*, 620-637.

Maddox, W.T., Ashby, F.G., Ing, A.D., & Pickering, A.D. (2004). Disrupting feedback processing interferes with rule-based but not information-integration category learning. *Memory and Cognition, 32:4*, 582-591.

Maddox, W. T., & Bohil, C. J. (1998). Overestimation of base-rate differences in complex perceptual categories. *Perception and Psychophysics, 60*, 575-592.

Maddox, W.T., & Filoteo, J.V. (2001). Striatal contributions to category learning: Quantitative modeling of simple linear and complex nonlinear rule learning in patients with Parkinson's disease. *Journal of the International Neuropsychological Society*.

Maddox, W.T., Filoteo, J.V., Delis, D.C., & Salmon, D.P. (1996). Visual selective attention deficits in patients with Parkinson's disease: A quantitative model-based approach. *Neuropsychology, 10*, 197-218.

Maddox, W.T., Filoteo, J.V., Hejl, K.D., & Ing, A.D. (2004). Category number impacts rule-based but not information-integration category learning: further evidence for dissociable category-learning systems. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 30:1*, 227-245.

Maddox, W.T., Filoteo, J.V., & Huntington, J.R. (1998). Effects of stimulus integrality on visual attention in older and younger adults: A quantitative model-based analysis. *Psychology and Aging, 13*, 472-485.

Manly, J.J. (2006). Deconstructing race and ethnicity: Implications for measurement of health outcomes. *Medical Care, 11:3*, S10-S16.

Markus, H.R., & Kitayama, S. (1991). Culture and the self: Implications for cognition, emotion, and motivation. *Psychological Review, 98,* 224-253.

Masuda, T., & Nisbett, R.E. (2001). Attending holistically vs analytically: comparing the context sensitivity of Japanese and Americans. *Journal of Personality and Social Psychology, 81*, 922-934.

Matsumoto, D., Weissman, M., Preston, K., Brown, B., & Kupperbush, C. (1997). Context-specific measurement of individualism-collectivism. *Journal of Cross Cultural Psychology, 28,* 743-767.

Matsumoto, D., & Yoo, S.H. (2006). Toward a new generation of cross-cultural research. *Perspectives on Psychological Science, 1:3*, 234-250.

McKinley, S.C., & Nosofsky, R.M. (1995). Investigations of exemplar and decision bound models n large, ill-defined category structures. *Journal of Experimental Psychology: Human Perception & Performance, 21*, 128-148.

McKinley, S.C. & Nosofsky, R.M (1996). Selective attention and the formation of linear decision boundaries. *Journal of Experimental Psychology: Human Perception and Performance, 22*, 294-317.

Medin, D.L., & Atran, S. (2004). The native mind: Biological categorization and reasoning in development and across cultures. *Psychological Review, 111:4*, 960-983.

Medin, D.L., & Schaffer, M.M. (1978). Context theory of classification learning. *Psychological Review, 85:3*, 207-238.

Medin, D.L., Wattenmaker, W.D., & Hampson, S.E. (1987). Family resemblance, conceptual cohesiveness, and category construction. *Cognitive Psychology, 19:2*, 242-279.

Medin, D.L., & Schwanenflugel, P.J. (1981). Linear separability in classification learning. *Journal of Experimental Psychology: Human Learning and Memory, 1*, 335-368.

Mishra, R.C., & Tripathi, N. (1996). Reproduction of patterns in relation to children's weaving experiences. In J. Pandey, D. Sinha, D. Bhawuk (Eds.) *Asian contributions to cross-cultural psychology* (pp. 138-150). Thousand Oaks, CA: Sage Publications, Inc., 366 pp.

Miyamoto, Y., Nisbett, R.E., & Masuda, T. (2006). Culture and the physical environment: Holistic versus analytic perceptual affordances. *Psychological Science, 17:2*, 113-119.

Nell, V. (2000). *Cross-cultural neuropsychological assessment: Theory and practice.* Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Nisbett, R.E. (2003). *The geography of thought*. New York, NY: The Free Press.

Nisbett, R.E., & Miyamoto, Y. (2005). The influence of culture: holistic versus analytic perception. *Trends in Cognitive Sciences, 9:10*, 467-473.

Nisbett, R.E., Peng, K., Choi, I., & Norenzayan, A. (2001). Culture and systems of thought: holistic versus analytic cognition. *Psychological Review, 108*, 291-310.

Nomura, E.M., Maddox, W.T., Filoteo, J.V., Ing, A.D., Gitelman, D.R., Parrish, T.B., Mesulam, M.M., & Reber, P.J. (2007). Neural correlates of rule-based and information-integration visual category learning. *Cerebral Cortex, 17:1*, 37-43.

Norenzayan, A. (2001). Rule-based and experience-based thinking: The cognitive consequences of intellectual traditions. Unpublished Ph.D. thesis, University of Michigan, Ann Arbor, MI.

Norenzayan, A., Smith, E.E., Kim, B.J., & Nisbett, R.E. (2002). Cultural preferences for formal versus intuitive reasoning. *Cognitive Science, 26:5*, 653-684.

O'Bryant, Sid E., O'Jile, Judith R., McCaffrey, Robert, J. (2004). Reporting of demographic variables in neuropsychological research: Trends in the current literature. *The Clinical Neuropsychologist, 18:2*, 229-233.

Oyserman, D., Coon, H.M., Kemmelmeier, M. (2002). Rethinking individualism and collectivism: Evaluation of theoretical assumptions and meta-analyses. *Psychological Bulletin, 128:1*, 3-72.

Oyserman, D., & Lee, S.W.S. (2008). Does culture influence what and how we think? Effects of priming individualism and collectivism. *Psychological Bulletin, 134:2*, 311-342.

Park, D., & Gutchess, A. (2006). The cognitive neuroscience of aging and culture. *Current Directions in Psychological Science, 15:3*, 105-108.

Peng, K., & Nisbett, R.E. (1999). Culture, dialectics, and reasoning about contradiction. *American Psychologist, 54*, 741-754.

Pérez-Arce, Patricia. (1999). The influence of culture on cognition. *Archives of Clinical Neuropsychology, 14:7*, 581-592.

Phinney, J.S. (1996). When we talk about American ethnic groups, what do we mean? *American Psychologist, 51*, 918-927.

Poldrack, R.A. (2006). Can cognitive processes be inferred from neuroimaging data? *Trends in Cognitive Science, 10(2)*, 59-63.

Posner, M.I., & Keele, S.W. (1968). On the genesis of abstract ideas. *Journal of Experimental Psychology, 77*, 353-363.

Rayner, K. Li, X., Williams, C.C., Cave, K.R., & Well, A.D. (2007). Eye movements during information processing tasks: Individual differences and cultural effects. *Vision Research, 47*, 2714-2726.

Reber, P. J., Stark, C. E. L., and Squire, L. R. (1998). Cortical areas supporting category learning identified using functional MRI. *Proceedings of the National Academy of Sciences of the United States of America*, *95*, 747-750.

Regehr, G., & Brooks, L.R. (1993). Perceptual manifestations of analytic structure: The priority of holistic individuation. *Journal of Experimental Psychology: General, 122*, 92-114.

Romney, A.K., Boyd, J.P., Moore, C.C., Batchelder, W.H., & Brazill, T.J. (1996). Culture as shared cognitive representations. *Proceedings of the National Academy of Sciences, U.S.A., 93*, 4699-4705.

Romney, A.K., Weller, S.C., Batchelder, W.H. (1986). Culture as consensus: A theory of culture and informant accuracy. *American Anthropologist, 88*, 313-338.

Ruiz, P. (2000). *Ethnicity and psychopharmacology. Review Of Psychiatry, Volume 19.* The Eurospan Group, London.

Serpell, R. (1979). How specific are perceptual skills? A cross-cultural study of pattern reproduction. *British Journal of Psychology, 70*, 365-380.

Schwartz, S.H. (1994). Beyond individualism-collectivism: New cultural dimensions of values. In U. Kim, H. Triandis, C. Kagitcibasi, S-C. Choi, & G. Yoon (Eds.), Individualism *and collectivism: Theory, method, and applications* (pp. 85-122). Thousand Oaks, CA: Sage.

Sheikh, A. (2006). Why are ethnic minorities under-represented in US research studies? Public Library of Science, 3:2, e49, 166-167.

Shore, B. (1996). *Culture in mind: Cognition, culture and the problem of meaning*. New York: Oxford University Press.

Shweder, R.A. (1999). Why cultural psychology? *Ethos, 27*, 62-73.

Simons, D.J., & Levin, D.T. (1997). Change blindness. Trends in Cognitive Sciences, 1, 261-267.

Singelis, T.M. (1994). The measurement of independent and interdependent self-construals. *Personality and Social Psychology Bulletin, 20:5*, 580-591.

Smedley, A., & Smedley, B.D. (2005). Race as biology is fiction, racism as a social problem is real: Anthropological and historical perspectives on the social construction of race. *American Psychologist, 60:1,* 16-26.

Smith, J.D., & Minda, J.P. (1998). Prototypes in the mist: the early epochs of category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 24,* 1411-1430.

Smith, E.E., Patalano, A.L., & Jonides, J. (1998). Alternative strategies of categorization. *Cognition, 65*, 167-196.

Snowden, L. R. (2003). Bias in mental health assessment and intervention. *American Journal of Public Health*, *93* (2), 239-243.

Sonke, C.J., Poortinga, Y.H., deKuijer, J.H.J. (1999). Cross-cultural differences on cognitive task performance: The influence of stimulus familiarity. In W.J. Lonner, D.L. Dinnel, D.K. Forgays, S.A. Hayes (Eds.) *Merging past, present, and future in cross-cultural psychology: Selected papers from the Fourteenth International Congress of the International Association for Cross-Cultural Psychology*. (pp. 146-158). Lisse, Netherlands: Swets & Zeitlinger Publishers, 531 pp.

Strauss, C. & Quinn, N. (1997). *A cognitive theory of cultural meaning*. Cambridge University Press.

Takane, Y., & Shibayama, T. (1992). Structures in stimulus identification data. In Ashby, F. Gregory (Ed.) *Multidimensional models of perception and cognition. Scientific psychology series.* (pp. 335-362). Hillsdale, NJ, England: Lawrence Erlbaum Associates, Inc.

Thompson, B., & Melancon, J.G. (1987). Measurement characteristics of the Group Embedded Figures Test. *Educational and Psychological Measurement, 47*, 765-772.

Triandis, H.C. (1996). The psychological measurement of cultural syndromes. *American Psychologist, 51(4),* 407-415.

Trompenaars, F. (1993). Riding the waves of culture. London: Economist Books.

Ungerleider, L. G., & Mishkin, M. (1982). Two cortical visual systems. In M. A. Goodale, D. J. Ingle, & R. J. W. Mansfield (Eds.), *Analysis of visual behavior* (pp. 549-585). Cambridge, MA: MIT Press.

Unsworth, S.J., Sears, C.R., & Pexman, P.M. (2005). Cultural influences on categorization processes. *Journal of cross-cultural psychology, 36:6*, 662-688.

U.S. Bureau of the Census (1990). *Profile of general demographic characteristics.* Washington, DC: Author.

U.S. Bureau of the Census. (2000). 2000 *Census of population: General population characteristics.* Washington, DC: Author.

U.S. Bureau of the Census (2001). *Nation's Asian and Pacific Islander population (profile).* Washington, DC: Author.

U.S. Census Bureau. (2004). U.S. Interim Projections by Age, Sex, Race and Hispanic Origin. http://www.census.gov/ipc/www/usinterimproj/ Internet Release Date: March 18, 2004.

U.S. Department of Health and Human Services (2001). *Mental Health: Culture, Race, and Ethnicity — A supplement to Mental Health: A report of the Surgeon General.* Rockville, MD: Author. CD ROM.

Waldron, E.M., & Ashby, F.G. (2001). The effects of concurrent task interference on category learning: evidence for multiple category learning systems. *Psychonomic Bulletin and Review, 8:1,* 168-176.

Wendler, D., Kington, R., Madans, J., Van Wye, G., Christ-Schmidt, H., Pratt, L.A., Brawley, O.W., Gross, C.P., & Emanuel, E. (2006). Are racial and ethnic minorities less willing to participate in health research? Public Library of Science, 3:2, e19, 201-210.

Wickens, T.D. (1982). *Models for behavior: Stochastic processes in psychology.* San Francisco, CA: Freeman & Company.

Witkin, H.A., & Berry, J.W. (1975). Psychological differentiation in cross cultural perspective. *Journal of Cross Cultural Psychology, 6*, 4-87.

Witkin, H.A., Dyk, R.B., Faterson, H.F., Goodenough, D.R., & Karp, S.A. (1974). *Psychological Differentiation*. Potomac: Lawrence Erlbaum Associates.

Witkin, H.A., & Goodenough, D.R. (1977). Field dependence and interpersonal behavior. *Psychological Bulletin, 84*, 661-689.

Witkin, H.A., Lewis, H.B., Hertzman, M., Machover, K., Messiner, P.B., & Karp, S.A. (1954). Personality Through Perception. New York: Harper.

Witkin, H.A., Oltman, P.K., Raskin, E., & Karp, S.A. (1971, 2002). *A manual for the Embedded Figures Tests.* Palo Alto, CA: Consulting Psychologists Press.

Whorf, B.L. (1956). *Language, thought, and reality.* Cambridge, MA: MIT Press.

Yancey, A.K., Ortega, A.N., & Kumanyika, S.K. (2006). Effective recruitment and retention of minority research participants. Annual Review of Public Health, 27, 1-28.

Zhang, L. (2004). Field-dependence/independence: cognitive style or perceptual ability? *Personality and Individual Differences, 37:6*, 1295-1311.

Zea, M.C., Asner-Self, K.K., Birman, D., & Buki, L.P. (2003). The abbreviated multidimensional acculturation scale: Empirical validation with two Latino/Latina samples. *Cultural Diversity and Ethnic Minority Psychology, 9:2*, 107-126.