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"User Profiles for Directly Competing Brands Seldom Differ: Re-Examining the Evidence"

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User Profiles for Directly Competing Brands Seldom Differ: Re-Examining the Evidence[1]

Abstract

It has been claimed that the user profiles of directly competing brands seldom differ. This surprises many in marketing, leading some commentators to express doubts about the validity of the claim. In the empirical generalization tradition, we: (i) re-examine the previous claim using newer data; (ii) consider the scope of the claim in terms of brands in emerging markets, private labels, variants and composite segments; and (iii) discuss potential boundary conditions. Despite attempts by marketers to differentiate brands and provide customized features for distinct target audiences, our evidence confirms user profiles of directly competing brands seldom differ.

Introduction

The traditional belief in marketing is that distinct brand segments exist. That is, competing brands such as Coke and Pepsi or Sony and Panasonic appeal to distinct segments or groups of users, identified with demographics, psychographics, behaviors and the like. Marketers spend significant effort trying to target products and advertising to such "distinct and unique" groupings of buyers, thereby avoiding head-on competition (e.g. Schiffman et al. 2011). Consistent with this approach, segmentation studies are now routinely undertaken in marketing, media planning and strategy formulation, with marketing researchers and analysts drawing upon socio-demographic, behavioral and attitudinal data.

The underlying commercial rationale here is the belief that it is more profitable to treat certain types of buyers in different ways than to treat them all the same (Bock and Uncles 2004). One-way to do this is to present specific groups of buyers with distinct and differentiated brands, an idea integral to the logic of STP (segmentation-targeting-positioning). Where marketers have been effective in implementing STP, then the profile of competing brands should differ radically. However, extensive empirical analyses

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reveal the opposite – user profiles of directly competing brands seldom differ (Hammond et al. 1996; Kennedy and Ehrenberg 2001a; Kennedy and Ehrenberg 2001b).

Although empirically robust, the above findings have drawn criticisms and led to attempts to defend segmentation (e.g., Wedel and Kamakura 2001). Kannan (2004), for instance, asserts: "… extensive simulation tests … indicate that these segmentation methodologies are very effective in uncovering brand segments that exist in the market" (ibid. p 1327). Indeed, to support brand profiling efforts, considerable investments have been made in technique development and many different models and procedures are now available (e.g., clustering techniques, mixture unfolding models, latent class analysis, hierarchical Bayesian models – see Wedel & Kamakura 2000). Typically, the use of these techniques is illustrated by an in-depth analysis of a few product categories or with simulations (e.g., Kannan and Wright 1991; Kannan and Yim 2001; Andrews et al. 2002). This is understandable, in that the purpose of these studies often has been to develop techniques to find the "best" grouping of consumers given particular data, rather than derive generalized empirical findings. It is also the case that many of these techniques are quite adept at grouping consumers in terms of their product category choices (e.g., distinguishing between those who do and don't regularly buy carbonated drinks).

By contrast, our research and the focus of the work cited earlier (Hammond et al. 1996; Kennedy and Ehrenberg 2001a; Kennedy and Ehrenberg 2001b), is in deriving generalized knowledge based on systematic comparison of the user profiles of directly competing brands (e.g., how Coke buyers differ from Pepsi or Dr Pepper buyers). This emphasis is important given that so much effort is directed to presenting specific groups of buyers with distinct and differentiated brands. We see that even though STP is logically appealing, and notwithstanding impressive technical advances, some of the foundations of brand segmentation are called into question with the claim that competing brand user profiles seldom differ. Given this contention, and in line with the empirical generalizations tradition espoused by Ehrenberg (e.g. Lindsay and Ehrenberg 1993), this paper seeks to: (i) re-examine the previous claim using newer and more varied datasets;

(ii) consider the scope of the claim in terms of brands in emerging markets, private labels, variants and composite segments; and (iii) discuss potential boundary conditions.

Research Approach

Data

We investigate brand user profiles drawing upon datasets for different time periods, sources, countries and categories, for brands, private labels and variants. An outline of the datasets is provided in Table 1, including those originally used to substantiate the claim. These large-scale datasets are typical of those regularly used by marketers around the world, enabling us to examine demographic, behavioral and attitudinal bases of segmentation. For example, from the 250+ attitudes included in the datasets in Table 1 many varied facets are captured (e.g., consumers' attitudes to buying local brands, to organically-grown products, to protecting environment, to the desire for prepared foods, to the importance of value-for-money, etc).

Our data and measures reflect industry norms used in advertising, media and marketing decision-making. Wherever possible, therefore, we use standard industry data or classifications and conduct analyses on all available measures. The approach is very comprehensive, although we acknowledge that researchers have used such a multitude of data and ways to segment people (from product/media usage, to benefits, to geography, to psychographics with all sorts of combinations), that it is not possible to consider all possibilities and we encourage others to examine our claims with their own datasets.

Table 1: The Datasets

Datasets	Categories	Sample	Data type / Measures
Previous data:			
US, UK, Germany and Japan, 1980s (used in Hammond et al. 1996)	23 grocery	n=1000–5,000	Demographics and household buying – scanner and diary-based panels.
UK, 1999 (used in Kennedy & Ehrenberg 2001)	42 grocery, durables, services	n=25,000, ave category n=10,000	Self-completion demographics, media and attitudes 200+ variables
New replications / extensions in this study:			
1. Australia, 2008	1 grocery	n=17,000+	Self-completion. Demographics, media and attitudes including composite segments
2. UK, 2009	2 grocery	n=8,000+	Retailer scanner data + demographics from loyalty card program
3. USA, 2011	3 grocery	n=800	Self-completion. Online panel - demographics and buying
4. Australia, 2008	2 grocery	n=500	Self-completion. Online panel - demographics and buying
5. China, 2004	6 grocery	n=400+	Self-completion. Panel - demographics, attitudes and buying
6. UK, 2005	7 categories	n=15,000	Panel data for 15 variants, 4 demographics

Analysis Method

Our analysis method is illustrated for soy sauce, drawing from the China dataset (a 6-month consumer panel that was run in Shanghai). Market shares are shown in Table 2 where the brand Laocai has a 29% share, Amoy 26%, and so forth. For each brand, user profiles are tabulated as profile percentages. This is demonstrated for two segmentation measures: age of principal buyer and number of shopping trips. For example, the user profile for Laocai is 22% young buyers, 41% middle-age buyers, and 37% older buyers. By comparing each brand's profile with the category profile, it is seen there are few differences between competing brands: typically, 19% of purchases come from the youngest group, 45% from the middle group, and 36% from the older group.

The analysis is formalized by calculating mean absolute deviations (MADs), namely the average size of the differences between the brand and category profiles (we also compared with the average brand profile, as in the previous work, which gave rise to the same findings). Thus, 22% of purchases of Laocai come from the youngest buyers compared to 19% of category purchases, a difference of three percentage points. Middle-age buyers account for 41% of purchases compared to 45% of category purchases, and older buyers account for 37% of purchases compared to 36% of category purchases. Therefore, the three absolute deviations for Laocai are 3, 4 and 1, giving a MAD of 2.7 (or 2.9 using un-rounded numbers).

Deviations are calculated for "brands" (i.e., the average MAD for an individual brand compared to the category) and "measures" (i.e., the average MAD for a measure, such as age, across all brands in a category). Thus, the average of the age MADs is 3.5, which compares to 1.9 for the average of the shopping trip MADs. Numbers below five are interpreted as showing no managerially useful segmentation (in line with Hammond et al. 1996; Kennedy and Ehrenberg 2001a). It is acknowledged that a threshold MAD of 5 is somewhat arbitrary, although we also looked at a threshold of 10 and were able to draw the same general conclusions. For consistency with earlier work we report on deviations of 5 or more. Isolated deviations below this threshold are unlikely to be actionable – they may simply reflect random variation that is difficult for marketing managers to exploit. We encourage readers to look at their own data to see if the differences really matter (especially when you look at the raw data) – occasionally they will, mostly they will not.

Table 2: User Profiles for Soy Sauce Brands – Sample Measures

	Market Share	Age Segments			Ave "brand" MAD	Shopping Trip Segments		Ave "brand" MAD
		Young	Middle	Older		Low	High	
Category	**100**	**19**	**45**	**36**		**92**	**8**	
Laocai	29	22	41	37	**2.9**	92	8	**0.2**
Amoy	26	17	46	37	**1.4**	94	6	**2.2**
Haiou	18	19	46	36	**0.5**	92	8	**0.0**
Haday	11	26	49	26	**6.6**	93	7	**0.9**
Others	11	12	47	40	**4.8**	86	14	**5.7**
No Brand	4	21	51	29	**4.5**	90	10	**2.1**
Av Measure MAD					**3.5**			**1.9**

Except for MADs, figures are percentages. "No brand" refers to products that have no "branding" and are typically sold in wet markets. This is distinct from private labels, which are sold through established retailers.

The same procedure is used to examine user profiles for all brands of soy sauce across the remaining measures (Table 3). The overall average MAD is 3.8, which is reasonably low. In effect, most individual profile percentages for different brands are within a few points of one another, revealing a lack of brand segmentation (i.e., the profile of Laocai buyers is not so different from that of Amoy buyers).

Table 3: User Profiles for Soy Sauce – MADs for All Measures

Soy Sauce	**Socio-Demographic Measures**					**Behavioral Measures**		
	Age	Hhod size	Education	Living space	Income	Shopping trips	Grocery spend	Car usage
Laocai	2.9	2.7	11.3	2.1	2.5	0.2	0.2	2.4
Amoy	1.4	2.3	3.0	0.1	3.2	2.2	0.7	2.2
Haiou	0.5	0.9	1.7	0.9	1.6	0.0	0.6	6.8
Haday	6.6	7.3	11.6	5.6	5.0	0.9	0.5	7.0
Others	4.8	1.6	13.3	0.8	5.0	5.7	1.4	0.4
No Brand	4.5	2.6	0.2	1.7	16.6	2.1	0.8	13.1
MAD	**3.5**	**2.9**	**6.9**	**1.9**	**5.7**	**1.9**	**0.7**	**5.3**

Soy Sauce	Attitudinal Measures				
	Time pressure	Price consciousness	Risk taking	Deal proneness	**Average "brand" MAD**
Laocai	4.6	1.9	1.9	2.1	2.9
Amoy	1.9	1.5	2.2	2.2	1.9
Haiou	6.0	4.4	4.3	6.9	2.9
Haday	1.4	6.5	4.7	6.3	5.3
Others	7.9	3.0	3.6	4.7	4.4
No Brand	7.1	1.1	4.6	7.9	5.2
MAD	**4.8**	**3.1**	**3.6**	**5.0**	**3.8**

Findings

Norms

We present high-level results across the available datasets in Table 4; namely, the average MADs for all variables for 50+ categories, using market share as the underlying metric. Average deviations of brand profiles are consistently below 3 points and generally indicate no brand segmentation. Results for the very wide range of measures we could access covering demographics, media, behaviors and attitudes are all similar, suggesting the results generalize. It is evident that the original claim still holds after 15 years and is now demonstrated in additional countries (i.e., Australia and China) using data from different sources (i.e., traditional consumer panels, scanner data and online panels).

Table 4: User Profiles for all Categories – Summary MADs

Category	Demo	Media	Atti-tudes	Av MAD	Category	Demo	Media	Atti-tudes	Behav	Av MAD
UK					Car insurance	3	1	1	n/a	**2**
Cigarettes	4	4	6	**6**	Coffee	2	1	2	n/a	**2**
Accounts	6	3	5	**5**	Home contents	2	1	1	n/a	**1**
Cat food	3	1	4	**4**	Paint	3	1	1	n/a	**2**
Mints	3	1	3	**3**	Shampoo	2	1	2	n/a	**2**
Toothbrush	3	1	3	**3**	Airlines	2	1	1	n/a	**1**
Health ins	4	2	3	**3**	Camera film	2	1	1	n/a	**1**
Sweets	3	1	2	**3**	Headache tablets	2	1	1	n/a	**1**
Crisps	3	1	3	**3**	Cars	2	1	1	n/a	**1**
Soap	3	1	2	**3**	Credit Cards	2	1	1	n/a	**1**
Packaged holidays	3	1	3	**3**	Mortgages	2	1	1	n/a	**1**
Batteries	3	1	2	**3**	Fuel	2	1	1	n/a	**1**
Other chocolate	3	1	2	**2**	Retailers	1	1	1	n/a	**1**
Kitchen rolls	3	1	3	**2**	**Australia**					
Nuts	3	1	2	**2**	Chocolate	2	1	2	n/a	**2**
Chocolate Bars	3	1	2	**2**	**China**					
Toothpaste	2	1	2	**2**	Packaged water	6	n/a	4	5	**5**
Toilet paper	2	1	2	**2**	Rice	3	n/a	6	2	**4**
Computers	3	2	2	**2**	Dried noodles	5	n/a	4	5	**5**
Baked beans	3	1	2	**2**	Soy sauce	4	n/a	6	4	**5**
Record shops	3	1	1	**2**	Laundry detergent	3	n/a	4	3	**4**
Store retail cards	3	1	2	**2**	Fresh milk	6	n/a	4	6	**5**
Computer games	3	1	2	**2**	**Private labels**					
Vitamins	3	1	2	**2**	Tea (UK)	2	n/a	n/a	n/a	**2**
Washing liquids	3	1	2	**2**	Instant Coffee (UK)	2	n/a	n/a	n/a	**2**
Grocers	3	1	2	**2**	Cookies (USA)	1	n/a	n/a	n/a	**1**
Yogurt	3	1	2	**2**	Fabric softener (USA)	1	n/a	n/a	n/a	**1**
Light bulbs (1)	2	1	2	**2**	Ice cream (USA)	1	n/a	n/a	n/a	**1**
Car tyres	2	1	2	**2**	Toilet paper (USA)	2	n/a	n/a	n/a	**2**
Stain removers	2	1	2	**2**	Tomato sauce (Aus)	1	n/a	n/a	n/a	**1**
Light bulbs (2)	3	1	1	**2**	Pasta (Aus)	1	n/a	n/a	n/a	**1**
					Average	**3**	**1**	**2**	**3**	**2**

Deviations

As can been seen in Table 3 isolated deviations do occur. This is evident in some of the other non-summary analyses (not shown) which underlie the averaged figures in Table 4. Around 8% of the individual deviations are more than five percentage points, but even these larger deviations are generally below 10 points. Marketers may be interested in particular deviations relating to their brands, but they need to keep in mind that while deviations certainly occur they are mostly exceptional and mostly small. Some of these may be already well known to those working in the specific product category or so small and exceptional they are unlikely to be actionable in marketing terms. Other deviations in the non-summary analyses could be traced back to small sample sizes, so we believe them to be unreliable and unreplicable.

Extensions

To examine the scope of the claim we conducted four extensions:

1: User Profiles of Brands in an Emergent Market

Cross-cultural researchers draw attention to the very different values and beliefs of consumers in emergent markets which, they argue, give rise to distinct attitudes, behaviors and responses to marketing activity. Despite these differences, generally small MADs are reported for the six Chinese datasets (covering traditional products like soy sauce and non-traditional products such as packaged water) (Table 4). There are a few individually high MADs, the highest being 26 – this very exceptional figure refers to people who make a lot of shopping trips and purchase more No Brand packaged water compared to category norms. A cultural explanation could be that these frequent shoppers patronize local shops and markets where they are more exposed to non-branded packaged water. A simpler explanation is that the high MAD arises because of sampling variation – this appears to be true because in the Shanghai packaged water market the market share of No Brand is only 5% and just 7% of people in the sample are in the high shopping trip segment, so the sample base is extremely small (Uncles et al. 2010).

2: User Profiles of Private Labels

Extension two relates to private labels. Private labels have witnessed rapid growth all around the world, far outpacing the growth of manufacturer brands (Nenycz-Thiel and Romaniuk 2011). Identifying the characteristics of these buyers has long been of interest, in part because private labels tend to be low priced and therefore those who buy them may comprise a price sensitive segment. Past research describing private label buyers provides mixed results, with some authors claiming there are no demographic differences (e.g., Ailawadi et al. 2001), while others point out differences on a number of demographics (e.g., Baltas and Argouslidis 2007).

In our datasets, across gender, age, income, employment status and education we do not find any segment that is more likely to buy private labels. Summary results are presented in Table 4 from three countries – UK, USA and Australia – and 8 categories. In terms of user profiles the results are consistent, with an average MAD below 2. Moreover, the profile of users tends to be very similar to that of manufacturer brands.

3: User Profiles of Product Variants

As most consumer products are available in varieties or variants, such as different pack sizes (small or large cereal packs), types (tube or pump action toothpastes), flavors (banana or strawberry yogurt), and forms (liquid, tablet or powder laundry detergents), all functionally differentiated, our third extension is to look at the user profiles associated with product variants.

Although much work has been carried out to understand the nature of brand-based segments, less is known about the existence of segments based on variants. Singh et al. (2008) report that competitive product variants appeal to very different numbers of consumers, but to the same kinds of consumers. Trinh et al. (2009) found differences in the market shares of product variants of the categories they studied and report these differences to be largest with demographic measures such as age and employment status. The two studies have limitations, with the former employing only two demographic variables, and the latter using only market shares to determine the variance in segments.

Here we analyse 15 variants across seven categories. We consider four demographic variables (household size, number of children, age, and social class) and examine patterns for performance metrics such as market share, penetration and average purchase frequency. Given their importance, it is not surprising that previous studies concentrated on market shares; however, performance metrics such as penetration and average purchase frequency are also of considerable interest to marketers. It is possible that while there may be no brand segmentation in terms of market shares, there could be segments in relation to these other metrics. Such an approach also addresses the criticism of past work that the way brand usage was defined might blur distinctions among users, especially for frequently purchased products (Wedel and Kamakura 2001).

Table 5 shows that, overall, MADs are low. Variants, even though functionally highly differentiated and targeted at specific consumer segments, are bought by much the same types of user. This is true regardless of whether the focus is on market share or other performance metrics.

Table 5: User Profiles of Product Variants – Summary MADs

Product Categories and Variants (UK data, 2005)	**Market Share**	**Penetration**	**Average Purchase Frequency**
Soup			
Flavors	1	3	0
Pack types	1	2	0
Instant Coffee			
Flavors	0	0	0
Pack sizes	1	2	0
Breakfast Cereals			
Pack sizes	2	6	1
Flavors	2	2	2
Toothpaste			
Pack types	1	3	0
Formula	1	2	0
Pack sizes	1	3	0
Packet Tea			
Flavors	0	2	1
Pack types	2	2	1
Laundry Detergents			
Pack sizes	2	3	0
Forms	2	3	1
Pack types	1	1	1
Yoghurt Drinks			
Flavors	4	1	1
Average	**1**	**2**	**1**

4: Composite Segment Profiles of Brands

It could be argued that effective segmentation rests on the analysis of interlocking variables (e.g., measures of household size, education *and* income); therefore, in our final extension, we investigate user profiles in the one dataset where we have information on industry-defined composite segments.

We looked at two composite segmentation solutions. One solution is based on geo-demographics and combines measures of education, income and other household characteristics. It is illustrated in Table 6. We initially looked at all the individual variables to see if any of the brand user profiles differed. Of the over 400 MADs, only seven were 5 or more (about 2%) and none were 10 or more. When we then looked at the composite segments (such as 'High Status Family') it was also the case that the brand user profiles seldom differed (Table 6).

Table 6: User Profiles based on Composite Segments – Deviations and MADs

Brand	High Status Family – type A	Mid Status Stronger Family	Mid Status Weaker Family	Low Status Stronger Family	Low Status Weaker Family	Disadvantaged
A	-2	1	0	0	1	1
B	-3	1	-1	2	0	2
C	0	1	1	0	-1	-1
D	-1	0	1	0	0	0
E	-2	0	-2	2	1	2
F	1	1	-1	2	-2	0
…..						
O	4	1	0	-3	0	-2
P	**5**	**-7**	3	-2	1	-2
MAD	**2**	**1**	**1**	**2**	**1**	**1**

Except for the MADs in the final row, all figures are deviations.

Slightly more and higher deviations are evident for Brand P, but it was a recent launch with less than 1% share. Rather than demonstrating that some brands strongly appeal to specific segments, we think this is an example of the need for successful brands to appeal to a broad market - Brand P failed to do this and was later withdrawn.

For the same dataset we looked at an alternative values-based segmentation that combined several measures to assess lifestyle priorities, such as the importance of career, family, fun, or the desire for a balanced lifestyle. This values-based segmentation is promoted as identifying distinct groups such as Fun Seekers, Success Driven and Health Conscious shoppers. We studied the output groups. Results are consistent with the other composite segmentation, once again leading us to conclude that user profiles of competing brands seldom differ.

Why is the Claim so Universally True?

From a consumer viewpoint it seems that many people see competing brands as substitutable, perhaps with good reason because many brands do *not* have unique attributes and are *not* highly differentiated. This being the case, there is no reason for the buyer profile of one brand to be markedly different from the buyer profile of another brand in the same product category. Consumers buying these similar brands will share similar characteristics (in terms of demographics, behavior, and even attitudes). This scenario is captured by the notion of a “Dirichlet market”, defined in terms of steady state and un-partitioned markets where market shares are (approximately) stationary and there is no (dramatic) clustering of particular brands (Ehrenberg et al. 2004).

For marketers charged with the responsibility of managing brands there may be windows of opportunity to offer something unique or highly differentiated which appeals to a particular profile of buyer, but typically such opportunities do not last long. Over time brands tend to copy each other’s sales-effective attributes and may even imitate each other’s marketing communications (Barwise and Meehan 2004), such that the buyer profiles of these brands, copy-cats and me-toos become indistinguishable. This is a natural consequence of competition within product categories and sub-categories.

Boundary Conditions

Despite support for the claim that user profiles seldom differ, we can conceive of conditions where the claim might not be true. This is about establishing the boundary conditions of our findings.

Empirically, there can be segmentation at the category or sub-category level: cat food buyers have cats, and dog food buyers have dogs (some both), buyers of luxury cars tend to have greater wealth than the typical economy car buyer (although some luxury car buyers buy economy cars as well), pre-sweetened cereals are eaten more by children (but by some adults too). To the extent that brands across these categories and sub-categories are not directly substitutable, we can expect user profiles to differ.

All the markets discussed thus far are characterized by having competing offerings, in many cases with only trivial attribute differences to distinguish them. This is typical of established markets whereas in pre-competitive markets the situation might be different (a first-mover brand may create a nascent product or sub-product category). However, markets are rarely "pre-competitive" for long (e.g., at the time of its launch, the technologically novel Apple iPad faced competition from 12+ tablet-style brands, as well as e-readers). The story for pre-competitive geographical markets is not fundamentally different; once markets have opened up, competitive offerings in the form of brands, me-toos, lookalikes, fakes and counterfeits quickly become available.

There are technical considerations too. Proponents of "no strong brand segmentation" mainly engage in *a priori* segmentation, whereby raw data about buyers is used to profile each offering. This approach tends to be descriptive, as is reflected in the choice of modeling techniques (e.g., contingency table analysis). When so much commercial data is presented and routinely analyzed this way, it is reasonable to approach segmentation in this manner. By contrast, those who doubt the claim tend to be engaged in *post hoc* segmentation. They again start with segmentation measures, but pool the data to identify clusters and latent classes. They assume segments are to be found, rather than test for the existence of segments. In forming clusters, a criterion such as "minimize within-group variance and maximize between-group variance" is used (such variance-based techniques *will* find clusters). The inputs to these models are similar (age, income, etc.) but the outputs (clusters/classes) may be difficult to label, interpret and utilize.

Conclusions

Through a series of replication studies and extensions, we re-confirm that user profiles of directly competing brands seldom differ. This is confirmed using data spanning 25 years, across 50+ categories and 60 datasets, and demonstrated for brands in emerging markets, private labels, variants and composite segments. Some marketers may be disheartened by this finding – competition appears to erode any distinct appeal a brand might have for particular users or buyers. Nevertheless, brands compete and thrive in all the markets we investigate in spite of them having similar within-category user profiles. To respond, marketers need to invest in strong brands (that can evolve in terms of attributes and features) and that remain physically available and salient to a broad range of category users (Barwise and Meehan 2004; Sharp 2010; Uncles 2011). When we think of Coke and Pepsi or Sony and Panasonic it is their appeal across users in a category that marks them out as leading and successful brands.

Endnote

Our paper honors Professor Ehrenberg for not only noticing and documenting the claim that we re-examine, but for the principles he espoused and which have been incorporated into our research, specifically: the importance of evidence-based studies (using many sets of data), the search for generalization (resting on the identification of norms), differentiated replication (to determine the scope of findings), reporting deviations and exceptions (to explore boundary conditions), and data reduction (to convey findings simply and with impact). The ultimate goal is a better understanding of consumers and markets, in a way that informs and assists marketing thought and practice.

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