SHARED SEMANTIC STRUCTURES
FOR AUTOMOBILE BRANDS AMONG U.S. RESIDENTS

BY NAMANH V. HOANG

Abstract

This research utilizes implementation of classic methods for systematic data collection using the medium of the Internet to investigate the idea of culture as a shared cognitive semantic structure. We used the material domain of automobile manufacturer brand names to investigate our intuition that a shared understanding exists within the American culture and is pervasive across a diversity of demographic groups. Semantic structure information for 48 automobile manufacturer brand names was obtained using two association tasks (free-list and pile-sort) for a sample of 927 English-speaking United States residents recruited from online sources. Using this data, we estimate the shared structure of perceived similarity among automobile brands within the sampled population, and investigate the extent to which this structure reflects a cultural consensus, which is shared across demographic groups. Employing multidimensional scaling methods, we explore the properties of this structure and provide our interpretation in terms of known brand attributes. Via an additional instrument, we also measure subjects' tendency to infer that novel information regarding one brand will be causally relevant for assessing the properties of other brands. We use this data to test the hypothesis that closely associated brands are seen as causally relevant, net of objective factors such as ownership by the same firm.

Major findings include the following: (i) a comparison of semantic structures on the semantic domain of automobile brand names among subjects shows strong consensus with little variation across demographic groups, (ii) the different elicitation methods give strong convergent results, (iii) the detectable properties in determining semantic structure are region of origin and perceived brand luxuriousness, and (iv) the semantic structure of automobile brand names shows weak correlation between closely associated brands and causal relevancy.

These results show that knowledge of the domain of automobile manufacturer brand names is representative of a systemic pattern with significant cultural investment, and that administration of cognitive association methods via an Internet-based instrument is appropriate for measuring these less intuitive domains and are adequate for producing large and diverse samples across vast geographic distances.

Introduction

This article outlines developments and research that have led to the theory of culture as a shared cognitive structure, and offers a practical example of methods for collecting, analyzing, and constructing semantic structural data. This study builds on previous methodological writings on free-list data and pile-sort data as a useful way to collect (e.g., Weller and Romney 1988; Romney, Moore, Batchelder, and Hsia 1999; Ryan, Nolan and Yoder 2000; Brewer, Garrett, and Rinaldi 2002; Quinlan 2005) and organize aggregate data (e.g., Weller and Romney 1988; Romney, Brewer, and Batchelder 1993; Smith 1993; Smith et al. 1995; Smith and Borgatti 1997; Sutrop 2001; Thompson and Juan 2006). We have organized this field of inquiry in a way that can enhance future research, particularly with regard to application of the methods in a real world setting with a focus on the following attributes: large first-world populations and large geographic areas.

Numerous methodological writings and analyses in cognitive anthropology and social networks have concentrated mostly on comparisons between intuitive domains using small sample populations. Our work, however, capitalizes on technological advances available today as a means for studying less intuitive domains using larger sample populations of complex cultures. To accomplish this, we will employ Web-based tools on traditional methods such as the use of free-listing (Romney, Moore, Batchelder and Hsia 2000; Romney, Brewer, and Batchelder 1993) and pile-sorting (Miller and Johnson 1981; Roberts and Chick 1979; Roberts, Golder and Chick 1980; Roberts, Chick, Stephenson, and Hyde 1981; Freeman, Romney, and Freeman 1981; Romney, Smith, Freeman, Kagen and Klein 1979) to infer extent of similarity in a domain, defined as the arrangement of the terms relative to each other. A summary of methods for systematic data collection is contained in Weller and Romney's Systematic Data Collection (1988).

To illustrate use of these methods in the context of a material domain within a large complex culture, we used free-list and pile-sort data collected from 927 United States residents, ages 18 and over, with a relatively even distribution across all 50 states (exception of slightly higher participation rates in Los Angeles and New York City), that does not differ from the 2000 U.S. Bureau of Census data in meaningful ways (with the exception of disproportionately higher participation rates for males than females). We used automobiles as the domain and automobile manufacturer brand names as the elements within the domain. Our claim is that the sample can be generalized to a majority of citizens of the United States and that the results are shaped by a United States frame of reference and represent culture as a shared understanding of this material domain.

The result or our research found that Americans do have a very clear and strong perception of the automobile manufacturer brand name domain. This consensus was so strong that it was consistent across all demographic groups, which confirms our hypothesis that automobile brand names serve as a significant symbol in American culture. From a substantive point of view, in relation to branding and marketing, it become apparent that automobile manufactures cannot escape the fact that country of origin is one of the most important top of mind identifications made by consumers and therefore by that same token, brands will find it an arduous task to change the perceptions attached to a particular country or region in terms of automobile manufacturing.

From Systemic Patterns to Cultural Consensus

The concept of systemic patterns was first defined by Kroeber (1948) as a system of cultural material that has a functional utility within a culture that allows it to continue to persist throughout that culture, across time, as a unit. These cultural units are limited to only one aspect of culture (subsistence, religion or economics), can be diffused cross-culturally from one person or peoples to another, and can be modified over time but only with great effort. In other words, culture itself is made up of numerous culture units, primarily those that have proven utility to the culture and, as such, serve as a pattern that preserves that culture.

John M. Roberts would build upon Kroeber's theories on systemic patterns by suggesting that pattern nomenclatures could be used to make inferences about the internal structure of systemic patterns. Roberts suggested that the organization of these patterns are examples of high-concordance codes (pattern elements), and described this as follows:

> In the case of high-concordance patterns, i.e., those patterns known by the vast majority of adults in a culture, the linguistic codes for the patterns are well designed for general communication since they have been forged in the fires of millions of discussions of the pattern. Indeed, these pattern nomenclatures are themselves high-concordance codes. This linguistic integration of the pattern into the language of the host culture is most important. (Roberts, Strand and Burmeister, 1971:245)

Roberts explored the issue in a study using the tailored clothing complex as the systemic pattern across seven countries (Roberts, Strand, and Burmeister 1971) and in his classic study of intracultural sharing, "Three Navaho Household" (Roberts 1951) and later further by D'Andrade (1989). Gary Chick suggests "The elements that compose systemic patterns are assembled in high-concordance codes in that their meanings and the relationships among them are well understood by members of the culture or subculture to which they pertain" (Chick, 2000:369). These patterns also tend to exhibit low variance over time or space, and are common in linguistic terminology for numbers, colors, kin, and so on. This indicates a significant cultural investment in these patterns that allows them to both persist and evolve.

Romney and Moore (2001) observed that paradigmatic structures may be well represented in low-dimensional Euclidean space. This allows for the generalization of the paradigmatic structure of the prototypical systemic culture patterns to structures with large or uncountable numbers of features. Built upon Kroeber's concept of systemic culture patterns (Roberts, Chick, Stephenson, and Hyde 1981), the key method was the collection of judged similarity data among domain elements and subsequent analysis with multidimensional scaling programs. Romney and Moore's classic papers *Systemic Culture Patterns as Basic Units of Cultural Transmission and Evolution* (2001) and *Towards a Theory of Culture as Shared Cognitive Structures* (1998) serve as a bridge of understanding between Kroeber and Roberts original theories and findings, which coalesce into a single theoretical and methodological foundation. Romney and Moore succinctly summarizes this concept:

> We can now measure with known accuracy the extent to which "pictures" or cognitive representations in the mind of one person correspond to those in the mind of another. Not only can we measure the extent to which a large number of individuals "share" the same picture, but we can make multiple measures of the picture in the mind of a single individual…. The structure of a semantic domain is defined as the arrangement of the terms relative to each other as represented in some metric system, such as Euclidean space, and described as a set of interpoint distances reflecting the dissimilarity between them. In this space, items that are judged more similar are closer to each other than items that are judged less similar. (Romney et al., 1996, p. 4699)

Numerous exemplar studies have been conducted in a variety of behavioral and semantic domains to validate both theory and methods. Examples range from eight-ball pool (Roberts and Chick 1979), tennis (Roberts, Chick, Stephenson and Hyde 1981), pilot error (Roberts, Golder, and Chick 1980), trapshooting (Roberts and Nattrass 1980, kinship terms (Romney 1965; Romney 1967; Romney and D'Andrade 1964; Matthews 1959; Lounsbury 1964; Lounsbury 1956), emotion terms (Romney, Moore, Batchelder and Hsia 1999), disease (Weller and Baer 2001), and colors (Moore, Romney and Hsia 2000). These studies confirmed the effectiveness of systematic data collections methods, analyses, and graph representation for interpreting systematic patterns as a measure of culture.

New Technology for Collecting Semantic Structural Data

There is a tremendous expansion of new technologies available today that allow us to consider new implementations of classic systematic data collection methods via the Internet. A number of Internet-based computer-mediated communications (CMC) tools have been developed for conducting pile-sort (CardZort, CardSort, WebCAT, IBM EZSort, Websort, BMC Card Sorting), although none to our knowledge have been developed for conducting free-list (word-list) tasks. Surprisingly, there has been little use of these tools to date in conducting cultural semantic structure research. For the most part, these applications have been developed primarily for commercial use in marketing and evaluating corporate organizational hierarchy. While tremendous innovations have been made in the analysis of semantic structure data, there has been little attempt to implement complementary Web-based data collection tools, which could be particularly valuable for conducting research that requires a large sample population and spans across a large geographical space.

We do agree that this approach is feasible only to the extent by which members of the culture in question are familiar with and have reasonable access to adequate computer technology. CMC methods may be completely viable under conditions such as those found in technologically advanced first-world nations, where it can be safely assumed that the requirement of computer access will not bias the representative sample in any major way so long as the target sample does not have distinct characteristics that would significantly restrict access to and/or not have operational knowledge of a computer. Examples of these demographics include the homeless, minor children, and lower SES individuals. Although the number of people who connect to or use the Internet is undetermined (to date), it is estimated that in 2007 there were approximately 223 million users in the United States (NUA Internet Surveys 2007), which accounted for a 69.9% population penetration against an estimated U.S. population of 301 million. In a review of issues and approaches to using Web surveys, Mick Couper suggested that,

> Web surveys make feasible the delivery of multimedia survey content to respondents in a standardized way using self-administered methods…More so than any other mode of survey data collection, the Internet has lead to a large number of different data-collection uses, varying widely on several dimensions of survey quality. Any critique of a particular Web survey approach must be done in the context of its intended purpose and the claims it makes. (Couper, 1999:465-467)

Clearly the judgment of the quality of Internet-based semantic structure data collection methods should be evaluated in light of alternative designs aimed at similar goals. Previous research in the field of systemic data collection and systemic patterns has been conducted to validate the theories for which they are based and, as such, are conducted in relatively intuitive domains that are generally universal (kinship terms, color, emotion terms, animals, and fruits). Most of these studies usually had an average sample population of approximately 30 (Romney, Brewer, and Batchelder 1993; Moore, Romney, Hsia 2000; Romney, Moore, Batchelder, and Hsia 1999; Roberts, Strand and Burmeister 1971; Roberts 1951; D'Andrade 1989) and rarely exceeded 100 (Osgood, Suci, and Tannenbaum 1957). Osgood and his associates noted as follows:

> Perhaps the greatest inadequacy has been in subject variance. Ideally, our subject sample should be a representative cross-section of the general population. As the reader will realize, it is difficult and expensive to obtain such a sample; it is also hard to use subjects of this sort in a prolonged study and get across instructions for what seems superficially to be a rather trivial and repetitious task." (Osgood, Suci, and Tannenbaum 1957:32)

However, if the research aims are more of a practical substantive focus in seemingly less intuitive domains, such as consumer products and commodities, music, and art, we might expect greater variability—particularly in diverse and complex cultures. In these situations, the sample population must be representative of the target population, which would require not only a larger sample population but also geographic representation. These constraints make it not only harder to conduct systematic data collection via traditional methods, but also present a number of critical dilemmas such as standardization of method routines and especially time effects on intermittent fads and phenomena for which particular domains such as popular culture and material culture would be keenly susceptible. The Internet as a tool for data collection, specifically among United States residents, with their 69.9% penetration rate of Internet access, makes them the ideal target population for the implementation of such a tool. The Internet allows us to not only acquire a subject sample that is a large and diverse cross-section of the general population, but it overcomes some critical challenges such as cost, time, and consistency. Another important advantage of the Internet as a tool for systematic data collection is its ability to inexpensively test the measurement instruments and make quick changes as that are instantaneously and globally implemented, which will ease the transition into the full launch of a study.

Why automobile brand names?

The domain of automobile brands has been central to a number of current theoretical issues across several studies on branding and consumer behavior. The domain of automobile brands offers the unique distinction against other consumer product domains because it involves significant financial investment on the part of the consumer and is ranked by the 2004 Bureau of Labor Statistics Consumer Expenditure Survey as the second largest expense per household; only 15% below shelter expenses. As a result, manufacturers have invested heavily in the brand perceptions through marketing and branding to produce clear distinctions between their brands and those of their competitors. In a 2005 report on car ownership by AC Nielsen, findings showed that the United States led the world in car ownership with 92% of its driving age Internet-user population claiming to own a car. The study also found that globally, price was the most frequently-cited driver of choice, and therefore was a universal consideration for new car purchases. Because automobile manufacturers are aware of the critical factor of price as a purchasing determinant, they often opt for tier dominance of the market as an effective marketing strategy rather than producing multi-tiered product lines. The consistency of their messaging and position therefore suggests that the domain of automobile brands is less subject to influences by demographic variations.

With this key assumption, previous research has often approached the study of the domain of automobile brands deductively by speculating that brand perception and brand preference is based on product quality, luxuriousness, and origin of manufacturer (Rao 1972; Dacin and Smith 1994; Han and Terpstra 1988; Rao, Qu, and Ruekert 1999), all of which are perceived to be correlated to price. Therefore, financial investment translated into monetary value is directly attributed to the brand perception and serves the function of allowing automobile brands to symbolize social status in addition to inherent utility.

This presumption that automobile brands serve as significant symbols in American culture presumes that there must be some reasonable consensus about the domain, one that would allow it to work effective cross-culturally. Let us propose the question: Under what conditions does a consumer product such as an automobile become a significant symbol of prestige, wealth, or power? In considering the works of Romney, Rogers and Kroeber we can begin to envision that social interaction is the condition through which the stimulus (in this case, automobile brands), acting as a culture unit, becomes extinct or fortified as a significant symbol when used by the culture in conjunction with another significant symbol (prestige, wealth or power). In other words, high concurrence of a particular culture unit or sign represents the extent to which that culture unit gives rise to shared meaning. The question that remains to be answered, however, is: What do automobile manufacturer brand names represent?

> This learning theory construct has been tentatively coordinated with our measuring operations by identifying this complex mediation reaction with a point in a multi-dimensional space. The projections of this point onto the various dimensions of the semantic space are assumed to correspond to what component mediating reactions are associated with the sign and with what degrees of intensity. The essential operation of measurement is the successive allocation of a concept to a series of descriptive scales defined by polar adjectives, these scales selected so as to be representative of the major dimensions along which meaningful processes vary. In order to select a set of scales having these properties, it is necessary to determine what the major dimensions of the semantic space are. Some form of factor analysis seems the logical tool for such a multidimensional exploratory task. (Osgood, Suci, and Tannenbaum 1957:31)

Osgood explains that by applying learning theory, we can identify this complex mediation reaction with a point in multidimensional space. Also, the various dimensions of the semantic space correspond to the components that are associated with the sign and allows for a measurement of the degree and intensity of that correspondence (Osgood, Suci, and Tannenbaum 1957). As such, we relied on some reasonably intrinsic attributes of the automobile manufacturer brand names domain, such as the ascribed attributes of origin and linguistic nomenclature, as well as achieved attributes like perceived reliability and luxuriousness. It should be noted that there is the possibility that we may produce artificial factors by deliberately inserting scales or concepts according to a priori hypotheses, but the persistence of a particular factor structure through reappearance in replications of the analysis, and through the convergence of different methods of data collection, will increase our confidence in its validity. To account for the possibility that we are merely reaffirming the biases that were present through the two methods and analysis, (a) we attempted to vary the subject populations as best we could to be representative of the target population, (b) we varied the concepts judged, and (c) we varied the type of judgment situation used in collecting the data (i.e. pile-sort and free-list). For our research in particular, the same primary factors kept reappearing despite these modifications. Thus we can persuasively conclude that the semantic structure operating in respondent judgments was not substantially dependent upon these variables.

Brand Attribution Effect and Causal Relevancy

Marketing scholars generally accept the intuition that some form of brand attribution occurs between Parent Brands and Brand Extensions, whether uni-directionally or bi-directionally. However, what continues to be discussed and debated is the direction and strength of that association. This transfer of attributes from one product to another within the same family of brands is called the "family branding effect," which postulated that via stimulus generalization and assimilation, consumers "transfer a favorable (or unfavorable) image from one product to others with the same brand" (Neuhaus and Taylor 1972). Notable theories that attempt to explain the factors involved in Attribution Transfer include the Family-Brand Effect (Fry 1967; Montgomery and Wernerfelt 1992), Categorization and Inclusion Effect (Pan and Lehmann 1993; Sujan 1985; Joiner and Loken 1998), and Brand Fit and Extendibility (Aaker and Keller 1990; Boush and Loken 1991; Dacin and Smith 1994).

Out intuition assumes that family brands would be perceived as more similar and as such would evidence higher instances of attribution effect than those that are perceived as dissimilar. However, consider for the sake of argument that for some particular brands positions in semantic space are not representative of our intuition that family brands are perceived as more similar but rather are perceived as dissimilar. Would that causal relevancy still exist between the two brands and to what extent?

Causal relevancy is a measure of whether brands that are seen as more similar based on positions in semantic space are also seen as more causally relevant, i.e. variations in the perceived attribute of one brand cause positively correlated variations in the same perceived attributes of semantically similar brands. By that same token, variations in the perceived attribute of one brand would not be expected to cause correlated variations in the same perceived attributes of semantically dissimilar brands.

Questions

We address three questions here: (1) does the estimated shared structure of perceived similarity among automobile brands within the sampled population reflect a cultural consensus across demographic groups? Results will be valid based on correlations of the individual semantic structures and stress of the aggregate semantic structure. If it does reflect a cultural consensus, this finding would support the hypothesis that knowledge of this domain is representative of a systemic pattern with significant cultural investment. Alternatively, if this finding does not reflect a cultural consensus while still being representative of the target population, then it would suggest that knowledge of this domain is not representative of a systemic pattern. (2) Are there detectable properties of this structure, providing interpretation in terms of known brand attributes? (3) To what extent do subjects infer that novel information regarding one brand will be causally relevant for assessing the properties of other brands, thus testing the hypothesis that closely associated brands are seen as causally relevant, net of objective factors such as ownership by the same firm? (4) Are the methods via an Internet-based instrument appropriate for measuring cultural consensus and adequate for collecting systematic data from large target populations that are diverse and span vast geographic distances?

Data Collection

Sample Recruitment

The referent population for this study was the general United States population, ages 18 and over, with a demographic profile resembling that collected by the 2000 United Status census. Participants were recruited via online advertising through Google Adwords, and through snowball sampling using our "refer-a-friend" program. The "refer-a-friend" program was conducted with the implementation of a page at the conclusion of the experiment that allowed participants to invite other users to participate in the experiment by providing a list of referral email addresses. Our system would then forward a general information email that included information about the incentives for participation and did not include significant details about the study or the experiment itself. The Google Adwords campaign consisted of keywords pertaining only to the incentive. The advertisement itself made no mentions of the automobile domain and was mostly generic copy, which alluded to participation in a general university research study and the potential incentive.

Google Adwords analytics reports shows the following statistics regarding our sample population during the active period of data collection from March 5, 2007 to April 5, 2007. Just over 88% (88.34%) of the total Website visitors were New Unique Visitors, while 11.66% were Returning Visitors. More than 90% (92.36%) of the completed surveys were by New Unique Visitors, while 7.64% were by Returning Visitors. The Website bounce rate (i.e. visits in which the person left the site from the entrance page) was 36.83%, with 28.73% staying to complete the survey. Of this roughly 29% who began the survey, nearly 100% of them completed the survey. This implies that the Website introductory page was a very effective determinant in properly informing visitors of the true breadth of the task at hand and the incentives involved. This statistic, however, is deficient as a measure of the completed survey quality. Of the 927 participants, 727 participants completed the free-list task, and 564 participants completed the pile-sort task. This would reduce our true completed survey statistic to 78% for the free-list task and 60% for the pile-sort task. An assumption to the cause of this is that approximately 40% of the participants bypassed most of the survey with the intention of only entering their email to participate in the incentive raffle. Traffic statistics showed that 71.61% of all visits were generated from the Google search engine through the Google Adwords campaign. Almost 20% (19.97%) were from direct traffic, meaning either through our refer-a-friend program or other direct sources such as shared links to the site through emails. Finally, 8.42% were from referring sites, which included digg.com, myspace.com, and ps3network.com.

Website Development

The Carlab Website was developed by James Yum and Andrew Lombardi. Here we will note some of the key features unique to the Website layout. The introduction page that visitors first encountered was composed of three parts. First was an overview of the requirements for participation and information about the incentive. Second was a graphic that listed the five tasks involved and approximated the time involved to complete each task (approximately 18 minutes). This is important in providing participants sufficient information to make a well-informed judgment about the time necessary to complete the survey in the attempt to reduce the number of incomplete surveys. Third was a scrolling text box, which included the study information such as disclaimers, privacy statements, and contact information. One essential aspect of this format was that at no time prior to beginning the survey were participants informed of the automobile domain being used for the study, which we hoped would reduce the potential for bias by domain experts who would have personal interest in participating.

Another key Website feature was the progress bar located on the top of every page. This marked a participant's progress through the survey and gave him/her a clear visual representation of where he/she was in the survey and how much more he/she needed to complete. We believe that this reinforced the participant's willingness to complete the survey by giving them a realistic overview of how much time they had already invested and how much more it was likely to take to complete the survey.

Another key feature throughout the Site was that the use of the "back" history button enabled participants to return to the previous page, but did not replace or update previously entered data. Once a task was completed, it was flagged in the database as "read-only," thus preventing participants from returning to the previous task and updating results with new, biased information that they may have acquired during successive tasks. Because we could not restrict the "back" history button from functioning, when a participant clicked the "back" history button, he/she would be presented with the same task as it was initially presented, but new data would not be recorded into the database.

Finally, overall color use in the Website was designed in a way to clearly distinguish the working area from the surrounding support information. The surrounding support information and frame was dark with light text, while the extraneous information, such as the progress bar and logo, were muted to be as unobtrusive as possible. The main area where the survey was conducted was in a white box so that it would stand out in the design and keep participants focused on the center area.

Defining The Automobile Domain

The 48 automobile manufacturer brand names used for our study were reduced from a list of 64 makes of automobiles obtained from the autotrader.com Website. We chose autotrader.com as a reliable source because the list of makes available represented automobiles that were both current and relevant to American automobile consumers. The 16 makes of automobiles we eliminated were those we interpreted as either not currently in production or uncommon, such a foreign makes with no national dealership presence. This decision was made in an attempt to reduce the number of domain items to make the instruments used more feasible to complete by respondents. Appendix A includes a list of all 48 automobile manufacturer brand names.

Task Overview

A group of 927 participants responded to a number of tasks including the following: (i) a general demographic survey following the 2000 United States census format, (ii) free-list elicitation of automobile manufacturer brand names, (iii) similarity judgment of the 48 automobile manufacturer brand names via a pile-sort task, (iv) an evaluation of reliability and luxuriousness via a five-point Likert scale, and lastly (v) a measure of causal relevancy for pairs of automobile manufacturer brand names via a Likert scale based on five general scenarios.

Free-list Task Methods

Similarity judgments were inferred from a free-list (Weller & Romney, 1988) of the domain of automobile brand names. Participants were instructed to type as many automobile manufacturer brand names (one per line) as they could within the two-minute time limit, after which they were restricted from entering any additional items. The two-minute limit was chosen to create a challenging situation that we presume would promote more natural cognitive responses. Of the **927** participants, **727** successfully completed the free-list task. Success is measured by an input of at least two automobile brand names. Inputs of specific automobile models or brands incomparable to the 48 cars specified for the pile-sort task were excluded from the final calculations.

Free-List Task Technical Notes

Participants were presented with a list of 60 numbered text fields. All text fields were locked from entry except for the currently active text field, beginning with the first text field. Pressing either the “Enter” or the “Tab” keys completed a text field entry. This method was important for two reasons. First, it prevented participants from editing previous entries. Second, it prevented the participant from moving forward to the next task before the current task was completed. Hiding the “next” button also allowed us to resolve the technical difficulty of accidentally moving forward when pressing the “Enter” key.

On the back end, our database recorded list entries in the following protocol format: cc:sss where “cc” was the double-digit car identification code and “sss” represented the time of the entry in seconds as recorded upon pressing the “Enter” or “Tab” keys.

The free-list task was tested for compatibility with all common Internet browser applications. The only technical difficulty we experienced with this was an error in the locking mechanism on the Safari 2.0 browser. On the Safari 2.0 browser, after the two-minute time limit had expired, the system failed to lock all text fields from additional entries. To account for this error, during data processing, we excluded all entries that occurred after two minutes.

Another complication we faced was inconsistency of participant data entry. Two common inconsistencies were: proper spelling of items (for example, “Lamborgini” or “Lamburghini” for “Lamborghini”) and not clearly distinguishing automobile manufacturer brand names from automobile product model names. Misspellings were corrected manually, and required our own personal judgment within some reasonable limits. If the entry was not clearly distinguishable, it was excluded from the data. An example of an indistinguishable entry would include Hondai, which could not be clearly distinguished as either Honda or Hyundai. Entries of product model brand names, such as Corolla, Camry, Civic, and Corvette, were excluded from the data.

Free-List Task Data Preparation

Each respondent's free-list results were entered into three 48 X 48 matrices based on three different criteria. The rationale for this procedure was based on our inexperience with interpreting the data, so we varied our analysis procedures to validate the various methods of interpretation. Below are the three variations for interpretation of the data from which the matrices were derived, with each accompanied by notation developed by Carter T. Butts Ph.D. For the subsequent mathematical notation, please note that $t_{i(j,k)}$ represents respondent's (*i*) time value (*t*) for a particular list item (*j,k*), $l_{i(j,k)}$ represents respondent's (*i*) list rank order value (*l*) for a particular list item (*j,k*), and $m_{i(j,k)}$ represents respondent's (*i*) mention logical value (*m*) as either 1 = present or 0 = not present for a particular list item (*j,k*).

The first matrix was based on **total time difference in seconds** for all pair combinations (1) coding the absolute value of the difference in seconds between pairs for every possible pair combination, (2) coding zeroes on the diagonal, and (3) coding 120 as the max time difference into the remaining (non-response) cells of the matrix. The distance calculations are represented by $d_i(j,k) = \left|t_{ij} - t_{ik}\right|$, and

inclusion was determined by $Ii_{jk}\begin{Bmatrix} 1 & if\ m_{ij}m_{ik} = 1 \\ 0 & otherwise \end{Bmatrix}$,

and the aggregate is represented by $$\frac{d(j,k) = \left(\sum_i I_{j,k} d_i(j,k)\right)}{\left(\sum_i I_{ijk}\right)}$$

The second matrix was based on the **pair-wise time differences** (1) coding the absolute value of the difference in seconds between adjacent pairs, (2) coding zeroes on the diagonal, and (3) coding 120 as the max time difference into the remaining (non-response) cells of the matrix. The distance calculations are represented by $d_i(j,k) = \left|t_{ij} - t_{ik}\right|$, and

inclusion was determined by $Ii_{jk}\begin{Bmatrix} 1 & if\ (m_{ij}m_{ik} = 1) \wedge (\left|l_{ij}l_{ik} = 1\right|) \\ 0 & otherwise \end{Bmatrix}$,

and the aggregate is represented by $$\frac{d(j,k) = \left(\sum_i I_{j,k} d_i(j,k)\right)}{\left(\sum_i I_{ijk}\right)}$$

The third matrix was based on **pair-wise co-occurrence** (1) coding ones for all adjacent brand pairs, (2) coding a one on the diagonal and (3) entering zeroes into the remaining (non-response) cells of the matrix. The distance calculations are represented by $d_i'(j,k) = \min\left(\left|l_{ij} - l_{ik}\right|, d^*\right) - 1$ however for this case $d^* = 1$ to set the constraint to the lowest value in order to capture only adjacent pairs, and

inclusion was determined by $Ii_{jk} \begin{Bmatrix} 1 & if\ m_{ij}m_{ik} = 1 \\ 0 & otherwise \end{Bmatrix}$,

and the aggregate is represented by $$\frac{d(j,k) = \left(\sum_i I_{j,k} d_i'(j,k)\right)}{\left(\sum_i I_{ijk}\right)}$$

Pile-Sort Task Methods

Immediately after the word list task was completed, similarity judgments were collected on 48 automobile manufacturer brand names with an unstructured pile-sort task (Weller & Romney, 1988). Participants were presented with 48 individually randomized automobile manufacturer brand names and asked to organize them as they saw fit. No constraints were placed on the number or size of groups, and participants were allowed to set aside brands they claimed they did not know well enough to group. Basis for the groupings were determined entirely by the participant. The pile-sort task served the double purpose of measuring the judged similarity among the automobile manufacturer brand names and provided a means for convergent validity against the word list task results. Of the **927** participants, **564** successfully completed the pile-sort task.

Pile-Sort Task Technical Notes

The pile-sort task was developed using Javascript and was compatible with all common Internet browser applications. Card items were all equal height and length, with approximately three pixels of space above and below the text and a maximum of three pixels of space to the left and right of the longest single line text item. All card items were a neutral beige color that was dark enough to distinguish it from the background but light enough to prevent it from becoming distracting. Consistently sized and colored cards were crucial to preventing bias that might have otherwise been created by cards of varying sizes and colors. Group boxes featured a header to distinguish it as a group but were identified only by the word "group" and a number based on the order in which the group was created. Closing a group dumps all of the items that it contains in place onto the desktop. Card items could be moved between groups and the desktop as the participant saw fit. On the back end, our database recorded all interaction of the cards including additions and removal to a group using the following protocol format: cc:a|r:gg:sss where "cc" is the double-digit car identification code. The second code of "a" or "r" represents the type of interaction as either addition or removal, respectively. The group number was identified by the double-digit "gg" and "sss" represents the time of the interaction in seconds.

An additional feature we included with the pile-sort task was a brief animated tutorial that was accompanied by motion graphics, supporting text, and voice narration to help participants understand how to interact with the pile-sort task. The animated tutorial used the domain of fruit as a general example of how to interact with the pile-sort application.

Pile-sort Task Data Preparation

Each respondent's pile-sort results were entered into a 48 X 48 matrix by: (1) coding a one (1) for all brand pairs within each group, (2) coding a one (1) on the diagonal and (3) entering zero (0) into the remaining cells of the matrix. (4) The symmetric matrices were aggregated across individuals by summing all individual symmetric matrices and the cell totals were subtracted from the max value to produce a dissimilarity matrix. (5) The max value was then coded across the diagonal. The numbers contained in the lower (or upper) triangle of the final matrix represents subjects' aggregated ratings of different brands' dissimilarity.

Reliability and Luxuriousness Measurements

Following the pile-sort task, participants were asked to evaluate all 48 automobile brand names on the attributes of "luxuriousness" and "reliability." Participants were presented with two separate list of 48 randomized automobile brand names and asked to rate each item on a five-point bi-polar scale ranging from 1 = substantially below average reliability/luxuriousness to 5 = substantially above average reliability/luxuriousness), with the additional 6^{th} point option (6 = don't know) if the participant did not wish to comment or state an opinion. The measures of "luxuriousness" and "reliability" were each aggregated into two lists, with the mean scores for each of the 48 automobile manufacturer brand names.

Causal Relevancy Measurement

Lastly, the participants were presented with five scenarios that introduced novel information about one brand's attribute (source) and measured the likelihood that it would affect another brand (target). Participants were asked to rate each item regarding the likelihood that the information would be causally relevant on a five-point bi-polar scale ranging from 1 = Much less likely up to 5 = Much more likely. Of the 1,128 possible brand pair combinations, 50 pairs were randomly selected to obtain adequate statistical power for pair-wise comparison while minimizing the number of questions per respondent. We also added four additional brand pairs that we presumed share close kinship ties, under the expectation that they might offer us results directly relevant to our theory. For each of the five scenario questions, a pair was selected randomly, and assignment as "target" or "source" was randomized to account for bi-directionality of information transfer.

One apparent flaw in our methods for the causal relevancy measure that should be considered is the use of a nine-point Likert scale as opposed to the five-point bi-polar scale we used in this study for the measure of likelihood. In reviewing our findings, we note that a majority of responses were "No more or less likely" which could reasonably be due to fatigue effect considering that the last five scenario questions appeared after a relatively long 20-minute survey session. The use of the nine-point Likert scale would allow us to generate more usable data by imposing a rational choice of positive or negative value rather than allowing them to opt out of decision-making by choosing the neutral value. Also, randomizing the order of the scenario question between the beginning and the end of the test could decrease the effects of fatigue on the data collected. However, we can't disregard the potential that the neutral value could just as likely reflect the actual respondent perceptions for this relationship.

Causal Relevancy Data Preparation

The measure of "causal relevancy" was aggregated into five 48x48 one-mode matrices (one for each question) where each (i,j) cell represented the mean scores for each pair. The five matrices where then aggregated again into three independent 48x48 one-mode matrices, the first with positive causal relevancy scenario means only, the second with negative causal relevancy scenario means only, and the third with the total mean causal relevancy scores for all five scenarios. The causality values are represented by $c_i(j,k)$, and $m_{i(j,k)}$ represents respondent's(*i*) mention logical value (*m*) as either 1 = present or 0 = not present for a particular list item (*j,k*).

inclusion was determined by $Ii_{jk}\left\{\begin{matrix} 1 & if\ m_{ij}m_{ik}=1 \\ 0 & otherwise \end{matrix}\right\}$,

and the aggregate is represented by $$\frac{c(j,k)=\left(\sum_i I_{j,k}c_i(j,k)\right)}{\left(\sum_i I_{ijk}\right)}$$

Measuring Brand Similarity

The R Statistics program (R Development Core Team 2006) was used to scale the dissimilarities using non-metric multidimensional scaling. The *as.dist* (R Development Core Team 2006) function was used to coerce the data into a dissimilarity object by using the Euclidean distance measure to compute the distances between the rows of the data matrix. The *cmdscale* (R Development Core Team 2006) function was used to normalize the data by dividing the aggregated cell totals by the product of their respective row and column totals and then find coordinates of brands in Euclidean space whose rank order of between-brand distances best reproduces the original rank order of the input dissimilarities. Once the semantic structure is available, the interpretation of the results is based on identifying nodes by known brand attributes and other perceived attributes collected through our survey methods.

Results & Analysis

The Sample Population

The Sample Population, for the most part, did not deviate significantly from the 2000 United States Bureau of Census demographics profile data. However, some significant exceptions were noted. *Figure 1* shows comparisons in population percentage totals from our study as compared with census data baseline.

A comparison of our sample and the United States census population estimates is depicted below using a variation on Edward Tufte's sparklines concept for graphical representation of data (Tufte 2006). The figure can be interpreted as follows: The center line in gray identified as the "Census Baseline," represents the baseline percentage values of each demographic segment in the total census population. The gray area identified as the "25% difference area," represents the 25% threshold above and below the census baseline. Each individual line extending above or below the census baseline represents the various demographic subsets, which are separated and categorized by the dimensions of race, age, educational attainment level, current marital status, current annual income, current occupation, and gender. Lines colored red imply specific subsets to be noted, and those colored black imply specific subsets whose percentage values were insignificant. The length of each line represents an exact calculation of the population percentage relative to the total population of our study. Colored dot indicators reference details of those points of interest in the accompanying legend. The legend identifies the specific demographic subset and its respective population percentage above or below the census baseline.

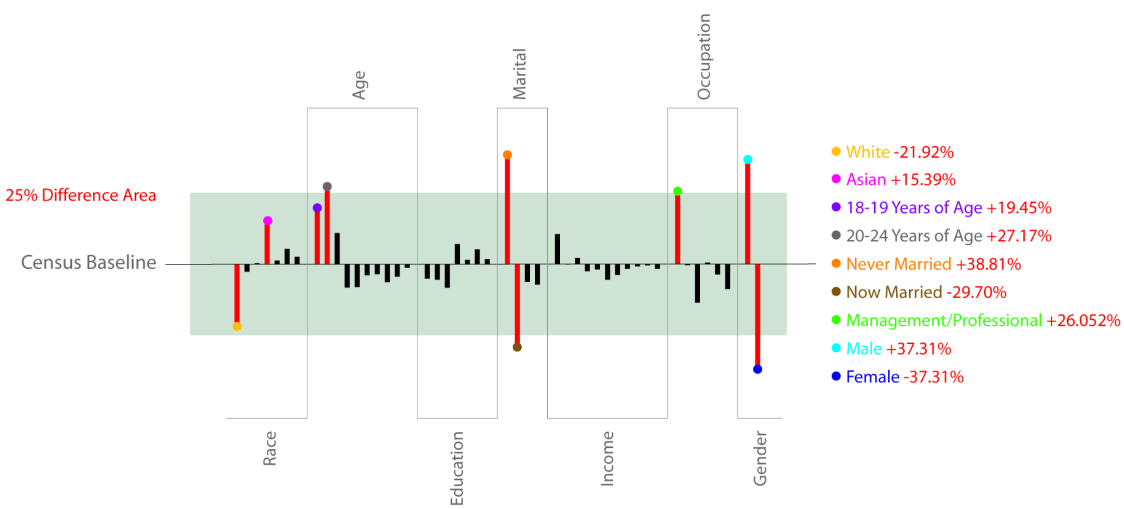

Figure 1

Important exceptions to be noted are that an approximately 22% decrease of the White population in the census totals was accounted for by an increase in the Asian population in our sample by 15%, and the remaining 7% was dispersed evenly among other race classifications. Our sample showed a disproportionately larger population of people under age 34 than would have been observed in proportion to the census population. Our sample also showed a disproportionately larger population of people with a marital status of "never married" which would account for a disproportionately smaller population of people with a marital status of "married." Also, as expected, males represented 86.41% of our population as opposed to the 49.1% we would have expected from the census population totals. The categories of education, income and occupation, however, did not show any major difference between our sample and the census population. Details of percentages can found in *Appendix B*.

Convergent Validity Between Pile-sort and Free-list Methods

For each participant (i), the pile-sort data was transformed into a 48 X 48 similarity matrix (j,k), and then collected into an additional three-dimensional array (i,j,k). Then a function was created in R to construct a 927 X 927 array of within-group correlations whose (j,k) cells represented the (product moment) graph correlation between labeled graphs i and i_n using the *gcor* function from SNA package version 1.4 (Carter T. Butts). The 927 X 927 array of within-group correlations was transformed via spectral decomposition, the *eigen* function (R Development Core Team 2006) in R being used to compute eigenvalues and eigenvector. The results are a principal components analysis and can be used to discover which variables in the set form coherent subsets that are relatively independent of one another. Analysis of the first ten eigenvalues as shown in *Figure 2* revealed that the first component accounted for 81% of the variance while the second component accounted for only 2.87% of the remaining variability, indicating strong reliability of the aggregate totals similarity matrix.

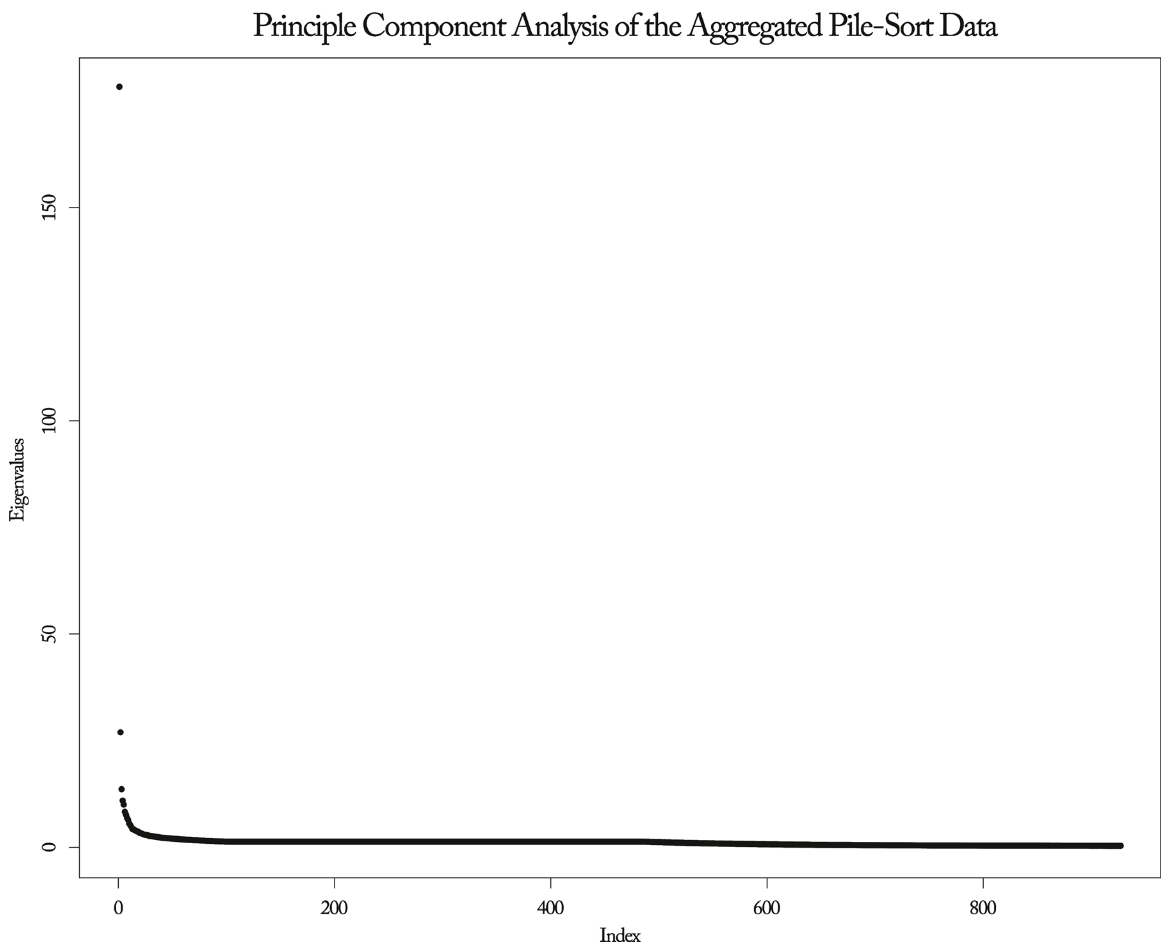

Figure 2

The pile-sort method provided a two-dimensional configuration of the 48 automobile manufacturer brand names in semantic space as shown in *Figure 3*. Configurations of the 48 automobile manufacturer brand names in the semantic structures showed three very distinct, visible similarity clusters.

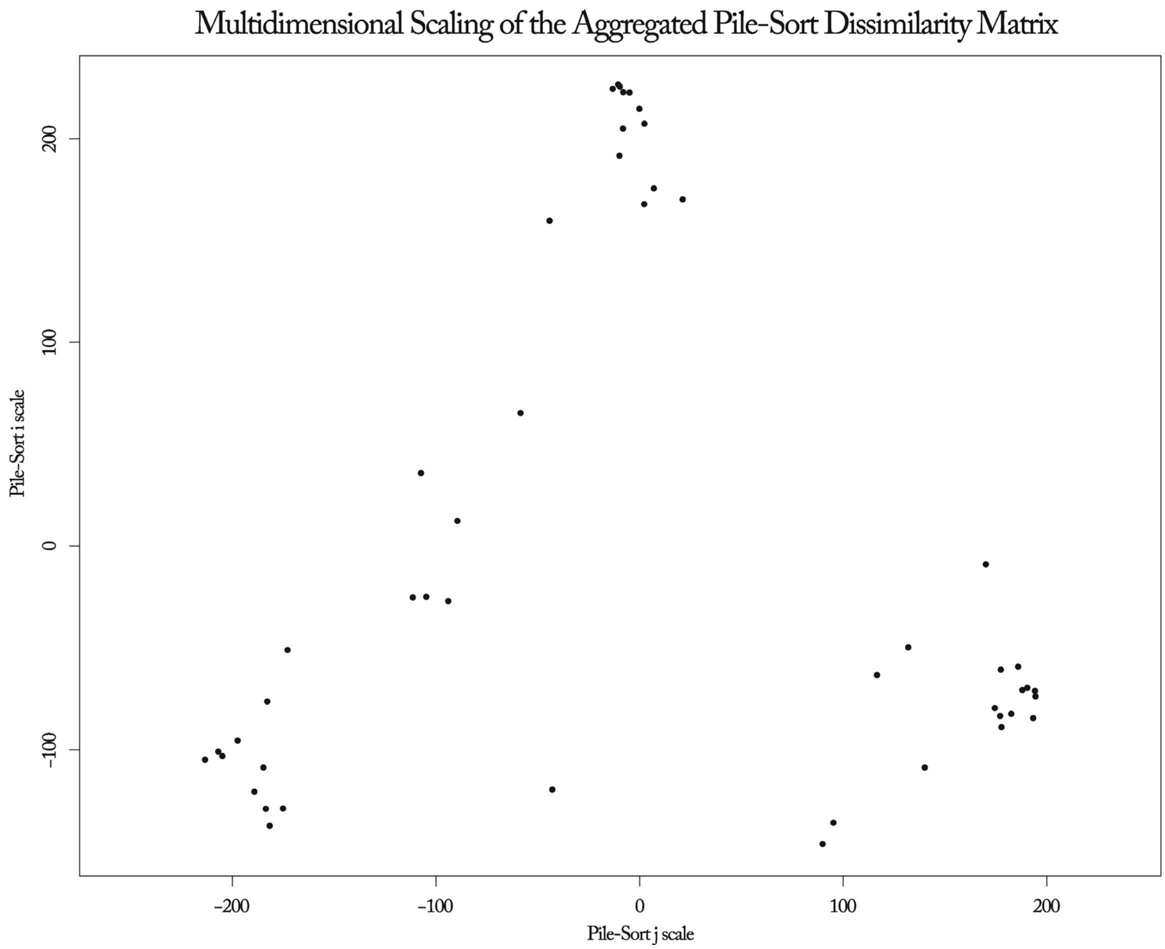

Figure 3

The same principal components analysis procedure was applied to the free-list results, which consisted of 727 individual dissimilarity matrices based on the methods described earlier for "total time differences" dissimilarity procedures. Analysis of the first ten loadings, as shown in *Figure 4,* revealed that the first component (factor) accounted for 65% of the variance while the second component accounted for only 1.89% of the remaining variability indicating satisfactory reliability of the aggregate totals.

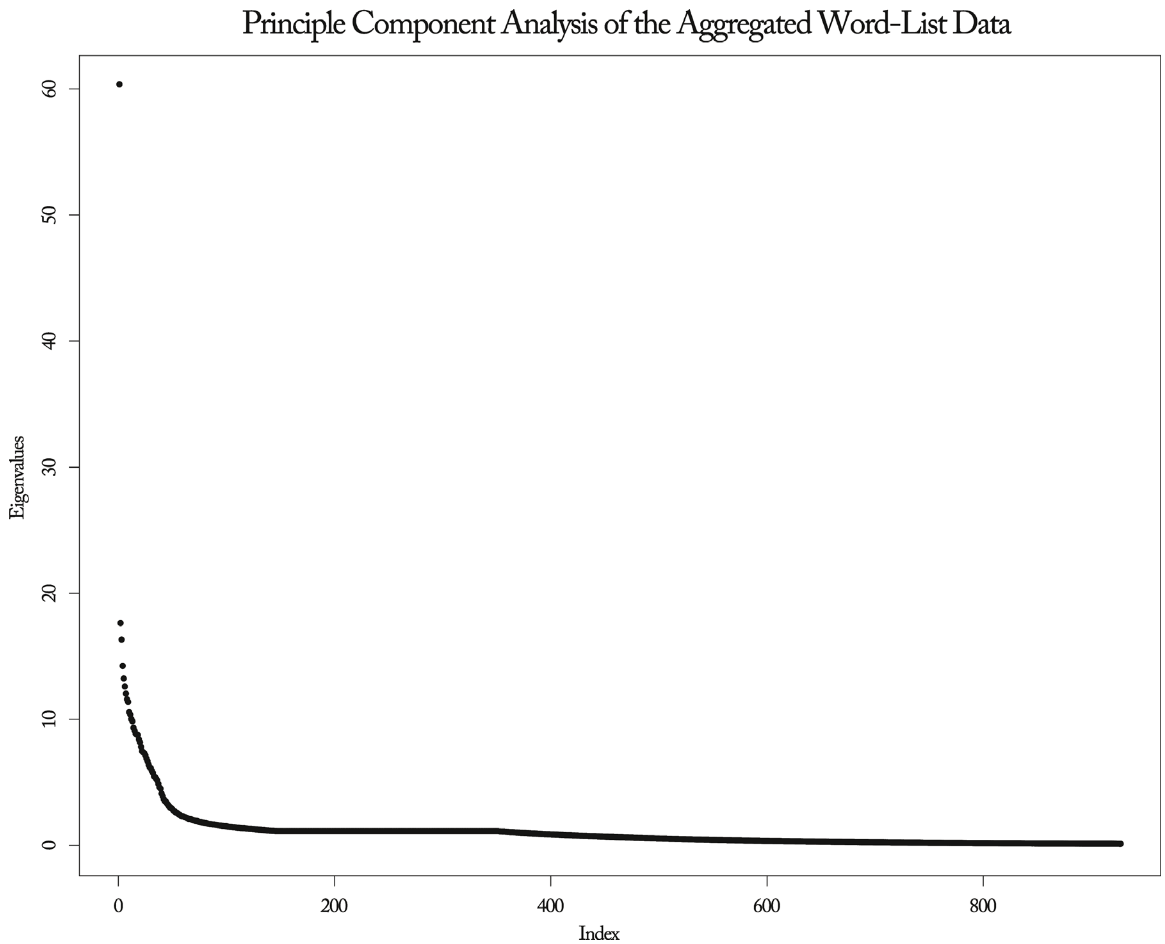

Figure 4

The first component is not quite as strong as the pile-sort results. We hypothesize that these results could be attributed to the fact that free-list data was relatively sparse in comparison to the pile-sort data, however the factor is robust enough to validate the aggregate total similarity matrix.

The free-list method provided a two-dimensional configuration of the 48 automobile manufacturer brand names for each of the three free-list approaches, based on total time difference in seconds (*Figure 5a*), pair-wise time differences (*Figure 5b*), and pair-wise co-occurrence (*Figure 5c*).

Multidimensional Scaling of the Aggregated Word-List Dissimilarity Matrices

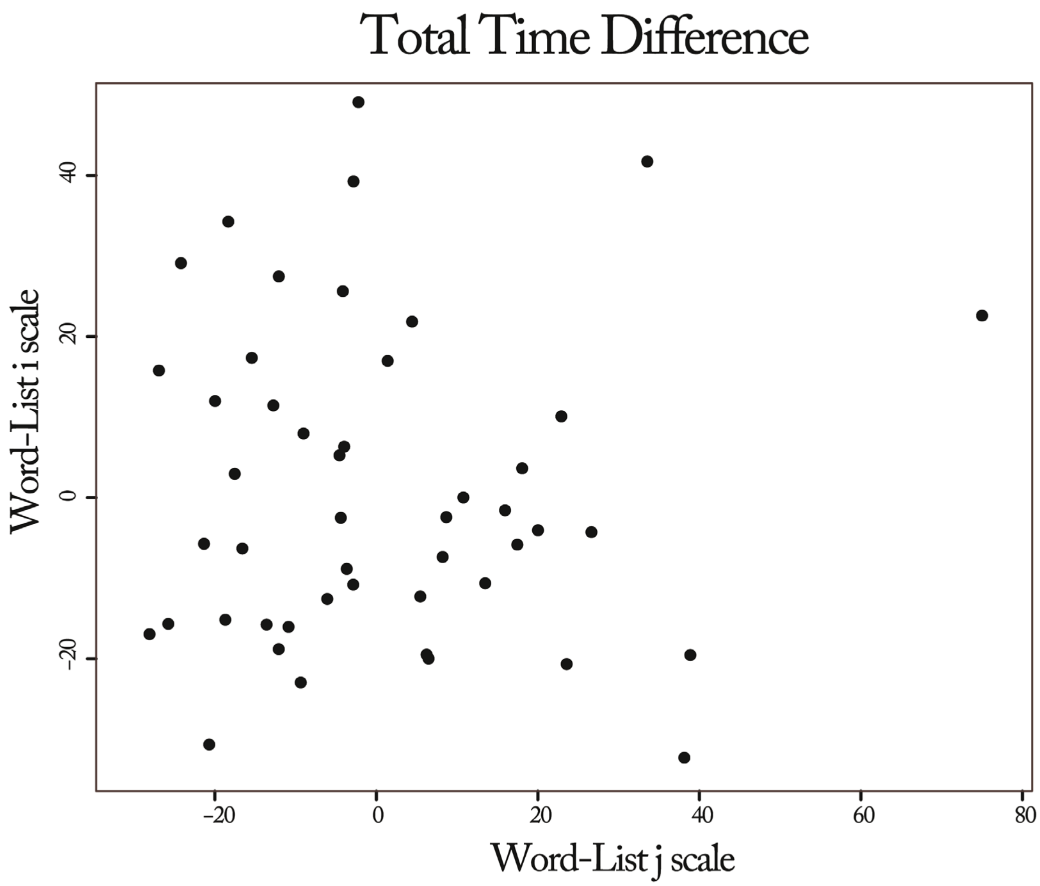

Figure 5a

Multidimensional Scaling of the Aggregated Word-List Dissimilarity Matrices

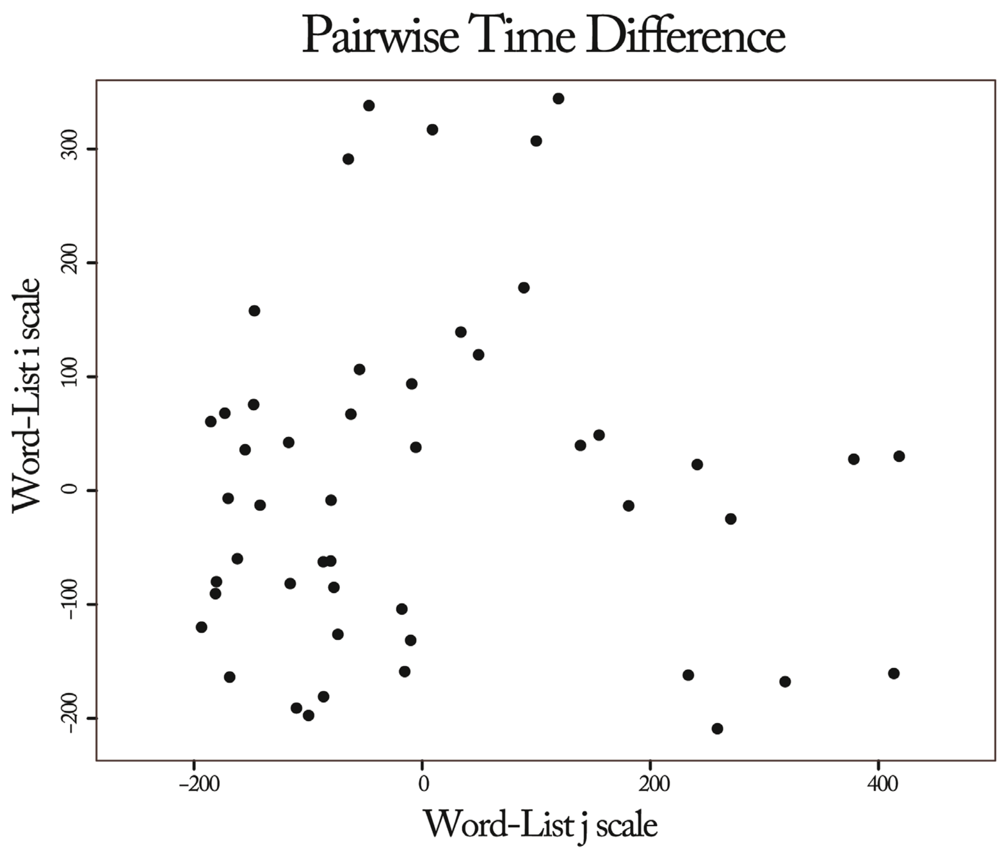

Figure 5b

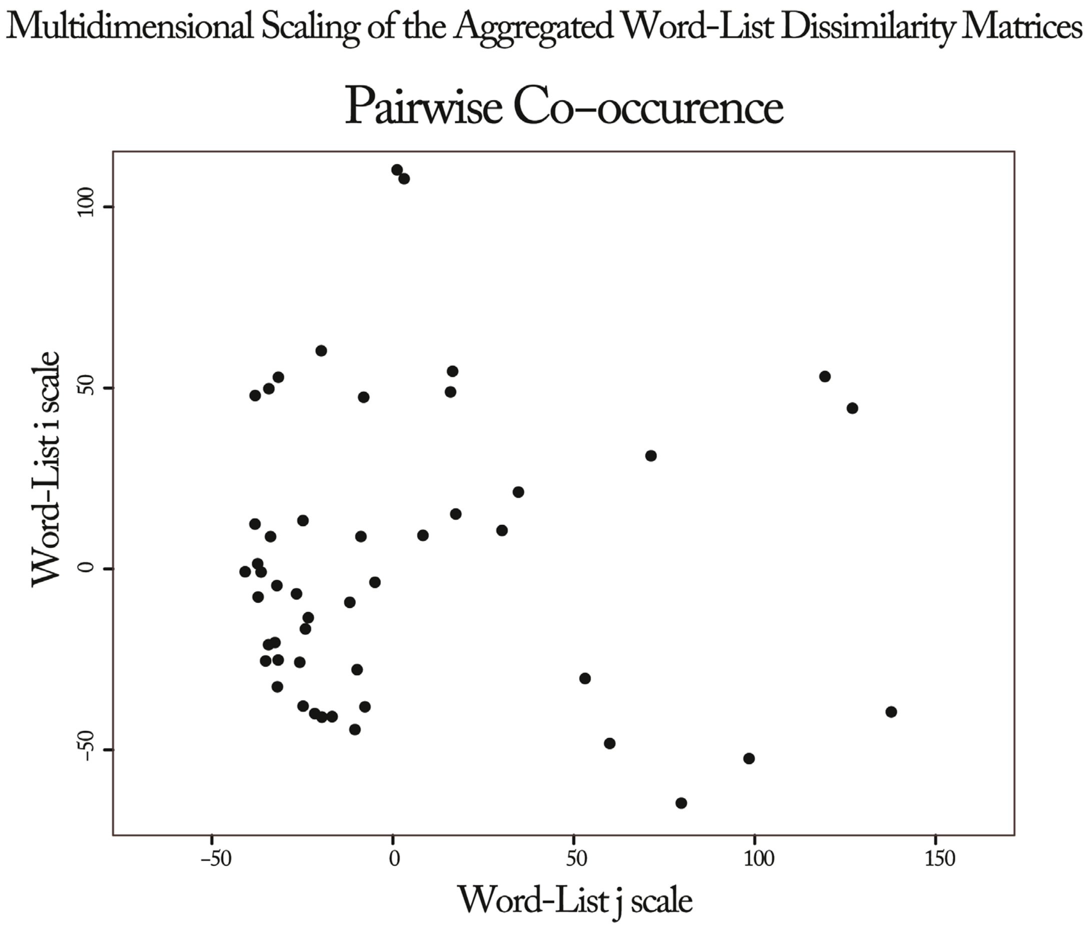

Figure 5c

The Pearson's correlation coefficients between the semantic spaces for all three free-list methods showed high correlation values of 0.965, 0.965, and 0.998, as are shown in Table 1. Configurations of the 48 automobile manufacturer brand names for the three free-list semantic structures did not show any distinct visible similarity clusters.

Table 1. *Results below show the Pearson's correlation coefficient between compared free-list methods.*			
Compared Free-list Method		Number of participant results[a]	Pearson's correlation coefficient[b]
Total time difference	Pair-wise time difference	564	0.965
Total time difference	Pair-wise co-occurrence	564	0.965
Pair-wise time difference	Pair-wise co-occurrence	564	0.998

[a] Number of participant results accounts for all individual free-list matrices with a minimum of one item pair (see methods for details).
[b] Pearson's correlation coefficient was calculated using the gcor function of the SNA package version 1.4 in the R Statistical Program, by analyzing the lower triangle portions of the compared free-list matrices.

Pearson's correlation coefficient between aggregated pile-sort similarity matrices and the three aggregated free-list similarity matrices based on total time difference, pair-wise time difference, and pair-wise co-occurrence also showed strong correlations of the semantic space against all three free-list methods with correlation values of 0.919, 0.927, 0.927 respectively as shown in Table 2. These results offer convergent validity between the two methods. As such we will refer only to the semantic structure for the aggregated pile-sort results in the following subset correlations.

Table 2. *Results below show the Pearson's correlation coefficient between the aggregated pile-sort similarity matrix and aggregated free-list matrices.*				
	Number of participant results[a]	Aggregated Free-list Matrices	Number of participant results[b]	Pearson's correlation coefficient[c]
Aggregate	727	Total time difference	564	0.919
Pile-sort	727	Pair-wise time difference	564	0.927
Matrix	727	Pair-wise co-occurrence	564	0.927

[a] Number of participant results accounts for all individual pile-sorts matrices with a minimum of one item pair (see methods for details).
[b] Number of participants accounts for all individual free-list with a minimum of one word pairs (see methods for details).
[c] Pearson's correlation coefficient was calculated using the gcor function of the SNA package version 1.4 in the R Statistical Program, by analyzing the lower triangle portions of the aggregated pile-sort matrix compared to the free-list matrix.

Cultural Consensus of the Semantic Structure

After analyzing the principle component results and verifying convergent validity, we calculated product moment graph correlations between the aggregated pile-sort matrix between the demographic subsets of gender, income, age, race, and education. All Pearson's correlations coefficients between subset show very high correlation values as shown in Figure 6, with an average value of 0.985 and the lowest value was 0.910, which could be attributable to the sparse subset data size of that particular subset. Refer to Appendix B for further details of all correlations.

A graphical representation of the Pearson's R correlations for each demographic subset and their respective sample proportion is depicted below using a variation on Edward Tufte's sparklines concept for graphical representation of data (Tufte 2006). This figure is divided into two portions. The top portion represents the percentage of the sample population for each demographic subset, while the bottom portion represents the correlation values for each respective demographic subset. The center line in gray identified as the "1.0 Correlation Baseline" represents the baseline for a 1.0 perfect correlation for all demographic subsets below this baseline and also represents a zero population percentage for all items above this baseline. The darker gray area above the baseline is identified as the "50% of Sample," and represents the 50% marker for the sample population percentages, while the lighter gray area below the baseline is identified as the .95 correlation threshold. An unidentified imaginary line of equal length to the .95 correlation threshold should be assumed to represent the .90 correlation threshold. Each individual line extending above the 1.0 Correlation Baseline represents the population percentages of the various demographic subsets that are separated and categorized by the dimensions of race, age, educational attainment level, current marital status, current annual income, current occupation, and gender. The lines below the 1.0 Correlation Baseline represent the respective correlations for each demographic subset against the aggregated pile-sort similarity matrix. Lines colored red imply specific subset correlations to be noted and those colored gray imply specific subsets whose values were well above the .95 correlation. The length of each line below the 1.0 correlation baseline represents an exact correlation of each demographic subset. Colored dot indicators reference details of those points of interested in the accompanying legend. The legend identifies the specific demographic subset and its correlation values in red and its respective sample population percentage in black.

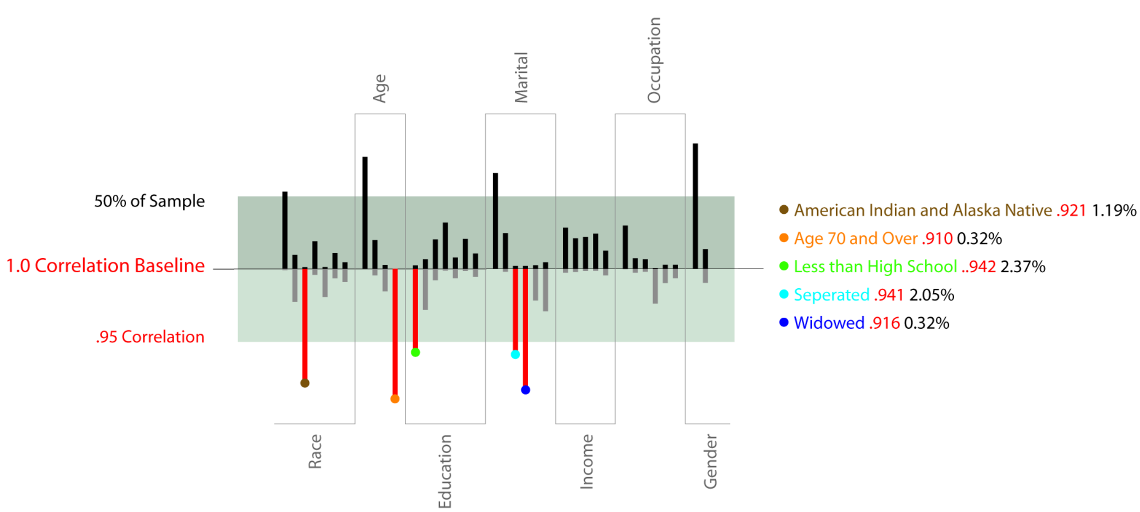

Figure 6

Findings thus far confirm that the results show a very robust consensus within our sample population with very little variation across all demographic groups.

Dimensions of Consensus

The robustness in judgment similarity allowed us to determine the extent to which each attribute factors into the judgments. Based on the results of the principal component analysis, we determined that the first component accounted for approximately 81% of the variance, while the second component accounted for approximately 3% of the variance. Once text labels were added to identify the nodes, it became reasonably clear that the approximate region of origin contributed to the first component. This distinction is important considering that in previous research the attribute of “origin of manufacturer” was classified by dimensions such as foreign vs. domestic or by countries. The semantic structure of the aggregated pile-sort results as shown in *Figure 7* has been color-coded to make the similarity clustering distinct and clear, with red representing Asian, green representing European, and blue representing American.

MDS of the Aggregated Pile-Sort Matrix (Region of Origin)

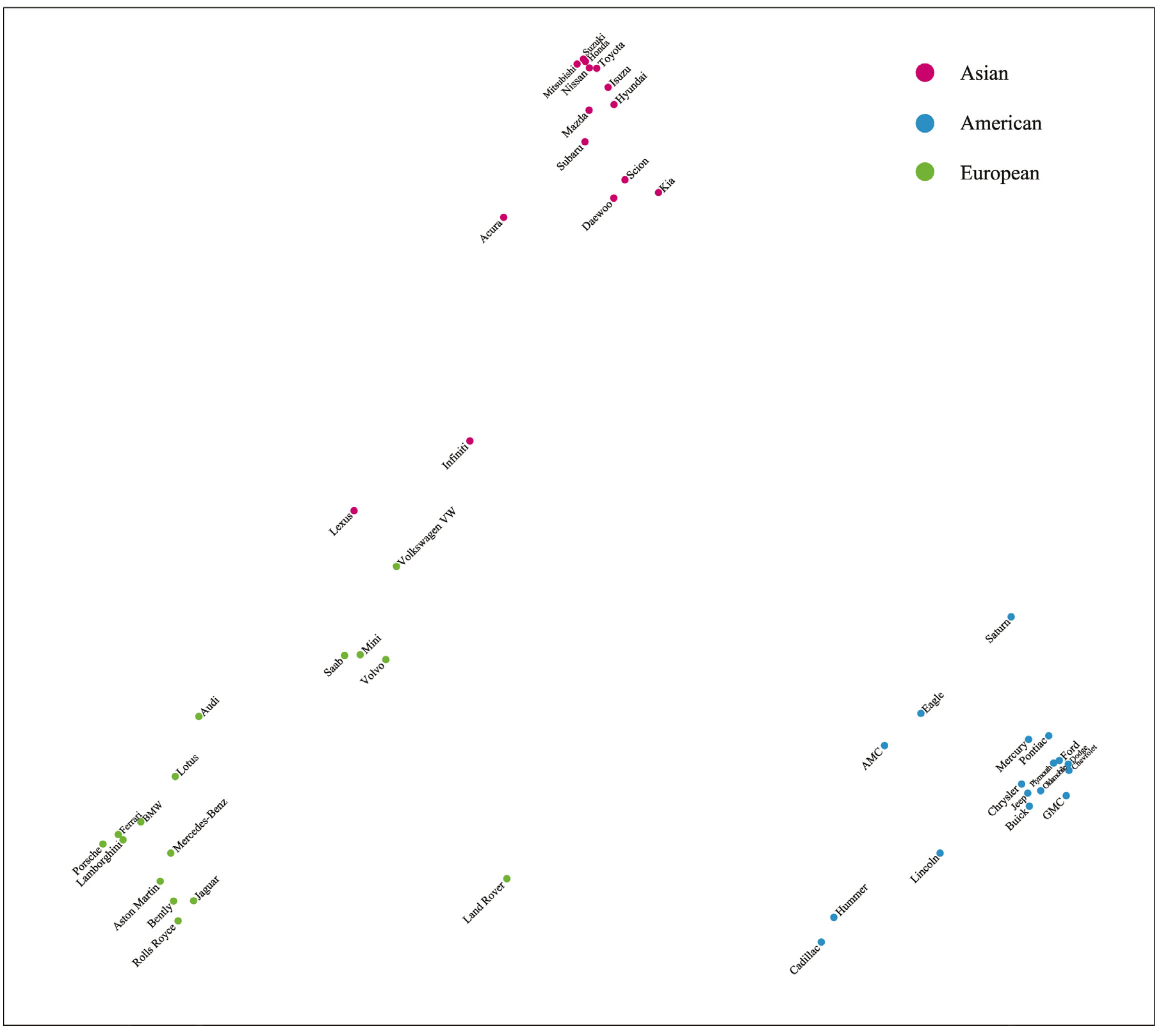

Figure 7

Further observation reveals that a number of brands from both the Asian and American clusters are judged to be more similar to the European cars. Based on known attributes of these particular brands, we speculated that the attribute of perceived luxuriousness could account for this second factor. A analysis of the semantic structure against a number of known attributes, including perceived reliability (a measure of quality) and perceived luxuriousness, confirmed our speculation that in fact perceived luxuriousness was observably correlated to the semantic structure as shown in *Figure 8*.

MDS of the Aggregated Pile-Sort Matrix (Perceived Luxuriousness)

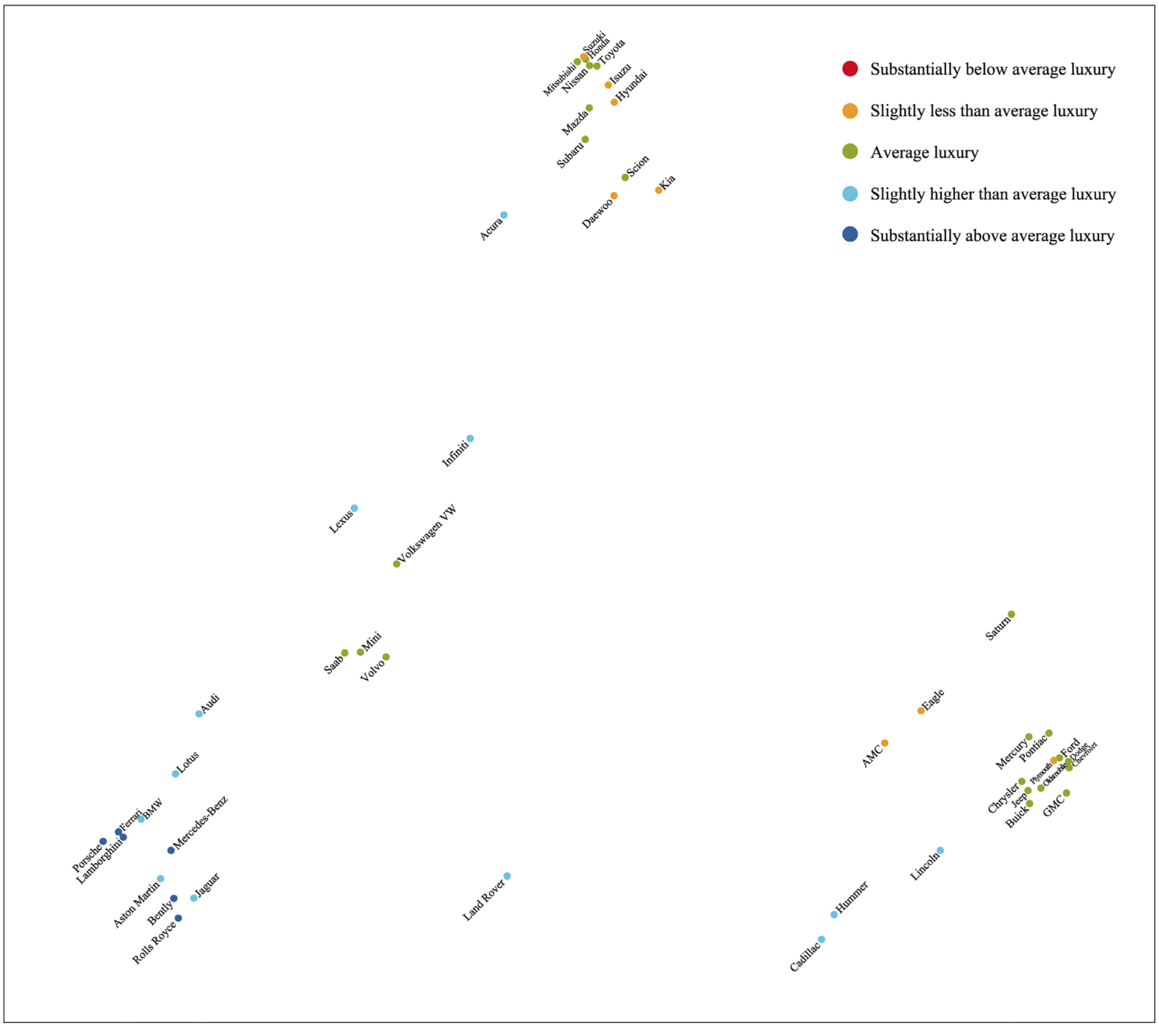

Figure 8

Based on analysis of the results, we conclude that the semantic structure on the domain of automobile brand names is determined first by the attribute of Region of Origin and, second, by the attribute of Perceived Luxuriousness. In addition, observation of some particular brands, including Lexus and Infiniti, contradict previous theories that brands with inherent kinship ties (family brands) are perceived to be more similar. However, it did not include an instrument as to measure whether kinship predicts general similarity, which should be a consideration for future study. Clearly, the second attribute of perceived luxuriousness plays a significant role in the perceived semantic structure.

Causal Relevancy

Pearson's product-moment correlation was calculated for each of the three likelihood matrices against the aggregated card-sort similarity matrix using the cor.test function in R. The results showed that none of the three likelihood matrices had significant correlation to support our hypothesis that closely associated brands were judged to be more causally relevant. *Table 3* below shows the results of the correlation test.

Table 3. *Results below show the Pearson's correlation coefficient between the aggregated pile-sort similarity matrix and three likelihood averages matrix*

	Number of participant results[a]	Likelihood Averages	Number of participant results[b]	Pearson's correlation coefficient[c]
Aggregated Pile-sort Matrix	727	Total (Positive & Negative)	396	0.120
	727	Positive Only	396	0.120
	727	Negative Only	396	0.118

[a] Number of participant results accounts for all individual pile-sorts matrices with a minimum of one item pair (see methods for details).
[b] Number of participants accounts for all individual completing at least one likelihood scenario question (see methods for details).
[c] Pearson's correlation coefficient was calculated using the cor.test function of the stats package in the R Statistical Program, by analyzing the lower triangle portions of the aggregated pile-sort matrix compared to the likelihood matrix.

Based on an analysis of the results, we conclude that the semantic structure of automobile brand names shows weak correlation between closely-associated brands and causal relevancy. In other words, distance in semantic space is not a strong determinant for whether novel information about one brand can be judged as causally relevant to another brand.

We produced a graph (*figure 9*) to provide a visual representation of causal relevancy and the strength of cultural consensus across all demographic subsets. This graph can be interpreted as follows: Region of Origin is represented by three distinct colors (magenta=Asian, blue=American, green=European); Perceived Luxuriousness is represented by opaque circles of varying sizes around their respective points (larger=higher perceived luxuriousness, smaller=lower perceived luxuriousness); Causal Relevance is represented by lines of varying thickness and transparency between brand pairs that were randomly selected (thicker, less transparent=higher causal relevancy, thinner, more transparent=lower causal relevancy); and finally, the smaller points scattered around represent the various points produced by MDS for the different demographic subsets and are colored by a lighter version of the three colors used for Region of Origin.

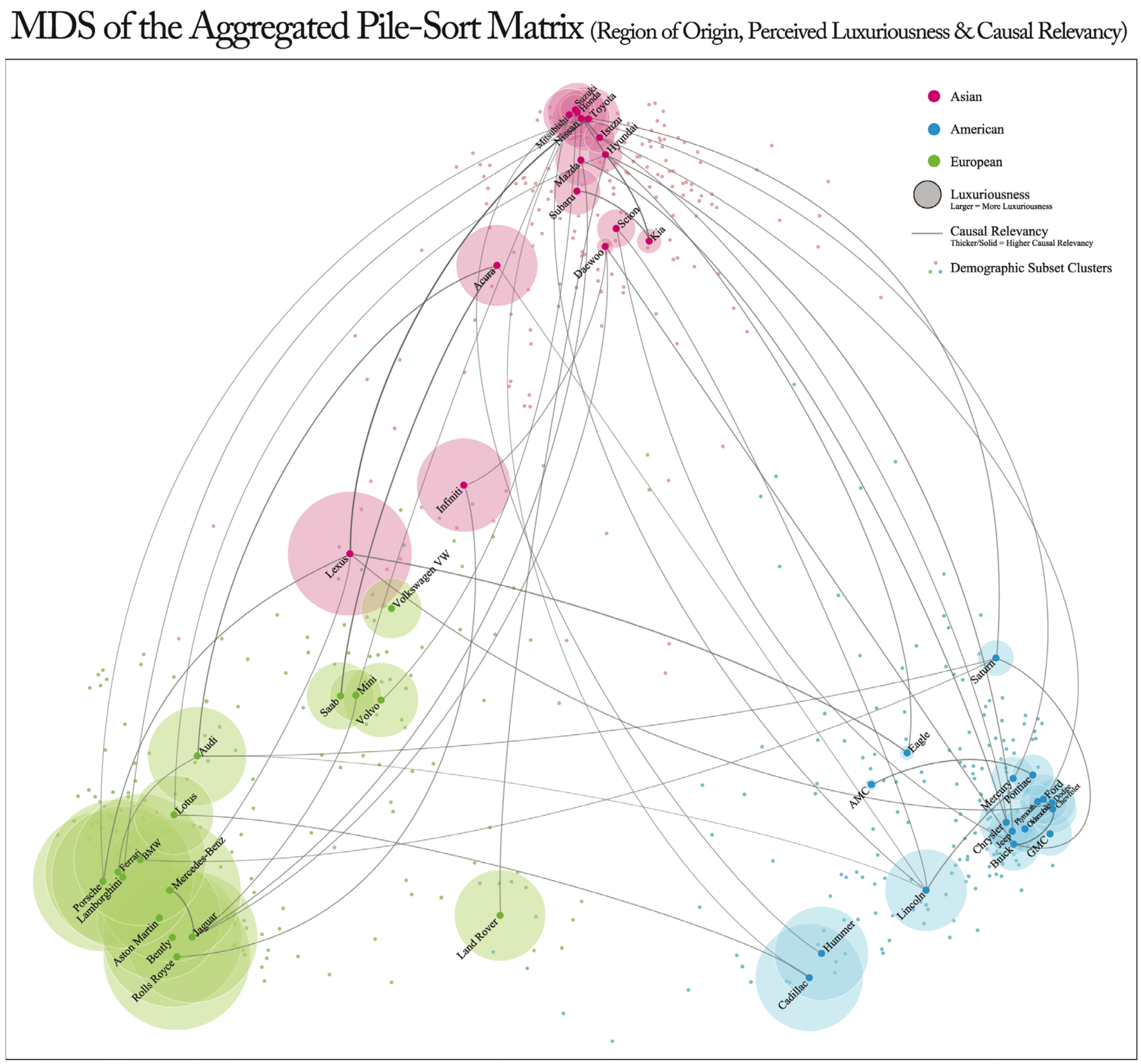

Figure 9

Conclusion and Discussion

Major findings:

A comparison of semantic structures on the semantic domain of automobile brand names among subjects shows strong consensus with little variation across demographic groups. In addition, both methods of the pile-sort task and the three transformations of the free-list all produced strong convergent results. What we found was that Americans do have a very clear and strong perception of the automobile manufacturer brand name domain. This consensus was so strong that it was consistent across all demographic groups, which confirms our hypothesis that automobile brand names serve as a significant symbol in American culture. Automobile manufacturer brand names are culture units that have been reinforced through generations of interaction and communication to become a undeniable systemic pattern within American culture, much of which we speculate is attributed to marketing and communication that is perpetuated within a material culture. Also, it is only because such a consensus exists that a novel commodity can be effectively used among Americans as a sign that is representative social status, particularly with regard to wealth or lack thereof. Consensus on the attribute of Region of Origin and Perceived Brand Luxuriousness allows American individuals to use automobile brand names through ownership to communicate their own social status and to accurately perceive the social status of others.

We also conclude that semantic structure of automobile brand names shows weak correlation between closely associated brands and causal relevancy, therefore our assumptions that we would expect a decay of causal relevancy relative to increasing semantic distance are unfounded.

In addition to the substantive findings, we have also shown the effectiveness of the Internet for conducting systematic data collection. Internet-based data collection allows us to effectively capture a representative sample while minimizing both cost and time. We were also able to vary the type of judgment situation used in collecting the data, including pile-sort and free-list, but certainly we could easily implement additional instruments such as triad task for additional validity. Also, we are able to employ a variety of factoring methods used in reading the data. Additionally the use of a website and multimedia features increased the ease and flexibility of implementing the experiment across a large geographic space. Some of these advantages include the following: a pile-sort how-to video enabled the presentation of the task consistently to all subjects. The previously arduous tasks of instrument order randomization and domain item randomization are relatively easy to implement and effective for reducing ordering effect and primacy effect. Web-based recruitment tools such as the refer-a-friend tool is an effective and easy means for recruiting snowball samples and, lastly, integrated web-based analytics allows for easy retrieval of sample statistics, and the raw data so that the experimenter can quickly and effectively react and adjust his/her experiment.

Discussion and Future Research

What we have established here is a practical example of how to implement Internet-based methods for empirically measuring the significance of culture units and the extent of consensus of a cultural systemic pattern. While we found strong cultural consensus among Americans in the domain of automobile manufacturer brand names, we should consider finding additional validation of this method as a measure of cultural consensus in other relevant material domains that are more apparent or have been intrinsically accepted in American culture. These domains include precious metals and stones, educational attainment, and occupational titles. These domains can further validate our methods as a measure of the significance of a symbol, which would then allow us to explore more novel domains that can be use for practical business and enterprise applications such as children’s toys, popular music, and other consumer product domains.

Acknowledgements & Notes

Special thanks to the University of California Irvine campus faculty including Carter T. Butts, Katherine Faust, Samuel L. Gilmore, Linton C. Freeman, Kimball A. Romney, and Douglas R. White for their tremendous support and guidance.

Also thanks to the University of California Irvine campus' Undergraduate Research Opportunities Program (UROP) for providing funding for this study during the 2006-2007 term and the University of California Irvine School of Social Sciences Research Participation Pool and Department of Distributed Computing Support (DAC) for their assistance.

This study was approved by the University of California, Irvine's Institutional Review Board under protocol number HS#2006-5399 on January 25th, 2007. For more information contact the UCI IRB office by telephone at (949) 824-6662, by email at IRB@rgs.uci.edu or by mail at University Tower – 4199 Campus Drive, Suite 300, Irvine, CA 92697-7600.

Appendix A. *The 48 automobile manufacturer brand names collected from the autotrader.com Website.*[1]

Brand Names	
Acura	
AMC	Mitsubishi
Aston Martin	Nissan
Audi	Oldsmobile
Bentley	Plymouth
BMW	Pontiac
Buick	Porsche
Cadillac	Rolls-Royce
Chevrolet	Saab
Chrysler	Saturn
Daewoo	Scion
Dodge	Subaru
Eagle	Suzuki
Ferrari	Toyota
Ford	Volkswagen VW
GMC	Volvo
Honda	
Hummer	
Hyundai	
Infiniti	
Isuzu	
Jaguar	
Jeep	
Kia	
Lamborghini	
Land Rover	
Lexus	
Lincoln	
Lotus	
Mazda	
Mercedes-Benz	
Mercury	
Mini	

[a] Reduced from a list of 63 automobile makes listed on the autotrader.com Website.

Appendix B. *Results below show the percentage of total population for both the United States Census data and our study for each demographic subset.*

Demographic	Census % of Total [a]	Sample % of Total [b]
Race		
White	**75.10**	**53.18**
Black or African American	12.30	9.60
American Indian and Alaska Native	0.90	1.19
Asian	**3.60**	**18.99**
Native Hawaiian and Other Pacific Islander	0.10	1.29
Some Other Race	5.50	10.79
Two or More Races	2.40	4.96
Age		
18-19	**7.20**	**26.65**
20-24	**6.70**	**33.87**
25-34	**14.20**	**25.03**
35-44	16.00	7.77
45-54	13.40	5.29
55-59	4.80	0.86
60-64	3.80	0.22
65-74	6.50	0.11
75-84	4.40	0.00
85 and older	1.50	0.22
Education		
Less than 9th grade	7.50	2.37
9th to 12th grade, no diploma	12.10	6.58
High school graduate (include equivalency)	28.60	20.28
Some college, no degree	21.00	27.94
Associate degree	6.30	7.77
Bachelor's degree	15.50	20.60
Graduate or professional degree	8.90	10.57
Marital Status		
Never Married	**27.10**	**65.91**
Married	**54.40**	**24.70**
Separated	2.20	2.05
Widowed	6.60	0.32
Divorced	9.70	2.48
Income		
Less than $10,000	**9.50**	**19.96**
$10,000 to $14,999	6.30	8.41
$15,000 to $24,999	12.80	10.25
$25,000 to $34,999	12.80	10.90
$35,000 to $49,999	16.50	11.00
$50,000 to $74,999	19.50	15.64
$75,000 to $99,999	10.20	8.52
$100,000 to $149,999	7.70	8.52
$150,000 to $199,999	2.20	2.70
$200,000 or more	2.40	4.10
Occupation		
Management, professional, and related	33.60	59.65
Service occupations	14.90	14.46
Sales and office occupations	26.70	13.16
Farming, fishing, and forestry occupations	0.70	1.19
Construction, extraction, and maintenance occupations	9.40	5.72
Production, transportation, and material moving occupations	14.60	5.83
Sex		
Male	**49.10**	**86.41**
Female	**50.90**	**13.59**

[a] Percentages were calculated by dividing the subset population as defined by the Census data set by the total population recorded.
[a] Percentages were calculated by dividing the subset population by the total population of the sample.

Appendix C. *Results below show the Pearson's correlation coefficient between the aggregated card sort similarity matrix and aggregated card sort similarity matrices of demographic subsets (gender, annual household income, age, race, and educational achievement)*

Demographic Subset[a]	Pearson's correlation coefficient[b]	Subset sample size	Percentage of total sample size
Gender			
Male	0.999	801	86.41%
Female	0.991	126	13.59%
Annual Household Income			
Less than $15,000	0.998	263	28.37%
$15,000 to $25,000	0.998	196	21.14%
$25,000 to $50,000	0.999	203	21.90%
$50,000 to $100,000	0.999	224	24.16%
$100,000 and over	0.995	117	12.62%
Age			
18 to 29 years	0.999	715	77.13%
30 to 49 years	0.995	184	19.85%
50 to 69 years	0.985	25	2.70%
70 years and over	0.910	3	0.32%
Race			
American Indian and Alaska Native	0.921	11	1.19%
Asian	0.996	176	18.99%
Black or African American	0.977	89	9.60%
Native Hawaiian and Other Pacific Islander	0.981	12	1.29%
Some Other Race	0.994	100	10.79%
White	0.999	493	53.18%
Two or More Races	0.991	43	4.64%
Educational Achievement			
Less than 9th grade	0.942	22	2.37%
9th to 12th grade, no diploma	0.972	61	6.58%
High school graduate (include equivalency)	0.992	188	20.28%
Some college, no degree	0.999	295	31.82%
Associate degree	0.994	72	7.77%
Bachelor's degree	0.999	191	20.60%
Graduate or professional degree	0.994	98	10.57%

[a] Individual card sort similarity matrices were created for each defined demographic subset.
[b] Pearson's correlation coefficient was calculated using the gcor function of the SNA package version 1.4 in the R Statistical Program, by analyzing the lower triangle portions of the aggregated card sort matrix compared to the word list matrix.

Appendix D. *The 50 randomly generated[a] automobile manufacturer brand names and four specifically selected automobile manufacturer brand names[b].*

Brand Names	
Audi	Acura
Audi	Ferrari
BMW	Saturn
Buick	Saturn
Buick	Scion
Cadillac	Lotus
Chevrolet	Buick
Chrysler	Mazda
Daewoo	Buick
Daewoo	Infiniti
Daewoo	Nissan
Ford	Chevrolet
Ford	Isuzu
GM	**Pontiac**
Honda	**Acura**
Honda	Cadillac
Honda	Hyundai
Hummer	Suzuki
Hyundai	Eagle
Hyundai	Jeep
Hyundai	Kia
Hyundai	Land Rover
Hyundai	Lotus
Isuzu	Chrysler
Isuzu	Honda
Jaguar	Daewoo
Jaguar	Mini
Lexus	Dodge
Lexus	Eagle
Lexus	Mercedes-Benz
Lexus	Porsche
Lexus	**Toyota**
Lincoln	Acura
Lincoln	Audi
Lincoln	Mitsubishi
Lincoln	Scion
Mazda	Jaguar
Mercedes-Benz	Jaguar
Mini	Mitsubishi
Mitsubishi	Saturn
Nissan	Mercury
Nissan	Porsche
Pontiac	AMC
Pontiac	Lincoln
Rolls-Royce	Infiniti
Saab	Acura
Saturn	Audi
Subaru	Kia
Subaru	Nissan
Suzuki	Volvo
Toyota	Bentley
Toyota	Lamborghini
Volkswagen VW	**Audi**
Volkswagen VW	Honda

[a] Automobile brand names were chosen at random using a computerized number generator.
[b] Reduced from a list of 63 automobile makes listed on the autotrader.com website.

References

Aaker, D.A., & Keller, K.L. (1990), “Consumer Evaluations of Brand Extensions” *Journal of Marketing*, Vol. 54, No. 1. (Jan., 1990), pp. 27-41.

ACNielsen (2005) *Consumers in Asia Pacific – Car Ownership and Our Purchase Intentions*, (March 2005) pp. 1-5

Boush, D.M. & Loken, B. (1991), “A Process-Tracing Study of Brand Extension Evaluation” *Journal of Marketing Research*, Vol. 28, No. 1. (Feb., 1991), pp. 16-28.

Brewer, D. D., Garrett, S. B., & Rnaldi, G. (2002) “Fee-listed items are effective cues for eliciting additional items in semantic domains” *Applied Cognitive Psychology,* Vol. 16 pp. 343-58

Butts, C. T. (2006) “Tools for Social Network Analysis” *The SNA Package for R*, Version 1.4 created on 2006-12-18. copyright (c) 2005, Carter T. Butts, University of California-Irvine

Chick, G. E. (2000) “Cognitive and Behavioral Consensus in a Tlaxcalan Festival System” *Paper presented in the Session in Honor of A Kimball Romney at the annual meeting of the Society for Cross-Cultural Research*, February 23-27. New Orleans.

Couper, M. P. (2000) “Review: Web Surveys: A Review of Issues and Approaches” *The Public Opinion Quarterly*, Vol. 64, No. 4. (Winter, 2000), pp. 464-494.

Dacin, P.A., & Smith, D.C. (1994) “The Effect of Brand Portfolio Characteristics on Consumer Evaluations of Brand Extensions” *Journal of Marketing Research*, Vol. 31, No. 2, Special Issue on Brand Management. (May, 1994), pp. 229-242.

D’Andrade, R. G. (1989) “Cultural Sharing and Diversity” *The Content of Culture: Constant and Variance*, ed. R. Bolton, pp. 349-62. New Haven.

Freeman, L. C., Romney, A. K., & Freeman, S. C. (1987) “Cognitive structure and informant accuracy.” *American Anthropologist*, Vol. 89, pp. 311-25

Freeman, L. C., White, D. R., & Romney, A. K. (1989) *Research Methods in Social Network Analysis*, Fairfax, Va. George Mason University

Fry, J.N. (1967), “Family Branding and Consumer Brand Choice” *Journal of Marketing Research*, Vol. 4, No. 3. (Aug., 1967), pp. 237-247.

Han, C. M. & Terpstra, V. (1988) “Country-or-Origin Effects for Uni-National and Bi-National Products” *Journal of International Business Studies* Vol. 19, No. 2 (Summer, 1988), pp. 235-55

Joiner, C. & Loken, B. (1998), “The Inclusion Effect and Category-Based Induction: Theory and Application to Brand Categories” *Journal of Consumer Psychology*, Vol. 7, No. 2. (1998), pp. 101-129.

Kroeber, A. L. (1948) *Anthropology* (Rev. ed.). Orlando, FL: Hardcourt Brace.

Lounsbury, F. G. (1956) “A semantic analysis of the Pawnee kinship usage” *Language*, Vol. 32, pp. 158-194

Lounsbury, F. G. (1964) “The structural analysis of kinship semantics” In H.G. Lunt (Ed.), *Proceedings of the Ninth International Congress of Linguist*, pp. 1073-1093. The Hague, the Netherlands: Mouton & Company

Matthews, G. W. (1959) “Proto-Siouan kinship terminology” *American Anthropologist*, Vol. 61, pp. 252-78

Miller, M. L., & Johnson, J. C. (1981) “Hard work and competition in an Alaskan fishery” *Human Organization*.

Montgomery, C.A., & Wernerfelt, B. (1992), “Risk Reduction and Umbrella Branding” *The Journal of Business,* Vol. 65, No. 1. (Jan., 1992), pp. 31-50.

Moore, C. C., Romney, A. K., & Hsia, T. (2000) "Shared cognitive representations of perceptual and semantic structures of basic colors in Chinese and English" *PNAS*, Vol. 97, No. 9, April 25, 200, pp. 5007-10

Neuhaus, C.F., & Taylor, J.R. (1972), "Variables Affecting Sales of Family-Branded Products" *Journal of Marketing Research*, Vol. 9, No. 4. (Nov., 1972), pp. 419-422.

NUA Internet Surveys 2007 Internetworldstats.com

Osgood, C. E., Suci, G, J., & Tannenbaum P. (1967) *The Measurement of Meaning*, University of Illinois Press, New Ed edition (September 1, 1967)

Pan, Y. & Lehmann, D.R. (1993), "The Influence of New Brand Entry on Subjective Brand Judgments" *The Journal of Consumer Research*, Vol. 20, No. 1. (Jun., 1993), pp. 76-86.

Quinlan, M. (2005) "Considerations for collecting freelists in the field: Examples from ethnobotany" *Field Methods*, Vol. 17, No. 3, pp. 219-34

R Development Core Team (2006) *R version 2.4.1* December 18, 2006 Copyright (C) 2006 The R Foundation for Statistical Computing

Rao, V. R. (1972) "Changes in Explicit Information and Brand Perception" *Journal of Marketing Research* Vol. IX (May 1972), pp. 209-13

Rao, A. R., Qu, L., and Ruekert, R. W. (199) "Signaling Unobservable Product Quality through a Brand Ally" *Journal of Marketing Research* Vol. 36, No. 2 (May, 1999), pp. 258-68

Roberts, J. M. (1951) "Three Navaho Households: A Comparative Study in Small Group Cultures" *Papers of the Peabody Museum of American Archaeology and Ethnology*, Harvard University, Vol. 40, No. 3, Cambridge MA.

Roberts, J. M. & Chick, G. E. (1979) "Butler County Eight Ball: A Behavioral Space Analysis. Sports, Games, and Play" *Social and Psychological Viewpoints*, ed. J. H. Goldstein. pp. 65-99. Hillsdale NJ.

Roberts, J. M., Chick, G. E., Stephenson, M., & Hyde, L. L. (1981) "Inferred Categories for Tennis Play: A Limited Semantic Analysis" *Play as Context*, ed. A. T. Cheska, pp. 181-95. West Point NY.

Roberts, J. M., Golder, T. V., & Chick, G. E. (1980) "Judgment, Oversight, and Skill: A Cultural Analysis of P-3 Pilot Error" *Human Organization*, Vol. 39, pp. 5-21.

Roberts, J. M., & Nattrass, S. (1980) "Women and trapshooting" In H. B. Schwartzmann (Ed.), *Play and Culture*, pp. 262-91 New York: Leisure Press

Roberts, J. M., Strand, R. F., & Burmeister, E. (1971) "Preferential Pattern Analysis" *Explorations in Mathematical Anthropology*, ed. P. Kay, pp. 242-68. Cambridge MA.

Romney, A.K. (1965) "Kalmuk Mongol and lineal kinship terminologies" *American Anthropologist*, Vol. 67, pp. 127-41

Romney, A. K. (1967) "Internal reconstruction of Yuman kinship terminology" In D. H, Hymes & W. E. Bittle (Eds.), *Studies in Southwestern ethnolinguistics: Meaning and history in the languages of the American Southwest*. pp. 379-86. The Hague, the Netherlands: Mouton.

Romney, A. K., Brewer, D.D., & Batchelder, W. H. (1993) "Predicting clustering from semantic structure" *Psychological Science*, Vol. 4, pp. 28-34

Romney, A. K. & D'Andrade, R. G. (1964) "Cognitive aspects of English kinship" *American Anthropologist*, Vol. 66, pp. 146-70

Romney, A. K., & Moore, C. C. (2001) "Systemic Culture Patterns as Basic Units of Cultural Transmission and Evolution" *Cross-Cultural Research*, Vol. 35 No. 2, May 2001 pp. 154-78

Romney, A. K., & Moore, C. C. (1998) "Toward a theory of culture as shared cognitive structures" *Ethos*, Vol. 26, pp. 314-37

Romney, A. K., Moore, C. C., & Brazill, T. J. (1998) “Correspondence analysis as a multidimensional scaling technique for non-frequency similarity matrices” In J. Blasius and M. J. Greenacre (Eds.), *Visualization of Categorical Data* pp. 329-45. San Diego, CA: Academic Press.

Romney, Moore, Batchelder, & Hsia 1999

Romney, A.K., Moore, C. C., Batchelder, W. H., & His,a T. (2000) “Statistical methods for characterizing similarities and differences between semantic structures” *Proceedings of the National Academy of Science*, USA Vol. 99, pp. 518-23

Romney, A. K., Smith, T., Freeman, H. E., Kagan, J., & Klein, R. E. (1979) “Concepts of success and failure” *Social Sci. Research*, Vol. 8, pp. 302-26

Ryan, G. W., Nolan, J. M., & Yoder, P. S., (2000) “Successive free listing: Using multiple free lists to generate explanatory models” *Field Methods*, Vol. 12, No. 2, pp. 83-107

Smith, J.J. (1993) “Using ANTHROPAC 3.5 and a spreadsheet to compute a free-list salience index” *Cultural Anthropology Methods*, Vol. 9, No. 3, pp. 8-12

Smith, J. J., Furbee, L., Maynard, K., Quick, S. & Ross, L. (1995) “Salience counts: A domain analysis of English color terms” *Journal of Linguistic Anthropology*, Vol. 5, No. 2, pp. 203-16

Smith, J. J., & Borgatti, S. P. (1997) “Salience counts—And so does accuracy: Correcting and updating a measure for free-list-item salience” *Journal of Linguistic Anthropology*, Vol. 7, No. 2, pp. 208-9

Sujan, M. (1985), “Consumer Knowledge: Effects on Evaluation Strategies Mediating Consumer Judgments,” *The Journal of Consumer Research*, Vol. 12, No. 1. (Jun., 1985), pp. 31-46

Sutrop, U. (2001) “List task and a cognitive salience index” *Field Methods*, Vol. 13, No. 3, pp. 263-76.

Thompson, E. C., & Juan, Z. (2006) “Comparative Culture Salience Measures Using Free-List Data” *Field Methods*, Vol. 18, No. 4, November 2006 pp. 398-412

Tufte, E. R. (1997) *Visual Explainations*, Graphic Press, (May 1997) Cheshire, Connecticut

Tufte, E. R. (2006) *Beautiful Evidence*, Graphic Press, (July 2006) Cheshire, Connecticut

United States Department of Labor Bureau of Labor Statistics (2005) “Consumer expenditures in 2005 (annual report)” *Consumer Expenditure Survey*, http://www.bls.gov/cex

Weller, S. C., & Romney, A. K. (1988) *Systematic Data Collection*. Newbury Park CA.

Weller, S. C., and Baer, R. D. (2001) “Intra- and intercultural variation in the definition of five illnesses: AIDS, diabetes, the common cold, empacho, and mal de ojo” *Cross-Cultural Research*, Vol. 35, pp. 201-226