Methods and Measures that Profile Heavy Users*

Brian Wansink

Associate Professor of Marketing
University of Illinois at Urbana-Champaign
350 Commerce West, 1206 S. Sixth Street
Champaign, IL 61820
Phone: (217) 244-0208
Email: wansink@uiuc.edu

Sea Bum Park

Research Assistant
University of Illinois at Urbana-Champaign
350 Commerce West, 1206 S. Sixth Street
Champaign, IL 61820
Phone: (217) 244-0208
Email: seapark@uiuc.edu

The article has been published. It's appropriate citation is . . .

Wansink, Brian and SeaBum Park (2000), "Comparison Methods for Identifying Heavy Users," Journal of Advertising Research, 40:4 (July/August), 61-72.

* Brian Wansink (Ph.D. Stanford) is Associate Professor of Marketing, of Advertising, and of Agricultural Economics at the University of Illinois at Urbana-Champaign. His Food and Brand Lab specializes in research relating to the usage frequency and revitalization of mature brands. Sea Bum Park is a graduate student at the University of Illinois at Urbana-Champaign.

Methods and Measures that Profile Heavy Users

Abstract

Heavy users can be a critical segment for packaged goods marketers to target. Yet many attempts to profile heavy users have proven to be unsuccessful because of methodological and measurement problems. This article shows the diagnostic shortcomings of the commonly used mean comparison method of heavy user segmentation, and it presents a clustering method that effectively differentiates different types of heavy users from light users. Characteristics that differentiate heavy users from light users were collected from academic and commercial studies, and they are shown to relate to five basic lifestyle factors and six personality factors. While providing a key starting point for studying heavy users, they also show the dominant role that personality characteristics (versus lifestyle or demographic characteristics) play in differentiating heavy users from light users

Methods and Measures that Profile Heavy Users

The "heavy-half" concept generally suggests that 80% of the volume of a product is consumed by 20% of its consumers (Twedt 1964). Ever since the introduction of the "80/20 Rule," many mangers of packaged goods have attempted to target consumers based on the volume they purchased (Haley 1968) or consumed (Wansink 1997a, 1998). Unfortunately, many efforts to identify characteristics of heavy users have been plagued with methodological or measurement problems that have limited the depth and usefulness of their conclusions. Many of these studies incorrectly concluded that heavy users are not especially different than light users (Clancy and Schulman 1993). This paper identifies methods and measures that can be most effective in differentiating heavy users.

Two methods -- the simple mean comparison method and the basic cluster method -- have been used to examine heavy users. Both have their shortcomings. The commonly used simple mean comparison method can lead to over-generalized, non-diagnostic profiles. The basic cluster method can lead to overly specific profiles which are mathematically valid, but empirically nonexistent. What deserves to be examined is a hybrid technique which combines the best features of a mean comparison method with those of two-stage clustering.

The question then turns to which measures of characteristics will most effectively differentiate heavy users from light users. Past marketing research has used demographics, psychographics, benefits, or behavioral variables to profile heavy user segments (Assael 1973; Assael and Poltrack 1994; Assael and Roscoe 1976; Bass et al. 1968; Goldsmith et al. 1994). Demographic data, however, have their limits in helping to generate insights about customers (Haley 1984), and psychographic data are costly to assemble and difficult to objectively interpret (Wells 1974). Likewise, the benefits a person seeks in a product are also limited in their ability to provide reliable profiles that are stable over time. While most of these variables seem to be indeterminant, by integrating them, we can better examine the common factors they might represent (Sheth 1974). In summary, this research examines two questions:

- Which segmentation method generates the most diagnostic heavy user profiles?
- Which characteristics best differentiate heavy users?

To answer these questions, we first review previous research on the methods and measures used to profile heavy users. Second, we report results from a national survey to show how different segmentation methods can profile the same user groups quite differently. The methods and measures we test show that a hybrid cluster method provides distinctly different profiles than the more commonly used mean comparison model. We also show that personality variables are more differentiating than lifestyle variables. Following this, the implications for identifying heavy users are discussed along with how this information can be used to investigate whether media preferences and shopping baskets ("affinity marketing") can be used to profile heavy users of a particular product.

Differentiating Heavy Users

What Segmentation Method Generates the Most Diagnostic Heavy User Profiles?

The performance of most marketing programs is determined by its effectiveness and efficiency. To this end, identifying and profiling heavy users has been a "Holy Grail" to some brand managers. Unfortunately, most of these studies have generated only modest descriptive and explanatory power (Goldsmith et al. 1994; Singh 1990). More disconcerting, however, is that other studies have generated inconsistent findings. For example, some studies found that heavy users are more deal prone, but other studies quite oppositely found that they are innovators or early adopters (Hackleman and Duker 1980; Morgan 1970). Why the inconsistencies? They may come from variations in measurement and methodologies. While some efforts captured differences between the segments, others found only noise.

Two basic techniques that have been used to cluster heavy users have been the simple mean comparison method and the basic clustering method. The commonly used mean comparison method simply divides "heavy half" consumers from the "light half," and evaluates the mean differences across these two groups. While a simple mean comparison method of profiling heavy users has often been seen as too crude, the basic clustering method has also met with skepticism (Frank and Green 1968; Wells 1975). From a methodological viewpoint, cluster analysis groups consumers together based on a set of relevant variables, such as personality and lifestyle, without any prior assumptions about important differences that might differentiate usage. Unless usage segments are very different, however, homogeneous groups identified from the cluster analysis can appear to be heterogeneous because researchers can arbitrarily choose the number of clusters.

To solve the ad hoc nature of the basic clustering method, Punj and Stewart (1983) suggested a two-stage cluster analysis that helps enhance external validity as well as internal reliability. Figure 1 describes how this hybrid two-stage cluster analysis can be used to profile heavy users.

Insert Figure 1 here

Considering that both mean comparisons and the two-stage cluster analysis have their own advantages and disadvantages, we believe that combining the two methods can generate more diagnostic segment profiles based on the same population (Punj and Stewart 1983). As described in Table 1, we expect that the hybrid two-stage cluster analysis may resolve some of the fundamental problems found with both the other methods.

Insert Table 1 here

Despite its robustness, any method will be ineffective if it collapses too may distinct segments of consumers together. Not all heavy users are created equal, and aggregating across two different groups of heavy users can give a blurry profile, because the result is a hybrid customer – perhaps one that does not even exist. For example, while one might be a heavy user for convenience, the other might be for price.

Or one might be a heavy user or a store brand while the other a heavy user of that same categories premium brands.

A two-stage cluster analysis enables different profiles to emerge as two and three cluster solutions are used. As has been found, when multiple clusters are examined, the first cluster is maximally different than subsequent clusters. That is the second and third clusters are often more likely to show overlaps in their profiles. A recent study done looking at soup preferences (Wansink and Park 2000) indicated that while the first cluster profiles very clearly differentiate soup lovers of various soup flavors (tomato, vegetable, chili, etc.), the second clusters were more similar than different (see Figure 2). This means that while multiple cluster solutions are important for differentiating heavy users, their real value comes more in their ability to provide distinct, highly differentiated first clusters than to provide highly differentiated second and third clusters.

Insert Figure 2 here

Which Characteristics Best Differentiate Heavy Users?

While some researchers believe demographic profiles of heavy users provide safe surrogates for psychographic profiles (Assael and Poltrack 1994; Grønhaug and Zaltman 1981), several researchers have expressed their skepticism about the use of demographic and psychographic data as a basis for market segmentation (Frank et al. 1972; Kassarjian 1971). Indeed, demographic variables have been shown to be poor predictors of brand choice behavior, partly because of narrowing differences in income, education, and occupational status in an affluent mass consumption society (Sheth 1974). Even when demographics discriminate heavy users of products, they still have their limits in helping generate insights about customer segments (Clancy and Schulman 1994).

Yet lifestyle and personality characteristics that are specific to certain consumers and product categories must be defined and measured in order to be useful to marketers. For instance, it would be relevant for a food company to identify a health-conscious segment, or for a clothing company to identify a fashion conscious segment. In other words, personality and lifestyle characteristics, in contrast to demographics, need to be defined by researcher's objectives. Even if marketers get managerial insights from the psychographics of consumers that are consistent over time, they are still costly and lack objectivity. For example, the Value and Lifestyle (VALS) typology provides rich description about a unique way of life and values (Mitchell 1981), but the pieces may or may not have any relevance for a certain brand. This also holds true for benefit segmentation, which has been considered the most preferred segmentation methodology for almost two decades (Haley 1968, 1984). If two competing brands provide an identical benefit that consumers want, benefit segmentation may not fully discriminate the target consumer segment for one brand from another.

When focusing on heavy users, however, the universe of potentially discriminating variables decreases. Heavy user studies are typically focused on food and fast moving consumer packaged goods (Wansink and Gilmore 1999), and issues of fashion leadership and aesthetic taste become less important.

To better begin developing a standard for personality and lifestyle characteristics that differentiate heavy users of foods and packaged goods, a collection of personality and lifestyle characteristics were collected from past studies. These variables were subsequently modified and combined through factor analysis to arrive at 14 lifestyle and 20 personality variables that have been effective in differentiating heavy users of various foods and packaged goods. A factor analysis of these variables was completed and the dimensions shown in Table 2 were found to be significant in differentiating heavy users.

Insert Table 2 here

The factor analyses of these variables showed that there were six lifestyle factors that differentiated heavy users (active lifestyle, family spirited, homebody, intellectually stimulating pastimes, TV lover, and pet lover) and five personality characteristics that tended to differentiate heavy users (mentally alert, social, athletic, carefree, and stubborn).

Of particular interest is that there were a number of variables that have been used in commercial studies, but which have not been used in academic studies. These revolved around lifestyles and interests and include to the extent to which a person is a pet lover, workaholic, good cook, churchgoer, TV addict, book lover, technology whiz, or world traveler.

Method

One key objective of this study is to determine how accurately the segments obtained through a mean comparison method and a hybrid two-stage cluster analysis differentiates heavy users. American adults from 18-72 years old (mean of 47) were surveyed by telephone in June of 1999. The survey collected the key personality and lifestyle traits outlined in Table 2 along with demographic information and behaviors and preferences related to soup and soup consumption. A total of 1,003 interviews were completed among 602 women and 401 men.

To create user profiles, two basic segmentation methods were used: a simple mean comparison and a hybrid two-stage cluster analysis. In the mean comparison method, consumers were categorized into three user groups, heavy-, light-, and non-users and comparisons of each user group's average responses were made. (This was conducted on lifestyle characteristics and on personality characteristics). In the hybrid two-stage cluster analysis, we modified the two-stage cluster analysis method proposed by Punj and Stewart (1983) by conducting three separate two-stage cluster analyses for heavy-, light-, and non-users.[1]

Results

[1] As shown in Figure 1, this clustering algorithm used a priori user group segment bases. We then obtained statistically significant numbers of clusters for each of three user groups by examining the percent changes in the agglomeration coefficients from a hierarchical cluster analysis. For example, in lifestyle cluster analysis we found a two-cluster solution most appropriate after noticing the highest percent changes of the agglomeration coefficient from two- to one-cluster solution in non-user (8.9%), light user (10.9%), and heavy user (9.6%). Also, in personality clusters analysis a two-cluster solution generated the highest changes of agglomeration coefficients in non-user (14.4%), light user (12.3%), and heavy user (12.0%). From these two-cluster solutions we obtained cluster centroids that were used as initial seed points for K-means cluster analysis. We then obtained final cluster centroids from the K-means cluster analysis and conducted a series of significance tests.

Which Segmentation Method Generates More Diagnostic Heavy User Profiles?

Consumers were categorized into three groups: heavy users (38% ate soup more than once a week), light users (47% ate any soup more than once a month), and non-users (15%). Our results indicate that a simple mean comparison method provided somewhat distinctive but limited profiles of heavy users. Heavy users are socially active, creative, optimistic, witty, and less stubborn than light- and non-users. Yet even though heavy and light users were compared across 34 characteristics, only 3 characteristics differentiated the two groups.

To allow more discrimination between profiles, hybrid two-stage cluster analyses were conducted across lifestyle and personality characteristics. As indicated in Figure 3, both personality and lifestyle hybrid two-stage clustering methods generated more diagnostic heavy user profiles than the mean comparison method. While the mean comparison method provided the least differentiation across light and heavy users (only 9% of characteristics differentiated the user groups), the clustering methods differentiate among 36% of the lifestyle characteristics and a 85% of the personality characteristics. Figure 3 illustrates these levels of differentiation and Appendix 1 and 2 provide additional detail.

Insert Figure 3 here

In contrast to the mean comparison method, both the lifestyle clustering method and the personality clustering method provide richer descriptions of heavy users. Both demonstrate that heavy users are not are not all the same. Furthermore, both show without further separating heavy users on the basis of an a priori variable (such as benefits sought, health consciousness, etc.) the simple mean comparison method inaccurately combines distinct types of heavy users together into one generic profile.

Insert Table 3 here

Which Characteristics Best Differentiate Heavy users?

Do all heavy users fit the same profile? As discussed earlier, our major concern is that not all heavy users are alike. One soup heavy user might be a heavy user for convenience, while another might be one for price. These two might have very different profiles. For example, even if our results indicate that heavy users are socially active, creative, optimistic, and witty, we believe there may be significant differences among heavy users that we have overlooked.

To examine which variables – personality characteristics or lifestyle characteristics -- better profiled heavy users, we compared the numbers of variables that showed statistically significant differences in means between soup users in segment (cluster) 1 and segment (cluster) 2. As indicated in Table 4, personality segment number 1 showed that light users were 100% different from non-users and heavy users were 85% different from light users in terms of their personality while the two lifestyle segments showed 71% and 36% respectively.

Insert Table 4 here

Consider the two personality segments of heavy users (Table 3). One segment might be classified as "traditionalists" while the other group might better be classified as "dynamos." The traditionalists enjoy home and family magazines, but are not affectionate, not sophisticated, not competitive, not trend-setting, not an intellectual, not nutrition conscious, not fun loving, and not sarcastic or stubborn. This segment is in dramatic contrast to the second segment. The "dynamo" segment likes reading sports magazines and is adventurous, creative, outgoing, athletic, optimistic, fun at parties, witty, spontaneous, detail-oriented, and down-to-earth. While it is interesting that the heavies user segments of soup could be so dramatically different, this is because both groups eat soup for different reasons. The "traditionalist" segment eats soup because it is an " inexpensive meal solution" which "goes with other foods." The "dynamo" segment eats soup because it is "quick and convenient" and perceived as "healthy."

All heavy users may not be uniformly considered the same customer segment, and there may be overlapping clusters among heavy-, light- and non-user segments (recall Figure 2). The hybrid two-stage cluster analyses for personality and for lifestyle characteristics supported the notion that the heavy users could be differentiated from each other because they were not all alike. While the distinctiveness between $Segment_1$ and $Segment_2$ depends on whether we use lifestyle or personality variables, $Segment_1$ appears to be more differentiated. This is consistent with the pattern shown in Figure 2. Interestingly, the new lifestyle variables that were tested -- pet lover, TV addict, book lover, and churchgoer – differentiated between heavy and light users <u>and</u> between the two segments of heavy users.

Summary and Discussion

Implications for Profiling Heavy Users

This research showed how two general segmentation methods, a simple mean comparison and a hybrid two-stage cluster analysis, can lead to very different lifestyle and personality profiles of heavy users. When the results of the two methods are compared, the hybrid two-stage cluster analysis – which combines the simple mean comparison method and basic cluster analysis -- is the more diagnostic method for building heavy user profiles.

Second, these results provide an important benchmark by specifying the characteristics that differentiate heavy from light users. Although personality variables generate more distinctive and unique heavy user profiles than the lifestyle and demographic variables, all help build rich heavy user profiles. In particular, it was found that there were six lifestyle factors that differentiated heavy users (active lifestyle, family spirited, homebody, intellectually stimulating pastimes, TV lover, and pet lover) and five personality characteristics that differentiated heavy users (mentally alert, social, athletic, carefree, and stubborn). Of particular interest is that there were a number of variables that have been used in commercial studies, but which have not been used in academic studies. These include the extent to which a person is a pet lover, workaholic, good cook, churchgoer, TV addict, book lover, technology whiz, or world traveler.

Last, this study provides useful guidelines and methodological implications for future research on heavy users as well as customer database management. Future research on heavy users needs to adopt a rigorous segmentation approach in order to provide accurate profiles of heavy users. One way to do this is to use consumer profiles generated from one method need to be supported by another method such as customer prototyping techniques (Wansink 1994; 1997b). Managers of customer databases need to take a holistic attitude in building and managing their customer database because any single variable alone, such as personality, lifestyle, demographics, or media preference, cannot provide full descriptions of customers.

Can Media Preferences Differentiate Heavy Users?

Media preferences have often been used as a segmentation device. While broadcast programming preferences have not always proved to be diagnostic, it may be that magazine subscriptions are a stronger indicator of preference since they necessitate action (subscribing) and payment. Can media preference – as measured by magazine subscribership -- differentiate heavy-, light-, and non-users? The results in Table 5 suggest so. When compared to light users, heavy users less likely to read sports and entertainment magazines and more likely to ready home and family magazines.

Insert Table 5 here

The result of these differences in magazine suggest that consumers' preferences across other products might also be differentiated across heavy-, light-, and non-users. "Affinity marketing" is of significant interest to e-commerce and to database marketing, because it suggests there is a bundle or a metaphorical "shopping basket" of products that an ideal target market might be attracted to (Wansink and Ray 1992; 1996). This provides new justification for marketers to try and build their customer prototypes based on their preference for certain products or brands along with building customer prototypes based on personality and lifestyle data.

Conclusion

We identified the methods and measures that can be used to effectively profile heavy users. The most effective market segmentation generates the most accurate, detailed, diagnostic, and in-depth profiles of heavy users. This article shows the shortcomings of the commonly used mean comparison method of heavy user segmentation, and it outlines a clustering method that effectively differentiates different types of heavy users from light users. The various characteristics that differentiated heavy users from light users are shown to relate to five basic lifestyle factors and six personality factors. While providing a key starting point for studying heavy users, they also show the dominant role that personality characteristics (versus lifestyle or demographic characteristics) play in differentiating heavy users from light users.

References

Assael, Henry and A. Marvin Roscoe, Jr. (1976), "Approaches to Market Segmentation Analysis," *Journal of Marketing*, 40 (October), 67-76.

Assael, Henry and David F. Poltrack (1994), "Can Demographic Profiles of Heavy Users Serve as Surrogate for Purchase Behavior in Selecting TV Programs?" *Journal of Advertising Research*, 34(1), 11-17.

Bass, Frank M., Douglas J. Tigert, and Ronald T. Lonsdale (1968), "Market Segmentation: Group versus Individual Behavior," *Journal of Marketing Research*, 5 (August), 264-270.

Clancy, Kevin J. and Robert S. Shulman (1994*), Marketing Myths That Are Killing Business: The Cure for Death Wish Marketing*, McGraw-Hill, Inc.

Frank, Ronald E. and Paul E. Green (1968), "Numerical Taxonomy in Marketing Analysis: A Review Article," *Journal of Marketing Research*, 5 (February), 83-98.

Frank, Ronald E., William F. Massy, and Yoram Wind (1972), *Market Segmentation*, New Jersey: Prentice-Hall, Inc.

Goldsmith, Ronald E., Leisa Reinecke Flynn, and Mark Bonn (1994), "An Empirical Study of Heavy Users of Travel Agencies," *Journal of Travel Research*, 33 (1), 38-43.

Grønhaug, Kjell and Gerald Zaltman (1981), "Complainers and Non-complainers Revisited: Another Look at the Data," in *Advances in Consumer Research*, 8, ed., Kent Monroe, Ann Arbor: Association for Consumer Research, pp. 83-87.

Hackleman, Edwin C. and Jacob M. Duker (1980), "Deal Proneness and Heavy Usage: Merging Two Market Segmentation Criteria," *Journal of the Academy of Marketing Science*, 8 (4), 332-344.

Haley, Russell I. (1968), "Benefit Segmentation: A Decision-Oriented Research Tool," *Journal of Marketing*, 32 (July), 30-35.

Haley, Russell I. (1984), "Benefit Segments: Backwards and Forwards," *Journal of Advertising Research*, 28 (3), 19-25.

Kassarjian, Harold H. (1971), "Personality and Consumer Behavior: A Review," *Journal of Marketing Research*, 8 (November), 409-418.

Mitchell, Arnold (1981), *Changing Values and Lifestyles*, California: SRI International.

Morgan, Fred W., Jr. (1979), "Are Early Triers Heavy Users?" *Journal of Business*, 52 (3), 429-434.

Punj, Girish and David W. Stewart (1983), "Cluster Analysis in Marketing Research: Review and Suggestions for Application," *Journal of Marketing Research*, 20 (May), 134-148.

Sheth, Jagdish N. (1974), "Role of Demographics in Consumer Behavior," faculty working paper #218, University of Illinois, Urbana-Champaign: Illinois.

Singh, Jagdip (1990), "A Typology of Consumer Dissatisfaction Response Styles," *Journal of Retailing*, 66 (1), 57-99.

Twedt, Dik Warren (1964), “How Important to Marketing Strategy Is the “Heavy User”? *Journal of Marketing*, 28 (January), 71-72.

Wansink, Brian (1994), “Developing and Validating Useful Consumer Prototypes,” *Journal of Targeting, Measurement, and Analysis for Marketing*, 3 (1), 18-30.

Wansink, Brian (1997a), Making Old Brands New,” *American Demographics*, 19:12 (December), 53-58.

Wansink, Brian (1997b), “Developing Accurate Customer Usage Profiles,” in Lynn Kahle (Ed.) *Values, Lifestyles, and Psychographics,* Cambridge, MA: Lexington, 183-198.

Wansink, Brian (1998), “Expansion Advertising,” in *Why Advertising Works,* John Philip Jones, ed., Thousand Oaks, CA: Sage Publishing, 71-84.

Wansink, Brian and Sea B. Park (2000), ““Accounting for Tastes”: Building Consumer Preference Prototypes,” *Journal of Database Marketing*, forthcoming.

Wansink, Brian and Michael L. Ray (1996), “Advertising Strategies to Increase Usage Frequency,” *Journal of Marketing,* 60:1 (January), 31-46.

Wansink, Brian and Michael L. Ray (1992), “Estimating an Advertisement’s Impact on One’s Consumption of a Brand,” *Journal of Advertising Research*, 26:4 (May-June), 9-16.

Wansink, Brian and Jennifer Gilmore (1999), “New Uses that Revitalize Old Brands,” *Journal of Advertising Research*,” Vol. 43, April/May 59-67.

Wells, William D. (1974), “Life Style and Psychographics: Definitions, Uses, and Problems,” in *Life Style and Psychographics*, ed., William D. Wells, Chicago: American Marketing Association, pp. 317-363.

Wells, William D. (1975), “Psychographics: A Critical Review,” *Journal of Marketing Research*, 12 (May), 196-213.

Wind, Yoram (1978), “Issues and Advances in Segmentation Research,” *Journal of Marketing Research*, 15 (August), 317-337.

Table 1

Three Methods to Profile Heavy Users

	Simple Mean Comparisons	Basic Cluster-Analysis	Hybrid Two-stage Cluster Analysis
Description and Procedures	• A priori segmentation basis is decided based on a single variable (e.g., product usage, loyalty, customer type). • Segment's size, socio-demographic, psychographic, and other relevant characteristics are compared.	• No prior assumptions about differences within a population • Cluster respondents are based on a set of relevant multiple variables (e.g. personality, lifestyle, preference, behavior). • Cluster's size, socio-demographic, psychographic, and other relevant characteristics are compared.	• Prior assumptions are made about differences within a population • Utilizes both hierarchical and non-hierarchical cluster analyses to group respondents • Cluster's size, socio-demographic, psychographic, and other relevant characteristics are compared. • Precise
Advantage	• Simple and easier to do and understand • Familiar and widely available variables • Cost and time efficient	• More scientific and empirical • Generates graphical structure of data (e.g., dendogram, overlapphing clusters) • Hidden dimension can be found	• Considers outright characteristics of population • Identifies overlaps within across segments • Identifies sub-segments of heavy users
Disadvantage	• Overemphasizes an a priori segmentation basis • Ignores possible overlaps between segments • May lead to overgeneralizations	• Choosing number of clusters can be sometimes arbitrary • The best clustering algorithm for one may not the best for another • Can generate unneeded clusters that are nonexistent within the population	• Time consuming • May lead to over-segmentation

Table 2

Lifestyle and Personality Variables that Differentiate Users and Preference

Lifestyle	Personality
Active Lifestyle	Mentally Alert
- I am outdoorsy	- I am intellectual
- I am physically fit	- I am sophisticated
- I am a workaholic	- I am creative
- I am socially active	- I am detail oriented
	- I am witty
Family Spirited	- I am nutrition conscious
- I am family-oriented	Social
- I am a churchgoer	- I am fun at parties
	- I am outgoing
Homebody	- I am not shy
- I enjoy spending time alone	- I am spontaneous
- I am a homebody	- I am trendsetter
- I am a good cook	Athletic
	- I am athletic
Intellectually Stimulated Pastimes	- I am competitive
- I am a technology whiz	- I am adventurous
- I am a world traveler	Carefree
- I am a book lover	- I am down-to-earth
	- I am affectionate
TV Lover	- I am fun lover
- I am addicted to TV	- I am optimistic
	Stubborn
Pet Lover	- I am stubborn
- I am a pet lover	- I am sarcastic

Note. Principal component analysis with varimax rotation was used. Suggested factors have Eigen values greater than 1 and explain 55% (lifestyle) and 50% (personality) of variances in total (see Wansink and Park 2000 for details). Variables were measured on a 5-point scale (1 = strongly disagree; 5 = strongly agree).

Table 3

Lifestyle and Personality Profiles of Soup Users:

Mean Comparisons vs. Cluster Analyses

	Mean Comparison Method		**Cluster Comparison Method**			
	Lifestyle Characteristics	Personality Characteristics	Lifestyle Characteristics		Personality Characteristics	
			Segment 1	Segment 2	Segment 1	Segment 2
Non User	• Bad cook • Introvert	• Stubborn • Not witty	• Not family oriented • No pets • Not a churchgoer • Not physically fit	• Socially active and outdoorsy • Technology whiz and book lovers • Good cooks	• Not competitive • Shy • Not affectionate and sophisticated • Not down to earth and sarcastic • Not detail oriented or intellectual	• Adventurous, creative, outgoing, athletic • Very optimistic • Fun at parties and witty • Fun lovers • Trendsetter • Spontaneous • Nutrition conscious
Light User	• Family oriented • Book lover	• Not creative • Not spontaneous	• Enjoy reading Hobbies magazines • Own a pet	• Enjoy reading Business magazines • Not a book lover	• Like reading Health & Fitness, Human Interest, and Entertainment magazines • Adventurous, creative, outgoing, athletic • Very optimistic but sarcastic and stubborn • Fun at parties, love fun and witty	• Enjoy reading Home & Family magazines • Shy • Not affectionate and sophisticated • Not competitive • Not spontaneous • Not nutrition conscious • Not a trendsetter or intellectual
Heavy user	• Socially active • Technology whiz • Good cooks	• Nutrition conscious • Optimistic • Down-to-earth	• Not a book lover • Not a churchgoer • Not a pet owner	• Outdoorsy • Technology whiz • Not addicted to TV	• Enjoy reading Home & Family magazines • Not affectionate nor sophisticated • Not competitive • Not a trendsetter or intellectual • Not nutrition conscious • Not a fun lover • Not sarcastic or stubborn	• Like reading Sports magazines • Adventurous and creative • Outgoing, and athletic • Very optimistic • Fun at parties and witty • Spontaneous but detail oriented • Down to earth

Table 4
Personality Profiles Differentiate Better than Lifestyle Profiles

	~~Segment (Cluster) 1~~		~~Segment (Cluster) 2~~	
	~~Non- and Light users~~	~~Light- and Heavy users~~	~~Non- and Light users~~	~~Light- and Heavy users~~
Lifestyle Cluster	71% (10/14)	36% (5/14)	36% (5/14)	29% (4/14)
Personality Cluster	100% (20/20)	85% (17/20)	95% (19/20)	95% (19/20)

Note. Percentages represent the percentage of characteristics which differentiated user groups

Table 5
Does Magazine Preference Differentiate Usage Volume?

	User Group			
	Non-users	Light users	Heavy users	Chi-square
Hobbies	23%	13%	18%	3.543
Health & Fitness	5%	5%	2%	1.775
Business	2%	2%	2%	0.297
Sports	3%	9%	2%	7.928**
Human Interests	8%	20%	15%	5.658*
Home & Family	15%	14%	23%	5.708*
News Magazine	8%	13%	14%	1.588
Entertainment	8%	11%	5%	4.528
Woman’s Magazine	6%	7%	8%	0.541

** $p < 0.05$. * $p < 0.1$.

Figure 1
Hybrid Two-stage Cluster Analysis

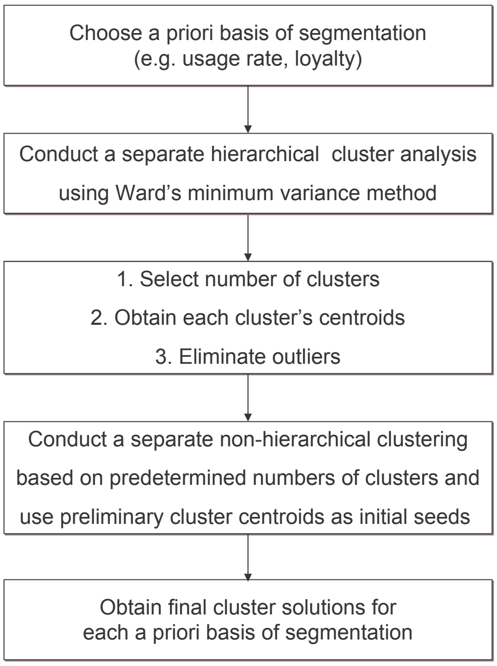
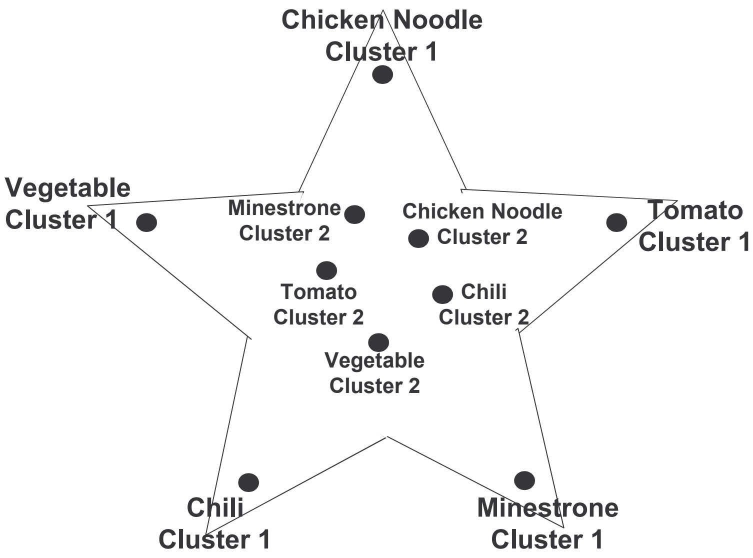


Figure 2

Initial Clusters Differentiate Better than Subsequent Clusters

Figure 3



Appendix 1

The Mean Comparison Method of Profiling Soup Users

		Non-user (n=147)	Light user (n=471)	Heavy user (n=383)	F-values/ Chi-square [a]
Lifestyle	Homebody	2.6	2.8	2.8	2.828*
	Socially Active	3.0	3.1	3.2	3.144**
	Workaholic	2.6	2.5	2.5	0.600
	Physically Fit	2.9	2.9	3.0	2.119
	Pet Lover	2.6	2.6	2.7	0.797
	Outdoorsy	3.2	3.1	3.2	1.420
	TV addict	2.4	2.3	2.3	0.087
	Book Lover	2.7	3.0	3.0	4.830***
	Family Oriented	3.4	3.6	3.6	3.704**
	World Traveler	1.9	1.9	2.0	2.477*
	Technology Whiz	2.0	2.2	2.2	3.728**
	Churchgoer	2.4	2.6	2.6	1.259
	Good Cook	2.8	3.1	3.1	4.376**
	Spending Time Alone	2.9	2.8	2.9	0.629
Personality	Adventurous	3.0	2.9	3.0	1.709
	Affectionate	3.4	3.5	3.5	0.833
	Creative	3.1	3.0	3.2	4.438**
	Outgoing	3.1	3.2	3.3	2.993*
	Athletic	2.5	2.6	2.7	1.501
	Down-to-Earth	3.5	3.6	3.6	4.096**
	Fun loving	3.5	3.5	3.6	0.791
	Shy	2.1	2.0	1.9	1.851
	Sophisticated	2.3	2.3	2.4	1.263
	Trendsetter	1.9	1.9	2.1	2.992*
	Nutrition Conscious	2.6	2.9	2.9	5.898***
	Optimistic	3.1	3.2	3.3	3.149**
	Detail Oriented	3.0	3.1	3.1	0.695
	Competitive	2.7	2.7	2.8	0.365
	Intellectual	2.8	3.0	2.9	1.541
	Spontaneous	2.8	3.0	3.1	3.152**
	Sarcastic	2.7	2.5	2.6	2.733*
	Stubborn	3.1	2.9	2.8	3.892**
	Fun at Parties	2.9	2.9	2.9	0.079
	Witty	2.8	2.9	3.0	4.158**
Demographics[b]	Gender	Female	Female	Female	
	Age	35 to 44	35 to 44	35 to 44	
	Education Level	Voc./Tech – Some College	Some College	Some College	
	Income Level	$15K to $34.9K	$35K to $50K	$35K to $50K	
	Primary Grocery Shopper	Yes	Yes	Yes	
	Primary Meal Preparer	Yes	Yes	Yes	
	# of Children under 17	None	None	None	

*** p < 0.01. ** p < .05. * p < .01.
a. F-values for lifestyle and personality; Chi-squares for magazine.
b. Central tendencies of demographics indicate median values.

Appendix 2

Clustering Methods and Measures that Differentiate Soup Users

		Soup Non-user		F-values / Chi-square [a]	Soup Light user		F-values / Chi-square [a]	Soup Heavy user		F-values / Chi-square [a]
		Cluster 1	Cluster 2		Cluster 1	Cluster 2		Cluster 1	Cluster 2	
Lifestyle Clusters	Homebody	2.5	2.6	0.110	2.8	2.7	2.114	2.8	2.8	0.007
	Socially Active	2.7	3.1	7.775***	3.1	3.1	0.017	3.2	3.2	0.073
	Workaholic	2.5	2.7	1.440	2.6	2.5	1.231	2.4	2.6	1.342
	Physically Fit	2.6	3.0	4.490**	2.9	3.0	1.289	3.0	3.1	0.683
	Pet Lover	1.4	3.4	133.228***	3.9	1.2	6544.462***	1.1	3.9	5358.208***
	Outdoorsy	2.8	3.4	13.920***	3.2	3.1	3.018*	3.0	3.4	20.649***
	TV Addict	2.4	2.3	0.591	2.4	2.2	3.012*	2.5	2.2	5.077**
	Book Lover	2.5	2.9	3.904**	3.1	2.8	5.454**	2.9	3.1	4.267**
	Family Oriented	3.1	3.7	16.243***	3.6	3.6	1.270	3.6	3.7	2.908*
	World Traveler	1.8	2.0	0.591	1.9	1.9	0.282	2.0	2.0	0.005
	Technology Whiz	1.6	2.2	14.756***	2.2	2.2	0.294	2.1	2.3	3.526*
	Churchgoer	2.1	2.7	9.273***	2.5	2.7	3.213*	2.8	2.5	5.064**
	Good Cook	2.1	3.2	43.781***	3.1	3.0	0.944	3.1	3.1	0.029
	Spending Time Alone	2.7	3.0	3.284*	2.8	2.8	0.325	2.8	2.9	2.215
Number of Cases in Each Cluster		57	89		254	209		152	224	
Personality Clusters	Adventurous	2.7	3.3	22.788***	3.3	2.4	138.859***	2.6	3.4	78.573***
	Affectionate	3.1	3.7	21.331***	3.6	3.4	15.460***	3.4	3.6	3.928**
	Creative	2.8	3.4	14.339***	3.2	2.7	39.113***	2.9	3.5	53.584***
	Outgoing	2.6	3.6	54.170***	3.5	2.7	147.654***	2.9	3.6	71.011***
	Athletic	2.1	3.0	33.759***	3.0	2.0	119.137***	2.1	3.2	143.345***
	Down-to-Earth	3.3	3.6	5.522**	3.6	3.6	0.118	3.7	3.6	4.523**
	Fun Loving	3.2	3.8	17.167***	3.8	3.3	70.760***	3.5	3.7	17.384***
	Shy	2.4	1.8	10.726***	1.9	2.2	18.861***	2.0	1.9	2.115
	Sophisticated	2.0	2.7	22.930***	2.6	1.9	90.105***	1.9	2.9	138.997***
	Trendsetter	1.5	2.3	33.363***	2.3	1.4	145.701***	1.6	2.6	112.778***
	Nutrition Conscious	2.2	3.1	32.515***	3.0	2.6	23.667***	2.9	3.1	4.115**
	Optimistic	2.7	3.4	21.128***	3.4	3.1	14.152***	3.1	3.4	10.222***
	Detail Oriented	2.7	3.4	16.166***	3.2	3.1	0.760	2.8	3.5	49.002***
	Competitive	2.2	3.2	31.577***	3.2	2.1	166.767***	2.3	3.3	103.711***
	Intellectual	2.5	3.2	26.523***	3.2	2.7	39.084***	2.5	3.3	109.243***
	Spontaneous	2.4	3.3	46.884***	3.3	2.6	90.568***	2.7	3.4	59.231***
	Sarcastic	2.3	3.1	15.115***	2.8	2.1	60.406***	2.2	2.9	45.236***
	Stubborn	2.9	3.2	3.689*	3.2	2.6	34.880***	2.5	3.1	37.800***
	Fun at Parties	2.4	3.4	43.433***	3.3	2.3	177.426***	2.5	3.3	76.220***
	Witty	2.5	3.3	34.788***	3.2	2.4	105.797***	2.7	3.3	58.190***
Number of Cases in Each Cluster		73	69		262	197		176	191	
Demographic Clusters	Gender	Male	Female		Female	Female		Female	Female	
	Age	25 to 34	35 to 44		35 to 44	35 to 44		45 to 54	35 to 44	
	Education Level	HS Grad	Some College		Some College	Some College		Some College	Some College	
	Income Level	\$15K to \$34.9K	\$35K to \$50K		\$35K to \$50K	\$35K to \$50K		\$35K to \$50K	\$35K to \$50K	
	Primary Grocery Shopper	Yes	Yes		Yes	Yes		Yes	Yes	
	Primary Meal Preparer	Yes	Yes		Yes	Yes		Yes	Yes	
	# of Children under 17	None	5 or more		None	None		None	None	

*** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$.
a. F-values for lifestyle; Chi-squares for favorite magazine
b. Numbers in parentheses indicate percents of each magazine chosen as their favorites by people in each user group.
c. Central tendencies of demographics indicate median values.