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Connie R. Bateman

Editor

University of North Dakota

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LETTER FROM THE EDITOR

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The articles contained in this volume have been double blind refereed. The acceptance rate for manuscripts in this issue, 25%, conforms to our editorial policies.

Our editorial policy is to foster a supportive, mentoring effort on the part of the referees which will result in encouraging and supporting writers. We welcome different viewpoints because in differences we find learning; in differences we develop understanding; in differences we gain knowledge and in differences we develop the discipline into a more comprehensive, less esoteric, and dynamic metier.

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Connie Bateman
University of North Dakota

A SEGMENTATION OF BEACH RENTAL-BY-OWNER ONLINE INQUIRING CUSTOMERS

William W. Hill, Mississippi State University

ABSTRACT

A growing segment that has emerged over the past decade is the vacation-rental-by-owner destination market. Indeed, many of today's beach house owners are using website promotion to rent their vacation properties versus the use of outside rental agencies. To better understand typical interested customers in this market, the rental inquiries for one beach house owner are examined. Using the beach house owner's website inquiry database collected over a six-year period from 2004 to 2010, unique characteristics about these vacationers relative to the property, the area, and the surrounding Gulf Coast region are identified. Key factors used to understand these interested vacationers include region, distance, inquiry lead time, length of stay, group size, adult group size, child group size, inquiring season, and vacation season.

INTRODUCTION

A recent phenomenon in vacation planning is the vacation owner rental market, and clearly much of this growth is occurring through online reservation channels. While hotels and resorts have had a direct line (online) to vacationers for almost two decades, in more recent years owners and vacationers have been able to connect directly through now very popular vacation-by-owner peer-to-peer (P2P) online reservation websites. One of the major features attracting vacationers is the opportunity for more spacious accommodations closer to that found at home (Yu, 2011). Other attractions include the autonomy and excitement of selecting their own getaway, discounts versus hotel resorts, and more. For whatever the reason, the Internet has spawned a unique marriage between the rental home owner and the vacationer, and as a result, is appreciably changing the dynamics of destination planning. In fact, by 2010, the vacation rental (privately owned homes and condos, and unoccupied timeshares) market had grown to a staggering \$26.4 billion, and \$4.5 billion of this total occurred through Internet channels (Yu, 2011). Accordingly, reservation websites report exponential growth spawning more reservation websites into the market (James, 2010). Yet, while there has been initial research in online reservations by vacation businesses (i.e., hotels, rental cars), the growing online vacation peer-to-peer (P2P) rental market has been given minimal, if any, notice in the marketing literature. This paper offers a refreshing beginning to a unique and uncharted area of the vacation destination market. The study uses rental inquiries for one beach house getaway over a seven-year period (2004 to 2010). The specific features of the property are outlined in Table 1.

Table 1. Beach House Description			
Inside Features	Description	Outside Features	Description
Style	3-Story	Distance to Beach	4 th row; 200 yards to beach
Square Footage	1450	Pool	Yes (Shared)
Sleeps	7	Tennis Courts (4)	Yes
Beds	5	Exercise Facility	No
Bedrooms	2	Gated	No
Bathrooms	2	Entrance	Yes
Stairs	Yes	Beach chairs	Yes
Elevator	No	Fishing equipment	Yes
Air Conditioning (Central)	Yes		
Satellite TV (3 locations)	Yes		
DVD & VCR	Yes	Miscellaneous	
Linens Provided	Yes	Smoking Friendly	No
Stove	Yes	Pet Friendly	Yes
Microwave	Yes	Child Friendly	Yes
Refrigerator	Yes	Handicap Access	No
Dishwasher	No		
Washer & Dryer	Yes		
Cooking Utensils	Yes		

Using the beach house owner's website inquiries from a leading reservation website, this study seeks to understand P2P vacationers through several key measures which include: distance (from beach house property), group size, length of stay, inquiry lead time, region of country, inquiry season, and vacation season. The paper first offers a discussion of the types of variables used, which are categorized into three general areas: region characteristics, temporal characteristics, and lodging characteristics. With these variables, the study assesses the overall results, regional results, vacation season results, and online inquiry customer types. For the latter, a cluster analysis is performed. First, the paper addresses the variables used in this study.

REGIONAL CHARACTERISTICS

Regional characteristics, within the context of this study, represent factors that relate to the location of the online inquiring party. These variables, described next, are: customer region and distance.

Customer Region

The customer regions highlighted in this paper follow the 8-region classification of the United States census (Census, 2000). Specifically, the home address of the inquiring party was

identified relative to the 8-region classification. The U.S. Census classifies U.S. citizens based on cultural and regional traits commonalities. Relative to this study, these common traits may have an impact on inquiry vacation particulars (e.g., Midwest vacationers may desire different features than vacationers living two hours from the beach house). Thus, the customer regions developed by the U.S. Census served as an ideal classification and categorical variable for this study.

Distance

The distance variable in this study represents the total miles from the home of the inquiring party to the address of the beach house of interest. This variable attempts to capture possible distance factors that could come into play with an online vacation inquiry.

TEMPORAL CHARACTERISTICS

Temporal characteristics represent factors that relate to the timing of the online inquiry. The time-based variables noted are: inquiring date, inquiry date of the week, inquiry time of day, vacation date of interest, vacation day of the week, and lead time. These variables are discussed next.

Inquiring Date

Another interesting aspect to understanding online vacation inquiries is the time of year when the inquiry is made. This measure is categorized into four seasons based on the calendar dates of the seasons for that year: winter (December 20-23 through March 20-23), spring (March 20-23 through June 20-22), summer (June 20-22 through September 21-24), and fall (September 21-24 through December 20-23). The basis for examining this measure ties to the belief that the time of the inquiry may suggest a great deal about the rental interest. That is, inquiring behavior may be different based on when the inquiry is made (e.g., planning a vacation in a warm beach climate may be influenced by the cold conditions outside).

Inquiry Day of the Week and Time of Day

Inquiry day of the week examines the actual day of the week an inquiry was made online. Considering the different lifestyle schedules individuals have, there could be days of the week that are more or less common with inquirers. Similarly, the inquiry time of day examines the time of day the inquiry was made by the interested party categorized into 8 intervals. Prior to categorization, the actual inquiry times were adjusted for time zone differences. For instance, if the inquiry was received to the website database in, for instance, the Central Time zone at 7pm, from the Eastern Time zone, the time was adjusted to 8pm since it was actually 8pm for the

inquiring party. Of course, with this variable, the assumption was made that the inquiry time data delivery to the website database was instantaneous.

Vacation Date of Interest

The vacation time of interest is the calendar season of the year that the inquiring party identifies in the online inquiry. This measure simply examines the time of the year identified for the vacation based on the same calendar season categories noted for the inquiry seasons: winter (December 20-23 through March 20-23), spring (March 20-23 through June 20-22), summer (June 20-22 through September 21-24), and fall (September 21-24 through December 20-23). All inquiries are labeled based on the season of the year of vacationing interest. The concept is important because the perception the season of the year provides some perspective about the vacation inquiry. Specifically, the inquiry behavior for a last-minute weekend vacation may be far different from that of a well-planned summer vacation. Keep in mind the selected vacation dates are influenced by the dates that are actually available, minimum night restrictions, changes in seasonal pricing at a minimum, etc.

Vacation Day of Week

The vacation day of week is the day of the week that the inquiring party seeks as the arrival day for the vacation time of interest. As noted with vacation dates, the day of arrival is influenced by selection restrictions. Most notably, summer rentals require one week Saturday to Saturday reservations.

Lead Time

Lead time is described as the time between the online inquiry and the actual vacation date of interest. This measure may encompass several interesting factors such as the vacationer's sense of urgency for planning the vacation, the personality of the inquirer, the complexity of the vacation, etc. Clearly, the lead time variable is influenced by availability and the selection restrictions previously noted.

LODGING CHARACTERISTICS

Lodging characteristics represent factors that pertain to the potential actual stay in the beach property of interest. These variables are: length of stay, group size, adult group size, and child group size. These variables are discussed next.

Length of Stay

The length of the stay is the total number of days between the vacation time of interest and the date of inquiry. By knowing the length of stay, there may be information relative to

financial commitment, what can be inferred from a one-month versus a three-night rental, etc. For the latter, specific features may be more critical. For instance, a small kitchen may be a greater negative for longer stays.

Group Size, Adult Group Size, and Child Group Size

The size of the party is the total number of people identified in the online inquiring process. The size of the party may affect inquiry behavior because greater numbers suggests greater complexity in the vacation. That is, with larger groups, the number of bedrooms and bathrooms are more relevant, as is the overall square footage of the beach house. Additionally, the number of adults and the number of children are variables examined with this research. The greater number of adults suggests many things, but most certainly that an extended family or an adult getaway is possibly at hand. Additionally here, the presence of children in the group, at all, signifies some type of family trip. Thus, the total group size as well as the number of adults and children should provide good information about group dynamics relative to this particular beach property.

METHOD

This research began with approval for use of inquiry data from a leading vacation rental website company, approval from the beach house rental owner of the property examined, and approval from the Institutional Review Board (IRB). The database consisted of inquiry data for a beach house property for the time period from mid-January, 2004 to mid-April 2010. The data period intentionally ends just prior to the Gulf Coast oil spill crisis which began in late April 2010, since the period after the spill provided minimal and sporadic online inquiry interest. The original data source consisted of 1101 inquiries. The researcher eliminated 183 inquiries due to missing values, key punching errors in the data, etc. An additional 15 inquiries were eliminated from the pacific coast, the mountain west, and New England regions because these areas represented such a small percentage of the overall sample. Thus, the overall data editing process lead to the elimination of 203 total inquiries providing a final sample of 903 inquiries.

Since the analysis used secondary data, all the values are single-item ratio measures. For this reason, an exploratory factor analysis (EFA) used to assess multi-item fit was not needed in this analysis.

FINDINGS

The study examines customer inquiry data in four areas: overall results, regional results, seasonal results, and customer type results. The overall results are detailed next.

Overall Results

Table 2 displays the frequency distribution for all of the variables examined in this study. Table 2 also displays the continuous variables as categorical variables to provide a better depiction of the data distribution for the reader. The mean values for the continuous variable are also shown in Table 2.

Table 2 offers some interesting facts about the beach house property inquiries. About 90 percent of inquirers live 800 miles or less from the beach property on the Gulf Coast. Less than 8 percent of the inquirers are 200 miles or less from the property. Thus, the proximity of being close to the vacation area does not necessarily spurn online inquiry. Indeed, the idea that living close to the beach makes the beach less desirable for vacationers may have merit.

About 76 percent of inquiring parties indicated a group size between 3 and 9 people. The most frequent number of adults was 2, which was about 41 percent of the time, and about one-third (33.3%) of the inquirers had children in their party.

In terms of the length of stay, about 80 percent of vacationers inquired to stay between 4 and 7 days. The inquiry lead time varied greatly with inquirers with the most common lead time between 8 and 42 days (37.3%) prior to the vacation time. Still, as many as 9 percent of interested parties inquired within one week of the potential vacation date. Thus, almost 10 percent of inquirers were very last-minute.

The largest region of inquirers came from Region 2 (East South Central) at 41.5%. Region 2 encompasses the states of Alabama, Mississippi, Tennessee, and Kentucky. The second most common region was Region 3 (West South Central) at 27.8%. Region 3 includes the states of Louisiana, Texas, Arkansas, and Oklahoma.

Vacationers most often inquire in the winter-spring time period (71.9%). Within a given week, inquiring typically occurs fairly evenly—but, slightly higher on Tuesday (16.4%) and Wednesday (16.1%) and slightly lower on Saturday (10.9%) and Sunday (14.5%). About 91 percent of inquiring occurs between 9am and midnight during the day, peaking between 12 noon and 3pm (20.4%). Still, 15.6 percent of inquiries occur between 9pm and midnight suggesting late-night inquiring is clearly common. Only 9 percent of the inquiries occur between midnight and 9am. Not surprisingly, the least popular time to inquire is between 3am to 6am (0.3%).

In terms of the vacation season of interest, spring (34.9%) and summer (50.1%) were the dominant seasons of choice following by winter (9.6%), then fall (5.4%). Most vacationers target a weekend arrival with Saturday (39%) being the most popular choice. This is followed by Friday (15.0%) then Sunday (13.6%). The least popular target day of the week to arrive is Tuesday (4.0%). Also provided in Table 2 are the mean (M) and standard deviation values (SD) for the continuous variables used in this study. These variables are: distance, lead time, length of stay, group size, adult group size, and child group size.

Table 2. Descriptive Characteristics					
Characteristics	Frequency	Percent	Characteristics	Frequency	Percent
Distance (M = 488, SD = 236)			Inquiry Date		
200 or less	70	7.8	Winter	287	31.8
201 to 400	316	35.0	Spring	262	40.1
401 to 600	234	25.9	Summer	198	21.9
601 to 800	195	21.6	Fall	56	6.2
801 to 1000	60	6.6	Total	903	100.0
1000 or greater	28	3.1	Inquiry Week Day		
Total	903	100.0	Sunday	131	14.5
Group size (M = 5.8, SD = 2.7)			Monday	141	15.6
2 or less	118	13.1	Tuesday	148	16.4
3-5	340	37.7	Wednesday	145	16.1
6-9	350	38.8	Thursday	139	15.4
10 or greater	95	10.5	Friday	101	11.2
Total	903	100.0	Saturday	98	10.9
Adult Group Size (M = 3.9, SD = 2.2)			Total	903	100.0
2 or less	375	41.5	Inquiry Time		
3 to 4	263	29.1	12:01am to 3:00am	39	4.3
5 or more	265	29.3	3:01am to 6:00am	3	0.3
Total	903	100.0	6:01am to 9:00am	36	4.0
Child Group Size (M = 1.9, SD = 1.7)			9:01am to 12:00noon	176	19.5
No children	301	33.3	12:01pm to 3:00pm	184	20.4
2 or less	308	34.1	3:01pm to 6:00pm	169	18.7
3 or more	294	32.6	6:01pm to 9:00pm	155	17.2
Total	903	100.0	9:01pm to 12midnight	141	15.6
Length of Stay (M = 6.1, SD = 3.4)			Total	903	100.0
3 or less	122	13.5	Vacation Date		
4 to 6	369	40.9	Winter	85	9.4
7	358	39.6	Spring	315	34.9
8 or greater	54	6.0	Summer	452	50.1
Total	903	100.0	Fall	51	5.6
Lead Time (M = 66.0, SD = 61.0)			Total	903	100.0
7 or less	81	9.0	Vacation Week Day		
8 to 42	337	37.3	Sunday	123	13.6
43 to 105	293	32.4	Monday	92	10.2
106 to 147	106	11.7	Tuesday	36	4.0
148 or greater	86	9.5	Wednesday	80	8.9
Total	903	100.0	Thursday	85	9.4
Region			Friday	135	15.0
Region 1 (South Atlantic)	119	13.2	Saturday	352	39.0
Region 2 (East South Central)	375	41.5	Total	903	100.0
Region 3 (West South Central)	251	27.8			
Region 4 (West North Central)	56	6.2			
Region 5 (East North Central)	102	11.3			
Total	903	100.0			

In Table 3, a correlation matrix for the continuous variables is provided. A number of significant associations can be stated. Distance is positively associated with lead time ($p < .01$), length of stay ($p < .01$), group size ($p < .01$), and child group size ($p < .01$) and negatively associated with adult group size ($p < .05$). There are a number of possible explanations here. Farther distance inquirers may feel the need to prepare earlier since they may be less certain of the beach vacation area. They would be more likely to stay longer to justify the longer distance travel. The fact that larger group sizes and more children associates with greater distance travel perhaps suggests family vacations inquirers are more willing to travel greater distances. The negative association with adult group size may indicate that interest in adult vacations is more likely to be for shorter trips. This seems reasonable since coordinating adult trips, dealing with the varying job schedules, may necessitate easier (i.e., short driving distance) travel options.

Lead time was positively associated with length of stay ($p < .01$), total group size ($p < .01$), adult group size ($p < .05$), and child group size ($p < .01$). These findings are not surprising since trying to reserve a property for a longer period of time should require greater online search time and thus earlier preparation. Further, reserving a vacation for a larger group would require more time to find a sufficiently large and reasonability priced property. The final relationship worthy of note is length of stay is negatively associated with adult group size ($p < .05$). This also makes sense in that as the adult group size increases, trips are probably more likely to be adult-oriented, shorter, “long weekend” vacations as compared to the week-long traditional family vacations.

Table 3. Correlation Matrix						
	1	2	3	4	5	6
Distance (miles)	---					
Lead Time (days)	.19**	---				
Length of State (days)	.15**	.17**	---			
Total Group Size	.02**	.12**	-.05	---		
Adult Group Size	-.07*	.07**	-.08*	.78**	---	
Child Group Size	.13**	.09**	.03	.57**	-.07*	---
* $p < .05$ (means are based on five-point disagree-agree scales)						
** $p < .01$ (means are based on five-point disagree-agree scales)						

Regional Results

The study also takes an examination of inquiries from the perspective of the region of the country from which the inquiry is received. The regional findings are shown in Tables 4 and 5, which display region/state breakdowns and state/city breakdowns, respectively. From Table 4, the greatest percentage of state inquiries by region is: Georgia (80.7%) from Region 1 (South Atlantic), Alabama (44.5%) from Region 2 (East South Central), Louisiana (45%) from Region 3

(West South Central), Missouri (83.9%) from Region 4 (West North Central), and Illinois (37.3%) from Region 5 (East North Central).

Table 4. Region Frequency by State		
Region	Frequency	Percent
Region 1 (South Atlantic)		
Georgia	96	80.7
Florida	12	10.1
Virginia	3	2.5
Maryland	0	1.7
North Carolina	2	1.7
South Carolina	2	1.7
West Virginia	2	1.7
Total	119	100.0
Region 2 (East South Central)		
Alabama	167	44.5
Tennessee	101	26.9
Kentucky	58	15.5
Mississippi	49	13.1
Total	375	100.0
Region 3 (West South Central)		
Louisiana	113	45.0
Texas	81	32.3
Arkansas	48	19.1
Oklahoma	9	3.6
Total	251	100.0
Region 4 (West North Central)		
Missouri	47	83.9
Kansas	5	8.9
Iowa	2	3.6
Minnesota	2	3.6
Total	56	100.0
Region 5 (East North Central)		
Illinois	38	37.3
Indiana	28	27.5
Ohio	20	19.6
Michigan	10	9.8
Wisconsin	6	5.9
Total	101	100.0

Table 5. State and City Frequency Summary					
States	Frequency	Percent	Major Cities	Frequency	Percent
Alabama	167	18.5	Atlanta, GA	44	4.9
Louisiana	113	12.5	Birmingham, AL	31	3.4
Tennessee	101	11.2	Baton Rouge, LA	22	2.4
Georgia	96	10.6	Nashville, TN	22	2.4
Texas	81	9.0	Huntsville, AL	20	2.2
Kentucky	58	6.4	St. Louis, MO	17	1.9
Mississippi	49	5.4	Memphis, TN	16	1.8
Arkansas	48	5.3	Lafayette, LA	14	1.5
Missouri	47	5.2	Louisville, KY	14	1.5
Illinois	38	4.2	Houston, TX	13	1.4
Indiana	28	3.1	Mobile, AL	13	1.4
Ohio	20	2.2	New Orleans, LA	13	1.4
Florida	12	1.3	Shreveport, LA	12	1.3
Michigan	10	1.1	Knoxville, TN	10	1.1
Oklahoma	9	1.0	Little Rock, AR	10	1.1
Wisconsin	6	0.7	Montgomery, AL	10	1.1
Kansas	5	0.6	Jackson, MS	9	1.0
Virginia	3	0.3	Tuscaloosa, AL	8	0.9
Iowa	2	0.2	Grand Prairie, TX	7	0.8
Maryland	2	0.2	Madison, AL	7	0.8
Minnesota	2	0.2	Tulsa, OK	6	0.7
North Carolina	2	0.2			
South Carolina	2	0.2			
West Virginia	2	0.2			
Total	903	100.0			

From Table 5 it is clear that Alabama, Louisiana, Tennessee, Georgia, and Texas are the states with the most frequent inquirers overall and Atlanta, Birmingham, Baton Rouge, Nashville, and Huntsville are the cities with the most frequent inquirers overall. Perhaps an even better picture of the inquiry geographic interest market is shown in Figure 1 (developed from Microsoft MapPoint) which is a map illustrating the frequency of inquiries. The larger bubbles indicate a greater concentration of inquiries. It is clear from Figure 1 that there are more inquirers in larger cities/suburbs. This is evident to the west in New Orleans (LA) and Houston (TX), to the north in Birmingham (AL), Memphis (TN), Nashville (TN), and Atlanta (GA), and even to the farther north in St. Louis (MO) and Cincinnati (OH).

Figure 1. Customer Inquiry Map*



*Microsoft MapPoint Map

Table 6 Region Findings

	Region 1: (n=119)	Region 2: (n=375)	Region 3: (n=251)	Region 4: (n=56)	Region 5 (n=102)
Distance (miles)*	422 ^c	389 ^c	447 ^c	789 ^b	860 ^a
Inquiry Lead Time (days)*	63.6 ^b	58.8 ^b	63.2 ^b	88.1 ^a	89.8 ^a
Length of Stay (days)	5.7	5.8	6.2	6.2	6.7
Group Size (vacationers)	5.8	5.7	5.9	6.1	5.6
Adult Group Size (vacationers)	3.8	4.0	4.0	3.9	3.4
Child Group Size (vacationers)	2.0	1.7	1.8	2.2	2.2
Date of Inquiry (p<.05)**					
Winter	34 (28.6%)	117 (31.2%)	60 (23.9%)	24 (42.9%)	52 (51.0%)
Spring	45 (37.8%)	147 (39.2%)	124 (49.4%)	20 (35.7%)	26 (25.5%)
Summer	36 (30.3%)	88 (23.5%)	55 (21.9%)	8 (14.3%)	11 (10.8%)
Fall	4 (3.4%)	23 (6.1%)	12 (4.8%)	4 (7.1%)	13 (12.7%)
Time of Inquiry (not sig.)**					
12:01 to 3:00 AM	3 (2.5%)	14 (3.7%)	13 (5.2%)	4 (7.1%)	5 (4.9%)
03:01 to 6:00 AM	0 (0.0%)	1 (0.4%)	1 (0.4%)	1 (1.8%)	0 (0.0%)
06:01 to 9:00 AM	5 (4.2%)	15 (4.0%)	13 (5.2%)	1 (1.8%)	2 (2.03%)
09:01 to 12:00 NOON	15 (12.6%)	74 (19.7%)	55 (21.9%)	7 (12.5%)	25 (24.5%)
12:01 to 3:00 PM	22 (18.5%)	76 (20.3%)	52 (20.7%)	17 (30.4%)	17 (16.7%)
03:01 to 6:00 PM	24 (20.2%)	77 (20.5%)	39 (15.5%)	8 (14.3%)	21 (20.6%)

Table 6 Region Findings					
	Region 1: (n=119)	Region 2: (n=375)	Region 3: (n=251)	Region 4: (n=56)	Region 5 (n=102)
06:01 to 9:00 PM	28 (23.5%)	63 (16.8%)	37 (14.7%)	11 (19.6%)	16 (15.7%)
09:01 to 12 MID	22 (18.5%)	55 (14.7%)	41 (16.3%)	7 (12.5%)	16 (15.7%)
Day of Week of Inquiry (p<.05)**					
Sunday	16 (12.6%)	43 (11.5%)	37 (14.7%)	11 (19.6%)	25 (24.5%)
Monday	21 (17.6%)	58 (15.5%)	32 (12.7%)	13 (23.2%)	17 (16.7%)
Tuesday	20 (16.8%)	64 (17.1%)	36 (14.3%)	6 (10.7%)	22 (21.6%)
Wednesday	17 (14.3%)	72 (19.2%)	33 (13.1%)	9 (16.1%)	14 (13.7%)
Thursday	18 (15.1%)	57 (15.2%)	51 (20.3%)	4 (7.1%)	9 (8.8%)
Friday	15 (12.3%)	39 (10.4%)	34 (13.5%)	5 (8.9%)	8 (7.8%)
Saturday	13 (10.9%)	42 (11.2%)	28 (11.2%)	8 (14.3%)	7 (6.9%)
Date of Vacation of Interest (p<.05)**					
Winter	8 (6.7%)	39 (10.4%)	15 (6.0%)	5 (8.9%)	18 (17.6%)
Spring	37 (31.1%)	138 (36.8%)	76 (30.3%)	23 (41.1%)	41 (40.2%)
Summer	67 (56.3%)	168 (44.8%)	150 (59.8%)	27 (48.2%)	40 (39.2%)
Fall	7 (5.9%)	30 (8.0%)	10 (4.0%)	1 (1.8%)	3 (2.9%)
Day of Week of Vacation of Interest (p<.05)**					
Sunday	17 (14.3%)	46 (12.3%)	34 (13.5%)	13 (23.2%)	13 (12.7%)
Monday	9 (7.6%)	31 (8.3%)	35 (13.9%)	10 (17.9%)	7 (6.9%)
Tuesday	3 (2.5%)	11 (2.9%)	11 (4.4%)	4 (7.1%)	7 (6.9%)
Wednesday	14 (11.8%)	38 (10.1%)	21 (8.4%)	2 (3.6%)	5 (4.9%)
Thursday	12 (10.2%)	25 (9.3%)	27 (10.8%)	6 (10.7%)	5 (4.9%)
Friday	16 (13.4)	78 (20.8%)	34 (13.5%)	3 (5.4%)	4 (3.9%)
Saturday	48 (40.3%)	136 (36.3%)	89 (35.5%)	18 (32.1%)	61 (59.8%)
*Mean contrasts are significant at p<.05 (according to Scheffe test). Values with different superscripts are significantly different from each other; superscripts are such that "a" always represents the highest score.					
**Chi-square tests were applied to these relationships					

The regional findings are summarized in Table 6 and statistical significances between regions are noted. There is not a significant difference evident with the group totals, adult totals, and children totals between the regions. Not surprisingly, there is a significant difference in the distances to the beach property. This, of course, was preset by the region categorization. Interestingly, lead time was significantly different between some regions. Region 4 and 5, the west north central and east north central regions of the Midwest generally inquired about 25 to 30 days sooner than regions 1 (South Atlantic), 2 (East South Central), and 3 (West South Central) to the south. Thus, distance may lead to earlier preparation as previously noted. Moreover here, regions 4 and 5 were more likely to inquire in the fall and winter. Regions 1, 2, and 3 were more likely to wait until spring.

In terms of vacation seasons of interest, region 5 (East North Central) displayed the greatest tendency to vacation in the winter (17.6%). This could relate to the "snowbird" phenomenon which is has been used to describe travel from the upper Midwest, Northeast, and Canada to the warm Florida sunshine (merriam-webster.com, 2011).

Regions 1 (56.3%) and 3 (59.8%) showed the greatest interest in vacationing in the summer. Region 2 (8.0%), the closest region, showed the greatest interest in vacationing in the least popular fall. It makes sense that inquiring vacationers closer in distance to the beach

property could easily make fall trips. It is also possible that since the fall is the cheapest vacationing season, unplanned/unbudgeted trips are more probable with Region 2 vacationers. Regions 4 and 5 are more likely to want to arrive on the weekend and less likely to arrive in the middle of the week as compared to the other regions.

Vacation Season Results

The study also takes an examination of inquiries from the perspective of the inquiring customer's vacation season of interest. The results of this analysis are summarized in Table 7.

Table 7 Vacation Season Interest Findings				
	Winter: (n=85)	Spring: (n=315)	Summer: (n=452)	Fall: (n=51)
Distance (miles)*	574 ^a	486 ^{a,b}	479 ^b	429 ^b
Inquiry Lead Time (days)	51.4	63.5	70.3	67.5
Length of Stay (days)*	6.5 ^{a,b}	6.0 ^{a,b}	6.0 ^b	7.0 ^a
Group Size (vacationers)*	5.5 ^a	5.8 ^a	6.0 ^a	4.4 ^b
Adult Group Size (vacationers)*	4.1 ^a	4.0 ^{a,b}	4.0 ^{a,b}	3.0 ^b
Child Group Size (vacationers)*	1.5 ^{a,b}	1.8 ^{a,b}	2.0 ^a	1.2 ^b
Region (p<.05)**				
Region 1 (South Atlantic)	8 (9.4%)	37 (11.7%)	67 (14.8%)	7 (13.8%)
Region 2 (East South Central)	39 (45.9%)	238 (43.8%)	168 (37.2%)	30 (58.8%)
Region 3 (West South Central)	15 (17.6%)	76 (24.1%)	150 (33.2%)	10 (19.6%)
Region 4 (West North Central)	5 (5.9%)	23 (7.3%)	27 (6.0%)	1 (2.0%)
Region 5 (East North Central)	18 (21.2%)	41 (13.0%)	40 (8.8%)	3 (5.9%)
Date of Inquiry (p<.05)**				
Winter	63 (74.1%)	146 (46.3%)	76 (16.8%)	2 (3.9%)
Spring	2 (2.4%)	153 (48.6%)	204 (45.1%)	3 (5.9%)
Summer	5 (5.9%)	2 (0.6%)	164 (36.3%)	27 (52.9%)
Fall	15 (17.6%)	14 (4.4%)	8 (1.8%)	19 (37.3%)
Time of Inquiry (not sig.)**				
12:01 to 3:00 AM	7 (8.2%)	13 (4.1%)	16 (3.5%)	3 (5.9%)
03:01 to 6:00 AM	1(1.2%)	0 (0.0%)	2 (0.4%)	0 (0.0%)
06:01 to 9:00 AM	6 (7.1%)	10 (3.2%)	18 (4.0%)	2 (3.9%)
09:01 to 12:00 NOON	15 (17.6%)	62 (19.7%)	88 (19.5%)	11 (21.6%)
12:01 to 3:00 PM	19 (22.4%)	67 (21.3%)	91 (20.1%)	7 (13.7%)
03:01 to 6:00 PM	11 (12.9%)	56 (17.8%)	91 (20.1%)	11 (21.6%)
06:01 to 9:00 PM	15 (17.6%)	51 (16.2%)	81 (17.9%)	8 (15.7%)
09:01 to 12 MID	11 (12.9%)	56 (17.8%)	65 (14.4%)	9 (17.6%)
Day of Week of Inquiry (not sig.)**				
Sunday	7 (8.2%)	52 (16.5%)	66 (14.6%)	6 (11.8%)
Monday	14 (16.5%)	43 (13.7%)	76 (16.8%)	8 (15.7%)
Tuesday	19 (16.8%)	57 (18.1%)	65 (14.4%)	7 (13.7%)
Wednesday	14 (16.5%)	57 (18.1%)	66 (14.6%)	8 (15.7%)
Thursday	10 (11.8%)	42 (13.3%)	75 (16.6%)	12 (23.5%)
Friday	12 (14.1%)	33 (10.5%)	50 (11.1%)	6 (11.8%)
Saturday	9 (10.6%)	31 (9.8%)	54 (11.9%)	4 (7.8%)

Day of Week of Vacation of Interest (not sig.)**				
Sunday	6 (7.1%)	42 (13.3%)	67 (14.8%)	8 (15.7%)
Monday	9 (10.6%)	34 (10.8%)	45 (10.0%)	4 (7.8%)
Tuesday	2 (2.4%)	12 (3.8%)	20 (4.4%)	2 (3.9%)
Wednesday	12(14.1%)	26 (8.3%)	34 (7.5%)	8 (15.7%)
Thursday	7 (8.2%)	31 (9.8%)	39 (8.6%)	8 (15.7%)
Friday	12 (14.1)	51 (16.2%)	62 (13.7%)	10 (19.6%)
Saturday	37 (43.5%)	119 (37.8%)	185 (40.9%)	11 (21.6%)
*Mean contrasts are significant at $p < .05$ (according to Scheffé test). Values with different superscripts are significantly different from each other; superscripts are such that "a" always represents the highest score.				
**Chi-square tests were applied to these relationships				

The winter season inquiry database is the third biggest season ($n=85$). For the winter vacation season, inquirers were found to be a greater distance from the target beach property than compared to the other seasons. In fact, as noted earlier, region 5 (East North Central) is more likely to inquire for winter vacations (21.2%) than other regions. Winter inquiries were more likely to inquire in the fall (17.6%) and winter (74.1%), and while not a significant effect, winter inquirers appear to inquire with a shorter lead time (54.1 days) versus the other seasons. That is, for the most part, winter vacationers both inquire and vacation during the winter season. Additionally, in the winter season, adult group size was slightly larger relative to the other seasons (4.1 adults). Again, this may relate to larger party "snowbirds" that vacation during the winter.

The spring season inquiry database is the second largest ($n=352$) of the seasons behind summer. The spring season numbers did not show dramatic differences comparably as compared to the other seasons. However, the spring season inquiries were higher for region 4 as compared to the other seasons (7.3%). Inquiry dates for spring vacations were split between the winter (46.3%) and spring (48.6%).

The summer inquiry database is the largest of the four seasons ($n=452$). The summer season inquirers have shorter distance to travel (479 miles) versus inquirers from the winter and spring. Summer inquirers target a shorter length of stay (6.0) and a greater number of children (2.0) than inquirers for the other seasons. Here, higher summer pricing may dictate shorter length stays. As for more children in the summer, children are out of school in the summer, so this is an expected result. The greatest percentage (37.3%) of summer inquiries is from region 2 (East South Central). Over 81 percent of the inquiries for summer occur in the spring (45.1%) and summer (36.3%) seasons.

The fall season inquiry database is the smallest of the seasons ($n=51$). Fall vacation inquirers are the closest to the beach property destination (429 miles) and fall inquirers ask for longer stays (7.0 days) as compared to inquirers in the other seasons. As previously noted here, cheaper fall pricing may stimulate longer stays. Fall inquirers showed to have the smallest group size (4.4), adult group size (3.0), and children group size (1.2). Region 2 (East South Central) has the higher percentage of inquirers in the fall (58.8%) as compared to the other seasons. Region 4 (2.0%) and Region 5 (5.9%), the west north central and east north central regions

respectively, have the smallest percentage representation in the fall as compared to the other seasons.

Online Inquiry Customer Types

In order to understand the different types of online inquiring customers for the beach house of interest, a cluster analysis was employed. A lineage of research has used the cluster analysis technique as an effective means for segmenting customer types. The key reason for using a cluster analysis is that it organizes variables information into homogeneous clusters or groups (Anderson, 1984; Lance and Williams, 1967). In this study, a hierarchical cluster analysis was used, followed by a k-means analysis. The following variables were used as the input variables: distance, inquiry lead time, length of stay, group size, adult group size, and child group size.

Distances were calculated between clusters using the Euclidean distance measure. For the aggregated clusters, distances were calculated using Ward's procedure. The elbow criterion was the mechanism used for deciding on the number of clusters. For this study, the threshold was determined to be six clusters indicating that the number of clusters groups (i.e., online inquiry customer types) was six. Thus, the results for a six cluster solution are shown in Table 8.

Table 8 Cluster Findings						
	Cluster 1: Small Family Casual Inquirers (n=268)	Cluster 2: Southern Adult Spring Breakers (n=247)	Cluster 3: Large Family Summer Vacationers (n=167)	Cluster 4: Abundant Adult Gatherers (n=131)	Cluster 5: Early Planning Midwesterners (n=74)	Cluster 6: Extended Stay Off seasoners (n=16)
<i>STEP 1: Cluster Identification</i>						
Distance (miles)*	512 ^b	420 ^b	486 ^b	449 ^b	685 ^a	548 ^b
Inquiry Lead Time (days)*	41.6 ^c	44.9 ^c	78.1 ^b	68.1 ^{b,c}	194.2 ^a	65.1 ^{b,c}
Length of Stay (days)*	5.6 ^c	5.3 ^c	6.2 ^{b,c}	5.4 ^c	6.9 ^b	26.6 ^a
Group Size (vacationers)*	5.4 ^c	3.1 ^d	9.2 ^a	7.9 ^b	5.0 ^c	3.4 ^d
Adult Group Size (vacationers)*	3.0 ^c	2.8 ^c	4.7 ^b	7.6 ^a	3.1 ^c	2.4 ^c
Child Group Size (vacationers)*	2.5 ^b	0.3 ^e	4.5 ^a	0.3 ^e	1.9 ^c	1.0 ^d
<i>STEP 2: Descriptor Variables</i>						
Region Number (p<.05)**						
Region 1 (South Atlantic)	36 (13.4%)	29 (11.7%)	27 (16.2%)	17 (13.0%)	9 (12.2%)	1 (6.3%)
Region 2 (East South Central)	98 (36.6%)	132 (53.4%)	70 (41.9%)	55 (42.0%)	13 (17.6%)	7 (43.8%)
Region 3 (West South Central)	80 (29.9%)	61 (24.7%)	41 (24.6%)	46 (35.1%)	17 (23.0%)	6 (37.5%)
Region 4 (West North Central)	16 (6.0%)	11 (4.5%)	12 (7.2%)	6 (4.6%)	11 (14.9%)	0 (0.0%)
Region 5 (East North Central)	38 (14.2%)	14 (5.7%)	17 (10.2%)	7 (5.3%)	24 (32.4%)	2 (12.5%)
Date of Inquiry (p<.05)**						
Winter	52 (19.4%)	59 (23.9%)	69 (41.3%)	64 (48.9%)	38 (51.4%)	5 (31.3%)
Spring	138 (51.5%)	100 (40.5%)	72 (43.1%)	40 (30.5%)	8 (10.8%)	4 (25.0%)
Summer	69 (25.7%)	76 (30.8%)	18 (10.8%)	22 (16.8%)	9 (12.2%)	4 (25.0%)
Fall	9 (3.4%)	12 (4.9%)	8 (4.8%)	5 (3.8%)	19 (25.7%)	3 (18.8%)
Time of Inquiry (not sig.)**						
12:01 to 3:00 AM	10 (3.7%)	12 (4.9%)	8 (4.8%)	6 (4.6%)	2 (2.7%)	1 (6.3%)
03:01 to 6:00 AM	1 (0.4%)	0 (0.0%)	0 (0.0%)	2 (1.5%)	0 (0.0%)	0 (0.0%)
06:01 to 9:00 AM	12 (4.5%)	11 (4.5%)	8 (4.8%)	4 (3.1%)	0 (0.0%)	1 (6.3%)

09:01 to 12:00 NOON	51 (19.0%)	48 (19.4%)	32 (19.2%)	30 (22.9%)	11 (14.9%)	4 (25.0%)
12:01 to 3:00 PM	57 (21.3%)	50 (20.2%)	28 (16.8%)	28 (21.4%)	16 (21.6%)	5 (31.3%)
03:01 to 6:00 PM	49 (18.3%)	50 (20.2%)	32 (19.2%)	21 (16.0%)	15 (20.3%)	2 (12.5%)
06:01 to 9:00 PM	38 (14.2%)	37 (15.0)	35 (21.0%)	27 (20.6%)	17 (23.0%)	1 (6.3%)
09:01 to 12 MID	50 (18.7%)	39 (15.8%)	24 (14.4%)	13 (9.9%)	13 (17.6%)	2 (12.5%)
Day of Week of Inquiry (not sig.)**						
Sunday	46 (17.2%)	30 (12.1%)	25 (15.0%)	12 (9.2%)	15 (20.3%)	3 (18.8%)
Monday	45 (16.8%)	39 (15.8%)	18 (10.8%)	23 (17.6%)	13 (17.6%)	3 (18.8%)
Tuesday	45 (16.8%)	29 (11.7%)	30 (18.0%)	30 (22.9%)	12 (16.2%)	2 (12.5%)
Wednesday	42 (15.7%)	44 (17.8%)	23 (13.8%)	22 (16.8%)	11 (14.9%)	3 (18.8%)
Thursday	39 (14.6%)	42 (17.0%)	30 (18.0%)	16 (12.2%)	10 (13.5%)	2 (12.5%)
Friday	31 (11.6%)	32 (13.0%)	15 (9.0%)	14 (10.7%)	8 (10.8%)	1 (6.9%)
Saturday	20 (7.5%)	31 (12.6%)	26 (15.6%)	14 (10.7%)	5 (6.8%)	2 (12.5%)
Date of Vacation of Interest (p<.05)**						
Winter	26 (9.7%)	19 (7.7%)	19 (11.3%)	22 (16.8%)	5 (6.8%)	3 (18.8%)
Spring	81 (30.2%)	98 (39.7%)	51 (30.4%)	46 (35.1%)	25 (33.8%)	3 (18.8%)
Summer	148 (51.8%)	109 (44.1%)	90 (55.2%)	59 (45.0%)	39 (52.7%)	5 (31.3%)
Fall	13 (5.1%)	21 (8.5%)	8 (4.9%)	4 (3.1%)	5 (6.8%)	5 (31.3%)
Day of Week of Vacation of Interest (p<.05)**						
Sunday	35 (13.1%)	38 (15.4%)	23 (13.8%)	12 (9.2%)	14 (18.9%)	1 (6.3%)
Monday	27 (10.1%)	32 (13.0%)	8 (4.8%)	14 (10.7%)	8 (10.8%)	3 (18.8%)
Tuesday	11 (4.1%)	10 (4.0%)	7 (4.2%)	4 (3.1%)	2 (2.7%)	2 (12.5%)
Wednesday	23 (8.6%)	24 (9.7%)	10 (6.0%)	16 (12.2%)	5 (6.8%)	2 (12.5%)
Thursday	41 (11.6%)	26 (10.5%)	8 (4.8%)	17 (13.0%)	6 (8.1%)	3 (18.8%)
Friday	31 (15.3%)	48 (19.4%)	13 (7.8%)	26 (19.8%)	39 (23.5)	1 (6.3%)
Saturday	100 (37.3%)	69 (27.9%)	98 (58.7%)	42 (32.1%)	74 (52.7%)	4 (25.0%)

**Mean contrasts are significant at p<.05 (according to Scheffe test). Values with different superscripts are significantly different from each other; superscripts are such that "a" always represents the highest score.*

***Chi-square tests were applied to these relationships.*

Interpretation and Description of Cluster Segments

The six-cluster solutions are named: "Small Family Casual Inquirers", "Southern Adult Spring Breakers", "Large Family Summer Vacationers", "Abundant Adult Gatherers", "Early Planning Midwesterners", and "Extended Stay Offseasoners". These groups are discussed in more detail in the following section.

Cluster one (n=268), the largest segment, categorized as the "Small Family Casual Inquirers" segment, displayed the shortest lead time of all the segments (41.6 days). While this segment is predominantly interested in a summer vacation like most segments, they inquire primarily in the spring (51.8%). Clearly, it would be excessive to describe this group "last-minute planners" but this groups' lead time is the shortest. The cluster one segment averages 3.0 adults and 2.5 children. Thus, it is evident that this segment includes small family units. It makes sense that this group is the largest in that the beach house property sleeps up to seven people (see Table 1) and small family units should be attracted to this size vacation dwelling.

Cluster two (n=247), categorized as the "Southern Adult Spring Breakers" segment, has the largest (n=132) and greatest percentage (53.4%) of inquirers from the east south region (Alabama, Mississippi, Tennessee, and Kentucky). Since Region 2 (East South Central) is closer in proximity to the beach house property of interest, it makes sense inquirers in this segments average the closest distance from the property (420 miles). Cluster two is also the smallest group (3.1) and is almost completely adults (2.8). Cluster two segment inquirers target the spring the

most (39.7%). This group is probably young college adults seeking spring break options. Since spring break is different for every school, any week in the months of March and April may in fact be potentially a spring break vacation. Additionally, this cluster, like cluster one, is more last-minute with a lead time of 44.9 days.

Cluster three (n=167), categorized as the “Large Family Summer Vacationers” segment, is the cluster segment with the largest group size (9.2). This segment averages 4.7 adults, and the largest number of children (4.5) as compared to the other segments. Interestingly, this segment includes the largest percentage (16.7%) of Region 1 (South Atlantic) inquirers, which based on early regional findings, is highly comprised of inquirers from Atlanta, Georgia and the surrounding areas. This group consists of the highest percentage of inquirers interested in a summer vacation (55.2%). This cluster group averages the second longest lead time (78.1) as compared to the other cluster segments. It would appear this group represents the big family beach gathering and might include extended adult family (grandparents, aunts, uncles, friends) and extended child family (cousins, friends).

Cluster four (n=131), categorized as the “Abundant Adult Gatherers” segment, is the cluster segment with the largest adult group size (7.6). This group averages very few children (0.3). The obvious number of adults as compared to children suggests this is an extended group of adults vacationing together. This group vacations all year long, even in the offseason. Relative to the latter, this cluster segment is the second highest offseason (fall-winter) vacationing group (19.9%).

Cluster five (n=74), categorized as the “Early Planning Midwesterners” segment, by far have the longest lead time between inquiry and vacation dates at 194.2 days. This group is also the largest group of fall-winter inquirers (76.1%). While this group is not solely Midwesterners, it has the largest contingent of Region 4 (West North Central) and Region 5 (East North Central) inquirers with 14.9% and 32.4%, respectively. Moreover and not surprisingly, this group of inquirers would have to travel the farthest to the beach property (685 miles). Additionally, this group has the second longest average length stay (6.9) as compared to the other segments. There are a few ideas that might explain this online inquiry behavior. Explanations for the long lead time might include the cold winter climate spurs early vacation planning, this region's culture is simply earlier planners by nature, and/or the distance away from the property influences uncertainty and earlier preparation needs. Relative to length of stay, it makes sense that if you travel farther, there is a need to stay longer to overcome the negative effects of distant travel.

Cluster six (n=16), categorized as the “Extended Stay Offseasoners” segment, is the smallest cluster segment. It is unique in that the 26.6 day average length stay is much longer than the other segments. Additionally, this group had the largest fall-winter vacation interest (50.1%). The largest percentage representation for Region 3 (West South Central) is in cluster six (37.5%). Clearly, region 3, while not necessarily considered as “snowbird” territory can exhibit colder winters—particularly Arkansas, Oklahoma, northern Texas, and northern Louisiana weather might stimulate winter beach travel. Moreover here, extended stay vacations may be becoming an attractive retiree phenomenon irrespective of a cold weather climate.

CONCLUSIONS

The findings from this paper are a notable beginning to research in the peer-to-peer (P2P) online vacation rental marketing area. The paper examines online beach inquiries for one beach property in the Gulf Coast region of the United States. The paper thoroughly examines the online database for this property from the overall, regional, seasonal, and inquiring customer perspective. The contribution to the marketing literature is very important because it initiates a unique new area of research. For marketers, both rental owners and vacation website companies, there is a better understanding about inquiry behavior that can be used to target future vacationers. There is a better understanding of the types of vacationing groups, when they inquire, where they inquire from, how long they will stay, etc., based on this research.

LIMITATIONS AND FUTURE RESEARCH

The findings from this study are for one beach house property with a unique mix of features. Thus, the generalizability of the results must be made with caution since comparison between properties is arguably a comparison of two different contexts. Moreover marketing influences like varying price points, online advertising approaches, word-of-mouth, etc., may bias inquiry behavior even for properties that appear quite similar.

The future research opportunities in this area are immense. Studies that could access the inquiry database for a large sample population of similar properties would make possible more highly quantitative studies that could be generalizable to the marketing literature. Additionally, there is a great opportunity for qualitative research—particularly seeking to understand rental owners in the P2P market.

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THE CHOICE OF CONTENT BY INFORMATION PROVIDERS IN WORD OF MOUTH COMMUNICATIONS

Luke Greenacre, University of Technology
Paul F. Burke, University of Technology
Sara Denize, University of Western Sydney, Australia
Rikki Pearce, University of Queensland, Australia

ABSTRACT

Word-of-Mouth communication is an invaluable source of information for consumers. A comprehensive understanding of the flow of market information through interpersonal networks is therefore of unique theoretical and practical importance. Present Word-of-Mouth research is receiver centric, largely ignoring the role of the information provider as a gatekeeper to information dissemination. The objective of this research is to develop a more comprehensive understanding of Word-of-Mouth by modelling the decision making behaviour of information providers. Adopting the network theory general assumption of altruistic exchange motivation, this research uses a choice modelling framework to demonstrate that information providers assign greater utility to (1) information about product features important to the receiver, and (2) information which disconfirms receiver preferences. In addition, these effects are found to be moderated by perceptions about the receiver's knowledge. Existing research has not previously considered information providers' perceptions of receivers as a potential moderator of WOM flow, with the results here suggesting this should be an area of future investigation.

Keywords: Word-of-Mouth; WOM; Information; Provider; Communication; Motivation

INTRODUCTION

Word-of-Mouth (WOM) communication is a central input to consumer decision making (Bansal & Voyer, 2000; Whyte, 1954). Understanding interpersonal exchanges is therefore important for both marketing theory and practice. The vast majority of WOM research has focused on three substantive areas: (1) how information flows through interpersonal networks (Burt, 1980; Granovetter, 1982); (2) the sources and types of information that decision makers seek (Brown & Reingen, 1987; Gilly, Graham, Wolfinbarger, & Yale, 1998; Price & Feick, 1984; Sweeney, Soutar & Mazzarol, 2008); and (3) how this information is used for purchase decisions (Bansal & Voyer, 2000; Still, Barnes Jr., & Kooyman, 1984; Nam, Manchanda, & Chintagunta, 2010). This research largely focuses on the receiver and their need for information. It demonstrates that receivers engage in WOM as an uncertainty reduction strategy during decision making. The literature often explains this phenomenon as a function of the perceived

credibility or usefulness of the information source (Grewal, Gotlieb, & Marmorstein, 1994; Jacoby *et al.*, 1994).

Despite consumer preferences for credible information, particularly in WOM communication, individuals are poor knowledge seekers (Graesser, Swamer, Baggett, & Sell, 1996). Generally consumers focus on common rather than unique knowledge, failing to identify what information is missing or needed (Stasser & Titus, 1985). Often their judgements are based on what has been provided whilst ignoring what has been excluded (Islam, Louviere, & Burke, 2007; Kardes, Posavac, & Cronley, 2004). Indeed, this can lead to a 'provision bias', even to the extent that non-diagnostic or irrelevant information can influence product choices (Meyvis & Janiszewski, 2002; Zukier, 1982). Such findings highlight the importance of the search for and use of WOM on the part of receivers, and the inadequacy of that search behaviour. Based on this, it can be argued that practitioners and researchers should balance their focus on receivers with attention to information providers and their choices regarding what information they provide. Supporting this argument is the recognition that information providers are higher order gatekeepers of information (Frenzen & Nakamoto, 1993). Providers have the ability to override the preferences of information seekers by providing alternative information to that requested.

The role of information providers in WOM exchanges remains relatively unexplored in WOM literature (Godes & Mayzlin, 2009). Information providers are motivated to engage in WOM communication for many reasons, including such things as reducing personal anxiety and the desire to help others (Dichter, 1966; Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004; Laughlin & MacDonald, 2010; Sundaram, Mitra, & Webster, 2007). In particular though, network based theories often assert that an altruistic type motive is necessary for the successful maintenance of relationships (Burt, 1980; Granovetter, 1982). Without some basis of altruism among exchange partners, relationship breakdown is all but inevitable leading to social malfunction. Thus, this altruistic type motive is assumed to be the basis for most WOM exchanges.

This research is motivated by the influential nature of WOM on receiver decision making, as well as the centrality of interpersonal networks to the dissemination of information (Frenzen & Nakamoto, 1993; Rogers, 1995). We aim to establish a more complete conceptualisation of WOM by modelling how information providers choose what to communicate under conditions of information scarcity. To do so, it is suggested that while the information that one consumer could provide to another is essentially unlimited, the actual amount of information that they can provide is limited, due to the provider and receiver's cognitive and time limitations (Lussier & Olshavsky, 1979). As a consequence, the provider is forced to make choices about what to communicate. This research not only enhances theoretical understanding, but facilitates new insights and opportunities for WOM management. By understanding what consumers are likely to communicate by WOM, marketers have the ability to meaningfully attempt to influence communication content, rather than just promote increased communication.

In order to gain these insights into provider decision making, a choice model relating information characteristics to receiver characteristics is introduced and tested using an online experiment. Implications of the findings are considered with specific reference to provider

information preferences. Of note is how this experiment brings into question the core assumption of altruism underpinning much of the network based literature.

CONCEPTUAL DEVELOPMENT

Information Providers and Information Flow in WOM

Research has found numerous factors that influence information flow. For examples see Brown & Reingen (1987), Gilly *et al.* (1998), Kempf & Palan (2006) and Sweeney *et al.* (2008). While much valuable insight has been gained from these research topics, very little WOM research has attempted to manipulate information content systematically as a variable, despite acknowledging that it varies across networks (Frenzen & Nakamoto, 1993). Most studies do not discuss the nature of the information being transmitted by consumers, or it is held constant as an *ex ante* construct (Arndt, 1967; Frenzen & Nakamoto, 1993; Gilly *et al.*, 1998). Ultimately, consumers acting as information providers have the ability to choose (a) what content to provide, and (b) how much information to provide (Schwartz, 2004; Ziamou & Ratneshwar, 2002). This research focuses on the first aspect; namely the choices made by an information provider about what information to communicate to another consumer.

A Model for Information Provision

The choice about what information consumers will provide to others is considered in the current research using Random Utility Theory (RUT). In RUT, choice behaviour is modelled as a function of measurable components (for example, product features) each of which plays a different role in determining overall judgements about available options. The choices themselves are described as being made based on utility maximisation (Thurstone, 1927). By observing choices and systematically relating these to measurable features, one can gain insight into what determines choice in a particular decision environment. There is some randomness when one observes such choices that cannot be explained or captured. To accommodate the presence of both the measurable and un-measurable components of utility, latent utility (U_i) is considered to be a function of both what one can observe to explain choices (V_i) and what one cannot (ε_i). The unobserved, or random, component of utility (ε_i) is assumed to conform to a specific distribution for the purposes of estimation. This assumption will be discussed shortly. Thus we can specify that,

$$U_i = V_i + \varepsilon_i \quad (1)$$

RUT assumes that, in order to determine utility, decision-makers consider each option ' i ' on ' k ' dimensions (x_{ki}) and weight each dimension on the basis of its perceived importance for delivering value (β_k). Subsequently, the systematic component can be modelled as a linear function and written in matrix form as $V_i = X_i\beta$ (Ben-Akiva & Lerman, 1985).

The choice of information by providers can be examined within such a framework. First, it is assumed that providers choose to disseminate a particular piece of information among several options, similar to a choice set a consumer faces when deciding among various products. Each option can be assessed prior to dissemination, with a utility value ascribed. The provider then chooses the option that maximises utility.

This model requires expansion on two aspects. First, it is unclear what defines the overall utility of information and how it is maximised. It is assumed that information providers judge each information option in terms of its ability to maximise the benefits to the receiver by improving his or her ability to discriminate among products in line with altruistic motivations. The validity of this assumption is discussed in the next section. Second, it is unclear what dimensions may be used as a basis for evaluating the information. This is analogous to what factors determine the value of a product such as price, brand, package dimensions, etc. This is also considered in the next section allowing us to build a model describing what information consumers choose to provide others.

Information Provider Motivation: The Role of Altruism

A motivational orientation that is focused on the benefits and costs that an exchange partner may receive, often described as an ‘other orientation’, is used to characterise altruism in most discussions of WOM motivations (Dichter, 1966; Horowitz *et al.*, 2006; Laughlin & MacDonald, 2010). Altruism reflects the motivation of the provider to give information freely with no regard for him- or her-self; and has been demonstrated among strangers as well as among those with close interpersonal ties (Constant, Sproull, & Kiesler, 1996). Literature examining communication altruism often focuses on the receiver’s desire to respond to an altruistic provider rather than on the provider’s original altruistic actions (Euhara, 1995).

Other provider motivations have been considered in the literature. Motivations include the desire to have further involvement with the product, to reduce personal anxiety, or to communicate a liked message previously received (Dichter, 1966; Kamins, Folkes, & Perner, 1997). While the provider’s choice to communicate by WOM at an individual level is likely to be more complex than any one of these motivations, we note that theories of social networks and social function broadly assumes altruism as a necessary feature to ensure ongoing relations (Granovetter, 1982). The current model thus assumes that information providers judge the utility of information on its ability to optimise receiver decision-making, an altruistic communication motivation. This assumption forms a reasonable basis to develop a model of the factors determining information utility.

Determinants of Information Utility

Our RUT based framework describes how providers judge each information piece ‘ i ’ on a particular dimension ‘ k ’ (x_{ki}) and weight each dimension based on its perceived importance for delivering value to receivers (β_k), as per the altruism assumption. Within this framework, two

information characteristics are explored. These are the importance of the product feature which the information concerns, and whether the information (dis)confirms existing preferences.

Information search literature has identified that consumers search for and use product attribute information by decreasing order of attribute importance (Meyer & Sathi, 1985; Saad, 1999; Saad & Russo, 1996). This implies information is more or less valuable depending on whether it references more or less important product features. Some research indicates a direct link between product feature importance and information value for providers, however this relationship is assumed and has not been formally tested (Arndt, 1967; Frenzen & Nakamoto, 1993; Gilly *et al.*, 1998; Grewal *et al.*, 1994).

Taking into consideration the role of product feature importance in determining information utility, it is proposed that information providers will be more likely to infer that the consumer whom they are helping will have a greater utility for information regarding important features relative to less important features (Bettman, Luce, & Payne, 1998; Swait, 2001). In most studies examining information search, importance is determined by the internal preferences of the individual searching (e.g., Saad 1991); in cases of information provision, it is assumed that an information provider must form expectations about what are important features for the receiver. The provider may form this expectation naively using their own preferences as a reference point. Alternatively, they may infer the preferences of the receiver based on previous interactions with them or what they have been told about them (e.g., they are a vegetarian). In either circumstance, the provision of such information about important product features would allow receivers to make more informed trade-offs among products.

H1 Information providers will assign greater utility to information about an important product feature compared to an unimportant feature.

Research has also identified that disconfirming information is particularly effective in reducing decision risk by improving consumer understanding of alternatives and correcting inaccurate beliefs (Herr *et al.*, 1991; Laczniak, DeCarlo, & Ramaswami, 2001). Disconfirming information is best characterised as that which refutes or corrects a prior perception. For example, a belief that a newly released film is worthwhile seeing based on viewing an enticing preview may be disconfirmed by reading a negative review or hearing the negative opinion of a friend who has already seen it. Beliefs and perceptions are more readily updated by negative, or disconfirming, information (Hogarth & Einhorn, 1992), and it has been found that receiver consumers prioritise its acquisition due to its diagnostic properties (Ahluwalia & Gurhan, 1998). Novelty effects have also been offered as an explanation for preferences for disconfirming information; that is, the novelty of disconfirming information increases its accessibility in memory and therefore its salience in the decision making process (Peracchio & Tybout, 1996; Sternberg, 2001). Subsequently, information providers may display a positive bias toward disconfirming information (Peracchio & Tybout, 1996; Sternberg, 2001). Based on this, it is expected that the altruistic information provider will prioritise disconfirming information when engaging in WOM exchanges.

H2 Information providers will assign greater utility to disconfirming information relative to confirming information.

The Receiver as a Moderator of Providers' Choices

A large proportion of research into WOM communication focuses on how providers are assessed by those receiving information (Gilly *et al.*, 1998; Grewal *et al.*, 1994; Yale & Gilly, 1995). The emphasis on examining receiver perceptions in the literature suggests that individuals in a WOM exchange do assess the nature of their exchange partner when communicating. This indicates that the presence of such an assessment on the part of the provider is reasonable, and thus important to consider.

Underlying communication decisions is the likely need for the provider to understand the different information requirements of various receivers as this permits them to meaningfully maximise receivers' utility (Kempf & Palan, 2006). Testing for such differential understanding on the part of the provider therefore makes an important contribution to testing the validity of the underlying framework. To address this knowledge gap, the construct of receiver expertise is introduced.

To discriminate among options and make product choices, novice consumers require basic knowledge of product features. Motivated by decision difficulty, the novice's decision-making process, however, may be simplified to focus on a few critical features, rather than the full range of possible product differences (Bettman *et al.*, 1998). In turn, information providers are likely to favour the provision of information regarding important product features when communicating with novice receivers.

H3 Information providers will assign greater utility to information about an important product feature compared to information about an unimportant feature, more so when the receiver is known to be a novice rather than an expert.

In contrast to the information needs of novices, experts' well-developed preferences may render information about important features irrelevant in assisting them to discriminate among options (Gilliland & Neal, 1993; Johnson & Katrichis, 1988). In addition, the receiver would benefit more from information that is unique and something they do not already know. Therefore, any information that disconfirms commonly held preferences among consumers could be beneficial, relative to information confirming existing knowledge (Ahluwalia & Gurhan, 1998). While this is true for both novices and experts alike, the ability for experts to deal with disconfirming knowledge and integrate it with existing knowledge may lead information providers to believe that experts are better equipped, relative to novices, to deal with the confusion that it creates (Maheswaran & Sternthal, 1990).

H4 Information providers will assign greater utility to receiver preference disconfirming information compared to receiver preference confirming

information, more so when the receiver is known to be an expert rather than a novice.

The Model

We revisit the RUT model of information provision and hypothesise that providers will judge the value of a piece of information ‘ i ’ on dimension ‘ k ’ (x_{ki}), and that this is moderated by the characteristics of those receiving this information (Z). It is possible to expand the systematic component of utility such that in matrix form:

$$V_{it} = X_i\beta + Z\zeta + (X_iZ)\gamma \quad (2)$$

where V_{it} is the utility of information ‘ i ’ to provider ‘ t ’, Z is a matrix describing characteristics of the receiver; in the two studies that follow, it represents an indication of whether they are an expert relative to one that is a novice. The random component (ε_i) of latent utility (U_i) is assumed to follow a Gumbel distribution, such that differences in the errors then follow a logistic distribution. This results in the multinomial logit (MNL) model (Ben-Akiva & Lerman, 1985):

$$P_{it} = \frac{e^{V_{it}}}{\sum_J e^{V_{jt}}} = \frac{e^{X_i\beta + Z\zeta + X_iZ\gamma}}{\sum_J e^{X_j\beta + Z\zeta + X_jZ\gamma}} \quad (3)$$

which describes the probability that information ‘ i ’ will be prioritised for dissemination by provider ‘ t ’ from the set of information available, with J pieces available in total. Hypothesis 1 and 2 can be tested by examining the significance of elements in the vector β that relate to the dimensions of importance and (dis)confirmation, respectively. The significance of the β associated with each dimension would indicate that providers are using that dimension when choosing information for communication. Hypotheses 3 and 4 can be tested by examining the estimated parameter γ with significant terms indicating that information providers judge the information features (X_i) differently for experts and novices (Z). The inclusion of the parameter ζ for the main effect of the expertise of the receiver (Z) on the utility of information i ensures that any extraneous effects arising from the manipulation of expertise do not bias the estimates associated with the research hypotheses.

EXPERIMENTAL APPROACH

Background and Sample Specification

A choice-based experiment was chosen to test the hypothesised effects as it allowed control over the information provided to respondents and also allowed manipulation of the

expertise of the hypothetical receivers between respondents. Three product categories were chosen as the context for these experiments with respondents allocated to complete the experiment in one. Each is a category where WOM is an important information source for consumer decisions. The categories chosen were a high involvement service (holiday package), a high involvement product (personal computer) and a low involvement product with service components (home-delivered pizza).

Participants were university students, randomly assigned to one of six surveys. This sample is considered reasonable as all products examined are relevant to this group (Greenberg, 1987). In total 50 people were sampled in each of the six conditions.

Experimental Procedure

Information statements were developed based on prior research into the importance of features for each of the selected products (Lenk *et al.*, 1996; Severin, 2000). An exploratory study verified the features as being of high or low importance. Statements that confirmed and disconfirmed preferences for each feature were developed and pre-tested. This resulted in eight possible statements per category. Each statement addressed one product feature and one preference substantiation type. Four product features (two of greater importance; two of lesser importance) and two preference substantiation types (confirmation; disconfirmation) for each product category were used. A fractional factorial design ascribed the levels of the attributes to ensure all main effects and two-way interactions could be estimated.

The eight statements for each product category were varied using a balanced incomplete block design (BIBD). The BIBD resulted in 14 choice sets, with four statements in each. In this BIBD each statement occurred 7 times with a pair frequency of 3. Two versions of this experiment were created by priming the respondent to believe that the receiver was either seeking information because (a) as a novice, they had no prior purchase experience and “knew nothing”, or (b) as an expert, they had a lot of purchase experience and they were just seeking a “second opinion”.

The experiment proceeded as follows. A description of the relevant product was provided to give context to the task and to establish baseline preferences for the (un/important) product features. The baseline preferences were necessary as the information in the statements available for the participant to choose had to later confirm or disconfirm such preferences in a systematic manner. Additional redundant product information was included to mask this objective. The primer for the receiver’s expertise was then included followed by the information choice experiment. For each set in the experiment the participant identified the statement that they would choose to communicate by WOM to the receiver described.

RESULTS

An MNL was estimated for each product. Main effects and interactions between the information and receiver characteristics were included. These are shown in Table 1.

Table 1: Model results for the choice of information based on its characteristics

Variable		Holiday Package		Personal Computer		Delivered Pizza	
		β	s.e.	β	s.e.	β	s.e.
Intercept		-.04	.07	-.47**	.06	-.57**	.06
Important	H1:+	.59**	.04	.38**	.04	.17**	.04
Confirmation	H2:-	-.26**	.04	-.22**	.04	.19**	.04
Important x Confirmation		-.07	.04	-.13**	.04	.42**	.04
Expert		.23**	.07	.15*	.06	.04	.07
Expert x Important	H3:-	.06	.04	.05	.04	-.06	.04
Expert x Confirmation	H4:-	-.11**	.04	-.09**	.04	-.08**	.04
Expert x Important x Confirm		-.05	.04	-.05	.04	.00	.04
Log-Likelihood:	Null	-2253.21		-2253.21		-2253.21	
	Model	-2031.93		-2121.95		-2103.33	

Note. The intercepts are coded as 1 for the choice of any statement or zero for no choice to remove any innate propensity to communicate. The reference value is the choice to not communicate any statement. The name of the parameter indicates the level coded +1 and the alternative coded as 0 for the information and -1 for expertise. * $p < 0.05$. ** $p < 0.01$

Hypothesis 1 proposed that providers assign greater priority to information concerning an important feature. In all three categories examined, the ‘importance’ parameter is both positive and significant, supporting hypothesis 1.

Table 2: Model results for each statement for the home-delivered pizza category

Statement		Attribute	Confirm/ Disconfirm	β	s.e.
1	This shop has one of the largest menu options around.	Range (Important)	Confirm	.41**	.09
2	The pizza shop is very fast at preparing the pizzas for delivery.	Delivery Time (Important)	Confirm	-.02	.09
3	Most of the pizzas on the menu tend to have very similar toppings.	Range (Important)	Disconfirm	-.82**	.12
4	There are a lot of road-works around the shopping centre that may delay delivery.	Delivery Time (Important)	Disconfirm	-1.24**	.14
5	The shop is always happy to deliver soft drink with the pizza.	Drinks (Unimportant)	Confirm	-1.62**	.16
6	The vegetarian pizzas have a great array of vegetable toppings.	Vegetarian (Unimportant)	Confirm	-.56**	.11
7	The brand of soft drink the shop stocks don't taste nice.	Drinks (Unimportant)	Disconfirm	-1.92**	.19
8	The last couple of times I ordered a vegetarian pizza it had meat on it.	Vegetarian (Unimportant)	Disconfirm	.15	.09
Log-Likelihood:		No coefficients:	-2253.21		
		Model:	-1996.79		

Note. The reference value is the choice to not communicate any statement. Each statement is dummy coded. * $p < 0.05$. ** $p < 0.01$.

The results for information about holiday packages and personal computers reveal that the parameter estimate labeled 'confirmation' is negative and significant in support of hypothesis 2. By contrast, the same parameter in the home-delivered pizza condition was positive and significant. To investigate this inconsistent result from the home-delivered pizza context, a model was estimated to examine the separate value of each of the eight information statements. This disaggregate model allowed the exploration of each statement to identify if any particular statement was the source of the inconsistency.

Table 2 reveals results that are inconsistent with expectations regarding the estimated value of some statements. Upon reviewing the language of the statements themselves, two phenomena were identified that may account for the different results for this product.

First, in relation to the feature 'the availability of vegetarian alternatives', the statements concerning this seemingly less important feature (statements 6 and 8) have an unexpectedly high propensity to be communicated. This may be explained by the method used in pre-testing to establish the feature's importance. Pre-testing asked individuals to rate this feature's importance to them. On average, respondents indicated it was relatively unimportant (to them). However, in the main experiment, priming indicated that the receiver was interested in this feature. Unlike other product features where this would be interpreted as mere preference, for vegetarian alternatives this is likely to be interpreted as a requirement for vegetarian consumption. Drawing on the assumption in the model that information providers will act in the best interest of receivers, it is reasonable to expect them to treat this feature as important for a receiver who appears to be a vegetarian, even if it is unimportant to themselves. This offers evidence towards the underlying assumption of altruistic motivations on the part of the provider.

The second phenomenon identified in the home-delivered pizza results was a unique language structure not present in the other categories. For the two statements that disconfirmed the important features (statements 3 and 4 in Table 3), the facts contained in the statement are potentially ambiguous. The use of the terms 'may' and 'tend' suggests that the events described have only a probability of occurring. For these statements it can be seen that the propensity to communicate drops dramatically compared to expectations. The results arising from the inclusion of this language structure are also in line with the altruistic assumption in the model. It can be expected that information that is not certain would be less helpful for an uncertain receiver decision-maker, and as a result would not be prioritised for communication by a helpful provider.

These two phenomena suggest that information providers assess information in a manner that considers how it will be useful in terms of the preferences of the receiver, and moves beyond the more general assessment currently described in hypothesis 1 and 2. This altruistic assessment is similar to the arguments underlying hypothesis 3 and 4, but suggests assessments are more extensive than those relating to the knowledge of the receiver and considers their specific tastes, beliefs and practices (e.g., vegetarianism).

We now consider the moderating role of the provider's perceptions of the receiver's knowledge (novice or expert) on their choice to disseminate information. Under hypothesis 3 it was predicted that receiver knowledge would negatively moderate the effects of feature

importance. The interaction between the expertise of the receiver and feature importance are insignificant in all categories. Thus, no empirical support for Hypothesis 3 is evident.

Hypothesis 4 proposed that information providers prioritise information that disconfirms existing preferences, more so when the receiver is known to be an expert rather than a novice. The results support this assertion in all three product categories: the interaction terms between the content dimension relating to preference confirmation and the term describing the receivers' expertise were negative and significant.

DISCUSSION

This research contributes to our understanding of one of the most important information sources in the marketplace, consumers. Through modeling provider WOM decision making under conditions of information scarcity a greater theoretical understanding of WOM is provided, offering new insights for targeted WOM management.

The results supported the research hypotheses for the most part. Information providers were found to attach higher utility values to communications concerning important product features as well as to disconfirming information. The research also suggests that consumers do indeed make inferences about receiver expertise and that this affects their judgements about the utility of information during WOM. Interestingly however this applies to the provision of disconfirming information, but not to that of information concerning important product features. Specifically, the model demonstrates that information providers value disconfirming information more highly and that this effect is greater for expert receivers. The result that expertise does not moderate the choice of information based on the importance of the product feature it concerns suggests that providers will choose to communicate information concerning important features (as found in Hypothesis 1) irrespective of the expertise of the receiver. This indicates the possible presence of a social norm for the provision of such important information to all receivers, irrespective of their characteristics. What is interesting is the limited nature of this norm to this one information characteristic. Whether this norm persists, and if other norms exist, presents an opportunity for further research.

The results of this research have particularly important implications for the underlying assumption of altruism present in this model and much of the network research. The high utility of information generally concerning important product features and disconfirming existing preferences is entirely compliant with this assumption. Although the support for the altruism assumption seems clear based on these individual results, as it is such a core assumption we opted to investigate it further.

The presence of the moderating effect of receiver expertise on the confirming nature of the information, but not on the importance of the feature that the information concerns, has important implications for our knowledge of exchange motivations. It was expected that the expertise of the receiver would moderate the choice of information concerning more or less important product features. What is interesting was not the support or refutation of any single hypothesis, but the combination of results that we observed here.

Taking a different motivational assumption, if a provider wished to reduce their own anxiety about purchase decisions and confirm their own beliefs about a product, the same information would be prioritised for WOM communication that we observed here. A provider would be more likely to provide information that disconfirms the receiver's preferences, as it would serve the dual role of confirming the providers' own beliefs and preferences for this less commonly known information (Dichter, 1966; Gilliland & Neal, 1993; Johnson & Katrichis, 1988; Sundaram *et al.*, 2007). This would be seen to an even greater extent when communicating with an expert receiver who is in a better position to, in return, confirm those beliefs. Furthermore, such confirmation of own beliefs would most likely be on less important product features as there is less commonly held belief about such features. Thus, in the presence of an expert receiver, if the provider were pursuing this motivation, information concerning more important product features would be of lower utility. Even under this other common motivational form described in the literature, the results in this research are still consistent with the behaviours we would expect in real markets. This suggests these results even have generalisability beyond purely altruistic contexts.

The research results reinforce the importance of segmented communication strategies and the search efficiencies awarded to consumers who engage in WOM. A managerial caveat to this is recognising the important role that information providers play in correcting the preferences of other consumers. A manufacturer or retailer may know more about the objective benefit of a product feature than consumers. For example, a firm may know that 'Pro-Vitamins' in shampoo offer little benefit to consumers, as vitamins have no impact on the dead cells making up hair, but consumers may not know this (Broniarczyk & Gershoff, 2003). Such incorrect beliefs can often be attributed to the asymmetries of marketplace information. So, marketers relying on asymmetries in information about their products need to be wary as information providers' value disconfirming information on behalf of misinformed receiver-consumers and their WOM communications may counteract such strategies. Of course, some companies position products that do address such misconceptions, and the support of consumers as information providers in highlighting how a new product addresses the negative aspects of prior offerings could be used to obtain competitive advantage.

CONCLUSIONS AND FUTURE RESEARCH

This research has highlighted the gatekeeper role of information providers in WOM communications. The findings suggest that future research into WOM communication should seek to accommodate both provider and receiver perspectives to achieve greater validity. During interpersonal exchange information providers also face natural demands, such as managing the choice of content in response to the propositions of other consumers (Thomas, 1992). Conversations involve turn taking, thus accommodating both sender and receiver actions is critical to understanding WOM.

The research approach has also provided a new methodological tool for examining WOM communication. Choice experiments provide the ability to understand the complex but systematic decisions providers make when selecting information for communication to various

receivers. Future research can continue to build on this initial methodological application. In everyday WOM, the choice of information is dictated by the knowledge of the consumer providing the information. Not only is a lack of knowledge an impediment to what can be communicated, but issues of recall and cognition need to be recognised (Lynch Jr., Marmorstein, & Weigold, 1988; Stafford *et al.*, 1987). Hence, one potential avenue for future research is to consider a provider's knowledge and recall on his or her decisions regarding what information to communicate by WOM.

Other information dimensions that may affect priorities during information communication can also be included into future research experiments. These may include such things as the linguistic features of the statements communicated by the provider and others that capture the possible economic impact(s) of the information for the receiver. There is a need to develop further understanding of which dimensions are the most critical in determining the nature of the information flows in WOM communication from both the provider and receiver perspectives.

The assumption of altruistic type motivations underlying much of the social network and systems literature also needs expansion. Presently the literature addressing individual level WOM has identified a number of alternative motivations that can drive communication behaviour (Cox & Deck, 2005; Dichter, 1966; Horowitz *et al.*, 2006; Sundaram *et al.*, 2007; Walsh, Gwinner & Swanson, 2004). These have not readily been incorporated into the social network perspectives of WOM function. While altruism clearly presents as one of the core motivations driving WOM communication exploring what other motivations may form part of this core offers an exciting avenue for future research.

A final avenue for future research is the examination of provider perspectives in other forms of WOM. This research emphasised interpersonal WOM, however online, viral and referral communication are growing areas of research interest (De Bruyn & Lilien, 2008; Dwyer, 2007; Laughlin & MacDonald, 2010; Schultz, 2010). The model developed here clearly delineates between motivations and behaviour with regard to WOM. A less personal online environment may lead a provider to be motivated by more selfish desires in their communications, providing information that helps them as much as any receiver (Ho & Dempsey, 2010). Likewise, the more explicit nature of online communication may lead providers to select information more suited to this type of medium (Mazzarol, Sweeney & Soutar, 2007). In both cases different communications may occur. Investigating the possible differences in provider motivation and behaviour between these communication contexts would provide a rich understanding of how consumers use communication to influence each others' decisions in everyday life.

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ASSESSING THE ACCURACY OF AUTOMATED TWITTER SENTIMENT CODING

Joel J. Davis, San Diego State University
Shannon O’Flaherty, San Diego State University

ABSTRACT

Social media have provided consumers with numerous outlets for disseminating their brand-related comments. Given the impact of these comments on brand image and brand success, marketers have begun to rely on third-party companies to automatically track, collect and analyze these comments with regard to their content and sentiment. There is, however, an absence of controlled research which objectively and systematically assesses the accuracy of these companies’ automated sentiment coding. This research evaluated the automated sentiment coding accuracy and misclassification errors of six leading third-party companies for a broad range of comment types and forms. Overall, automated sentiment coding appears to have limited reliability and appears to be accurately accomplished only for very simple statements in which a keyword is used to convey its typical meaning. Statements without keywords or statements in which keyword meaning is reversed through negation or context are accurately coded at very low levels. Neutral statements appear to be problematic for some, but not all, companies. Implications of the research for the use of automated sentiment analysis for brand decision-making are presented.

INTRODUCTION

Marketers’ attempt to manage brand image in the pre-social media era was straightforward. Brand managers would decide what they wanted consumers to think about their brand and then, through advertising and other consumer-directed communications, would tightly control the messages to which consumers were exposed. Ideally, these communications would create or reinforce the desired brand image. Communications planning took the perspective of “we’ll tell you the things that we think are really important [and what you should think] about our brand and product” (Bostic, 2010) as consumers had little opportunity to disseminate their own perspective.

Social media have fundamentally altered how brand image is created, maintained and changed. Today’s successful marketers understand that social media have reduced their control and they realize that they are but one (albeit important) contributor to a dialogue about the brand. These marketers realize that their brand’s image will not only be the result of what they say on their brand’s own behalf, but additionally, what consumers say and how they interact with and respond to these consumers’ comments (Davenport & Beck, 2002; Esch et al., 2006). Consumers are now in at least a shared leadership position with regard to brand image creation, in essence telling marketers “your brand is whatever [we] say it is” (Li & Bernoff, 2008).

Li and Bernoff (2008) refer to the transfer of power from businesses to individuals as “the groundswell.” Examples of the groundswell are the abundance of online brand and product reviews as well as online communities such as Get Satisfaction (<http://www.getsatisfaction.com>), which provides a forum for customers to raise questions or complain about a wide range of companies, and for the resulting discussions to be displayed for other consumers to search and view. Online product reviews and sites such as Get Satisfaction can have a profound effect on brand image and brand success given that the consumer decision-making process is greatly influenced by other consumers’ comments (Goldberg et al., 2001; Kelsey Group, 2007; Jansen et al., 2009), especially at the time of product evaluation and purchase (Zabin and Jefferies, 2008).

Clearly, it is important for marketers to understand what consumers are saying about their brands and products. Specifically, marketers need to be aware of *what* consumers are saying (i.e., the specific comments about the brand) and they need to understand what consumers are *feeling* (i.e., the sentiment associated with a brand comment, that is, whether a particular comment is positive, negative or neutral). Cai et al. (2010) provide a rationale for the specific focus on sentiment monitoring: “The voice of the web to gain consumer, brand and market insights can be truly differentiating and valuable to today’s corporations [and] one important form of insights can be derived from sentiment analysis.” The need for sentiment analysis is straight-forward since the total number of comments related to a brand provides only partial insights. Imagine two marketers, each of whose brand received 1,000 comments within the prior month. The marketer whose brand receives 70% positive comments versus 30% negative comments is in a much better position than the brand that receives the same number of comments but in a ratio of 30% positive and 70% negative.

Many leading marketers are using sentiment analysis to determine what customers are saying and feeling about their brands, products and communication campaigns (King, 2011). These marketers understand that the sentiments associated with brand-related comments can have both short- and long-term implications. Viewed short-term, spikes in either negative or positive sentiment can be an indicator of brand-related problems or opportunities, can provide insights into reactions to new communications campaigns, and may be a leading indicator of future sales. The spike in negative sentiment after the introduction of the “Motrin Moms” viral video (McNeil, 2008) is an example of how brand-related problems can be immediately reflected in increases in negative sentiment and of how corporate and brand reputation are put at significant risk when issues are not addressed early and effectively (Owyang, 2008, Esterline, 2009). Beyond short-term use, longer-term analyses of sentiment trends allow a marketer to determine the brand’s overall health by examining the relative proportion of positive-to-negative comments over time. Here, longer-term shifts in the ratio of positive to negative comments may reflect subtle but important changes in brand-related attitudes unrelated to any single event.

While most marketers acknowledge that tracking consumer sentiment related to their brands is important, they also realize that given the extraordinarily large number of potential sources and comments, it is quite time consuming (and therefore costly) to assign in-house personnel to track and then sentiment code brand-related comments. As a result, many marketers have turned to specialized companies to perform this task. These companies provide real-time

tracking of brand-specific comments across a range of social media platforms (e.g., Twitter and other microblogs, blogs, message boards, and reviews) and then, through the use of computer algorithms, sentiment code relevant comments. Annheiser-Bush, for example, might ask one of these companies to track all social media comments containing the word “Budweiser.” In response, a typical computer-generated summary report from one of these companies might state that “Sentiment Tuesday versus Monday is more positive. Monday the ratio of 2,209 comments was 46% positive versus 23% negative. Tuesday’s 2,387 comments had a ratio of 54% positive to 19% negative.”

Dozens of companies provide automated (i.e., computer-conducted) sentiment coding services. Some of these companies are fee-based while others provide automated sentiment coding free of charge. Given marketers’ reliance on these companies, it is critical to assess automated sentiment coding accuracy for the range of comments likely to be encountered. However, while anecdotal evidence and company materials claim that automated sentiment coding accuracy is in the range of 70% to 80%, there is a total absence of controlled research which objectively and systematically assesses automated sentiment coding accuracy. The research reported in this paper addresses this issue through two research questions:

RQ1 How accurately do third-party companies code various types of brand-related comments via automated sentiment analysis?

RQ2 When automated sentiment coding is incorrect, what types of misclassifications are made?

Relevant to each of the prior questions, the goal is to identify any differences in automated sentiment coding accuracy between companies that provide this information for a fee versus free of charge. The outcomes relevant to each research question have implications for marketers’ decisions with regard to the most advantageous way to use automated sentiment coding.

METHODOLOGY

A controlled test of automated sentiment coding accuracy requires two things. First, all selected companies need to code the exact same corpus of comments. Second, the corpus of comments must be systematically and objectively pre-coded as to sentiment so that accuracy can be assessed without subjective judgment.

Companies Selected

Six companies were selected as representative of the range of third-party companies that provide automated sentiment coding services. All of the companies are leading companies and all have been mentioned in articles or reviews of sentiment coding. Three companies are fee based while three offer sentiment coding services free of charge. Note that in the presentation of

results, these companies are coded as Fee Co. 1, Fee Co. 2 and Fee Co. 3 (for fee-based companies) and Free Co. 1, Free Co. 2, Free Co. 3 (for free sentiment coding companies). Since the research was designed to evaluate sentiment coding accuracy (and not serve as a basis for company promotion or denigration) the names of the specific companies have been suppressed. Each of the companies uses its own proprietary algorithm for automated sentiment coding.

Corpus of Comments

Twitter was used as the social medium through which brand-related comments were communicated. This was done because Twitter comments, also known as tweets, are short (and therefore tend to express a single emotion or sentiment) and are tracked by all third-party companies. In addition, Twitter has become the de facto source of consumer brand-related dialogue, providing consumers' affective reactions toward products at critical junctions of the decision-making and purchasing process (Pak & Paroubek, 2008; Jansen, et. al., 2009; Thelwall et al., 2011).

A fictitious beer, Dryekkix, was selected as the tweet focus. The use of a fictitious brand name allowed for complete control over and consistency in the corpus of tweets to be analyzed. All tweets contained this brand name.

A list of comments regarding the beer was generated by 107 undergraduate students. Students were instructed to provide 10 examples each of positive, negative and neutral comments. Once a master list of these comments was compiled, duplicate or very similar comments were eliminated. For example, "Dryekkix is good" remained on the list to represent the statements: "Dryekkix is really good," "Dryekkix, good" and "Dryekkix, good beer." Remaining comments were then shown to a second group of twenty undergraduate students who evaluated comments for "naturalness," that is, something they would actually tweet. Problematic statements were eliminated or revised.

Once the list of statements was finalized, two trained, independent coders coded each statement as either neutral, positive, or negative. Only those statements which coders agreed upon remained in the corpus.

Neutral Statements

Koppel and Schler (2005) note that not every comment related to a product or experience expresses positive or negative sentiment; some comments might report objective facts without expressing an opinion. They go on to point out the importance of paying attention to and properly coding these types of statements in any analysis of sentiment. As a result, neutral statements which appeared on the final list communicated a statement of fact or asked a question without emotional attachment or associated sentiment. 137 neutral comments appeared on the final list of tweets; representative examples are shown in Table 1.

Positive and Negative Statements

As indicated in RQ1, one of the goals of the research was to determine automated coding accuracy for different types of statements. An examination of the positive and negative statements on the master list conducted in the context of prior analyses of comment form and type (Kim & Hovy, 2004; Wilson et al., 2009; Thet et al., 2010) resulted in the creation of five tweet categories which were defined and then explained to two new, independent coders. After practice and feedback, the coders then independently coded each of the remaining positive and negative statements (on the master list) into one of the five categories. Only comments for which both coders agreed on category assignment remained in the corpus. Comments for which there was coding disagreement, or comments which did not fit into a category, were eliminated. An explanation of the five categories of positive and negative tweets follows.

Keywords. Automated sentiment coding has a heavy reliance on keyword identification (Thet et al., 2010), where a keyword is typically defined as a word that expresses either a positive or negative sentiment, such as “good,” “superb,” “horrible” and “disgusting.” Two categories focused on keywords.

Category 1 consisted of keywords present in simple statements or phrases. Tweets in this category embedded a keyword in a short sentence or phrase without elaboration.

Category 2 consisted of keywords present in complete/complex statements. Tweets in this category embedded a keyword in a longer sentence or a series of short statements.

Examples of positive and negative tweets falling into Categories 1 and 2 are provided in Table 1.

Sentiment Without Keywords.

Not all statements that express a sentiment contain a keyword (Kim & Hovy, 2004). As a result, Category 3 tweets in the corpus expressed a sentiment with no keyword present in the tweet. Sentiment coding of these tweets therefore required an analysis of the entire phrase or sentence in order to determine sentiment. Positive and negative examples of Category 3 tweets are provided in Table 1.

Reversed Polarity Keywords.

Keywords may be present, as in Categories 1 and 2, but the sentiment expressed can, in fact, be the opposite of the keyword’s typical sentiment. Wilson et al. (2009) label this phenomenon ‘contextual polarity’ and note that the meaning of sentiment-laden keywords can be reversed through either negation or context. With regard to negation, the word “good,” for example, expresses a positive sentiment in the phrase “it’s good to serve Dryekkix,” but negative sentiment due to negation in the phrase “it’s not good to serve Dryekkix.” Category 4 tweets contained tweets whose keyword’s typically expressed sentiment was reversed due to contextual polarity negation. As a result, negative keywords assumed positive meaning and positive

keywords assumed negative meaning. With regard to context, the presence of the word “bad,” for example, typically expresses negative sentiment, while “good” typically expresses positive sentiment. However, context can reverse each of these typical meanings: “it’s too bad we ran out of Dryekkix” expresses a positive sentiment while “only crazy people think Dryekkix tastes good” expresses a negative sentiment. Category 5 tweets used context rather than negation to reverse a keyword’s meaning. Examples of positive and negative tweets falling into Categories 4 and 5 are provided in Table 1.

Table 1: Tweet Categories and Exemplar Tweets		
Tweet Category	Number of Tweets	Exemplar Tweets
Neutral	137	Dryekkix has white foam. Tom drinks regular Dryekkix. Where is Dryekkix sold?
Category 1: Simple Keyword (Positive)	32	Dryekkix is a superior beer. Dryekkix, love it.
Category 1: Simple Keyword (Negative)	39	Dryekkix, one lousy beer. Dryekkix, hate it.
Category 2: Complex Keyword (Positive)	113	Chilling on the beach with Dryekkix. Life is good. When you come to my house bring the best, Dryekkix. I’m so relieved that I finally found such a great beer, Dryekkix.
Category 2: Complex Keyword (Negative)	92	How is it possible for one beer to taste so bad? I’m really disappointed with Dryekkix. I can’t believe how much worse I feel when I drink Dryekkix.
Category 3: No Keyword (Positive)	124	Always ask for Dryekkix. I need a Dryekkix now! More. I want more Dryekkix!
Category 3: No Keyword (Negative)	88	I don’t know why anyone would drink Dryekkix. I will never buy Dryekkix again. All my friends left when I brought out the Dryekkix.
Category 4: Reverse/Negation (Positive)	39	Dryekkix never tastes like crap. Dryekkix’s flavor - not bad Nothing about Dryekkix is disappointing.
Category 4: Reverse/Negation (Negative)	56	Dryekkix is never refreshing. Dryekkix is not great. It’s not good to bring Dryekkix to a party.
Category 5: Reverse/Context (Positive)	21	It’s too bad we ran out of Drekkix. I thought Dryekkix would be disgusting, but I was wrong. My friends were all sad until they discovered Dryekkix.
Category 5: Reverse/Context (Negative)	26	Everything tastes better than Dryekkix. No one I know likes Dryekkix. Only crazy people think Dryekkix tastes good.

Tweet Distribution

The final set of 767 statements was tweeted over approximately a three week period during which sentiment coding was collected from all participating companies. On rare occasions when a tweet was missed by a company in the initial tweeting, missed tweets were re-tweeted to ensure that a common/identical set of tweets was analyzed by all participating companies. All sentiment coding was computer rather than human generated. At the end of the three week period, each company had coded all 767 statements.

RESULTS

The results are presented in terms of the two research questions.

RQ1 How accurately do third-party companies code various types of brand-related comments via automated sentiment analysis?

Overall Coding Accuracy for Tweet Categories

The coding accuracy of neutral statements can be seen in the top row of Table 2. With regard to these statements, free companies coded these statements significantly more accurately than did the fee-based companies. All three free companies coded these statements at levels exceeding 90% accuracy, while only one of the fee-based companies exceeded 80% accuracy. A Z-test of proportions showed that the coding accuracy of the least accurate of the free companies was significantly higher than the best of the fee-based companies ($z = 1.80$, $p = .04$).

Table 2 also presents automated coding accuracy for the five tweet categories. Within each positive and negative category, the data presented reflects the unweighted average of positive correct codings and negative correct codings. (Unweighted averages were used to avoid bias due to unequal numbers of positive and negative tweets within each category.) There is a clear trend in automated tweet coding accuracy for the five tweet categories. While there is some variation across companies *within* a category, all companies show the same trend *across* tweet categories. Tweets with keywords used in their typical way (Categories 1 and 2) are coded with relatively high accuracy, with all but one of the companies displaying coding accuracy of at least 70%. Sentiment coding accuracy greatly declines when no keywords are present (Category 3). Here, the two best companies had accuracy levels in the 40% range with remaining companies achieving accuracy levels of less than 30%. Tweets in which the meaning of keywords are reversed due to negation or context (Categories 4 and 5) are very problematic, with accurate coding at extremely low levels.

All companies showed the prior pattern of decline in sentiment coding accuracy as one moved from tweet Category 1 to Category 5. On a comparative basis, however, no single company was consistently stronger than the others with regard to performance across all six

types of tweets (see Table 2). Five of the six companies showed a comparative mix of strengths and weaknesses, performing comparatively better in several areas but more poorly in others. Free Co. 1 comes the closest to being the “strongest” company. This company met or exceeded the accuracy levels of the remaining companies for four of the six tweet categories (neutral, Categories 1 through 3).

Table 2: Sentiment Coding Accuracy by Primary Tweet Category (% Correct)						
	Fee Co. 1	Fee Co. 2	Fee Co. 3	Free Co. 1	Free Co. 2	Free Co. 3
Neutral Statements (n=137)	31.4	59.9	82.5	90.5	94.9	98.5
Category 1: Simple Keyword (n=71)	88.4	79.8	62.3	85.1	84.4	77.5
Category 2: Complex Keyword (n=205)	78.2	79.9	73.3	90.3	76.2	77.1
Category 3: No Keyword (n=212)	42.3	29.8	28.7	47.1	23.7	16.3
Category 4: Reverse/Negation (n=95)	6.3	8.8	6.1	0.9	2.2	1.3
Category 5: Reverse/Context (n=47)	14.4	21.1	3.9	8.2	6.3	7.2

Coding Accuracy for Positive and Negative Statements within Tweet Category

The prior analysis provided overall accuracy levels for the neutral statements and the five categories of tweets. Each of the five tweet categories, however, is composed of both positive and negative statements (see Table 1). It is necessary, therefore, to determine if the overall coding accuracy percentages presented for each category (and shown in Table 2) are good descriptors of the positive and negative tweet types comprising each category.

Keywords Present (Categories 1 and 2)

Table 2 indicated that tweets in these categories were accurately coded by most companies, with overall category averages for all but one company exceeding 73%. Table 3 provides more detailed data by showing the percent of positive and negative tweets coded correctly within each category. Two patterns emerge. First, two of the fee-based companies' category unweighted averages are generally good indicators of their performance as these companies appear to code positive and negative statements in Categories 1 and 2 at comparable levels of accuracy (Fee Co. 1 and Fee Co. 2). The remaining fee-based company and the three free companies show a mix of accuracy levels, displaying greater coding accuracy for positive versus negative statements in one or both categories.

Table 3: Sentiment Coding Accuracy for Positive and Negative Comments in Tweet Categories 1 and 2 (% Correct)						
	Fee Co. 1	Fee Co. 2	Fee Co. 3	Free Co. 1	Free Co. 2	Free Co. 3
Keyword Present, Simple (Category 1)						
Positive (n=32)	84.4	75.0	65.6	90.6	96.9	78.1
Negative (n=39)	92.3	84.6	59.0	79.5	71.8	76.9
Keyword Present, Complex (Category 1)						
Positive (n=113)	72.6	81.4	81.4	90.3	85.0	87.6
Negative (n=92)	83.7	78.3	65.2	90.2	67.4	66.6

No Keyword Present (Category 3)

Table 4 provides the data relevant to each company's coding of positive and negative tweets in which no keyword was present. Three companies (Fee Co. 1, Free Co. 2 and Free Co. 3), although at different levels, coded positive and negative statements with approximately equal levels of accuracy. Two companies (Fee Co. 3, Free Co. 1) more accurately coded negative statements while the remaining company (Fee Co. 2) more accurately coded positive statements.

Table 4: Sentiment Coding Accuracy for Positive and Negative Comments in Tweet Category 3 (% Correct)						
	Fee Co. 1	Fee Co. 2	Fee Co. 3	Free Co. 1	Free Co. 2	Free Co. 3
No Keyword Present (Category 3)						
Positive (n=124)	46.0	37.9	21.0	36.3	23.4	16.1
Negative (n=88)	38.6	21.6	36.4	57.9	23.9	17.0

Negated and Context Reversed Keywords (Categories 4 and 5)

Table 5 provides the data relevant to each company's coding of positive and negative tweets when the meaning of the keyword was reversed due to negation or context. Coding accuracy for both categories of tweets was very low. With this in mind, however, companies were generally more accurate in coding negative versus positive sentiment. Companies were, for example, more successful in classifying "not good" as a negative, as opposed to "not bad" as a positive.

RQ2: When sentiment coding is incorrect, what types of misclassifications are made?

Misclassification error types for neutral statements varied across companies. Among those companies with high levels of classification error (the three Fee Companies) two companies were more likely to classify neutral statements as positive while the remaining company was equally likely to misclassify a neutral statement as either positive or negative (see Table 6).

Table 5: Sentiment Coding Accuracy for Positive and Negative Comments in Tweet Categories 4 and 5 (% Correct)

	Fee Co. 1	Fee Co. 2	Fee Co. 3	Free Co. 1	Free Co. 2	Free Co. 3
Negated Keyword (Category 4)						
Positive (n=39)	0.0	5.1	5.1	0.0	2.6	2.6
Negative (n=56)	12.5	12.5	7.1	1.8	1.8	0.0
Context Reversed Keyword (Category 5)						
Positive (n=21)	9.5	19.0	0.0	4.8	4.8	14.3
Negative (n=26)	19.2	23.1	7.7	11.5	7.7	0.0

Two patterns of misclassification emerge for the five tweet categories. Table 7 provides the misclassification data for tweets in which a keyword is present and used in its typical way (Categories 1 and 2) and in which no keyword is present (Category 3). Here, misclassifications tend to be “neutral” where incorrectly coded positive and negative tweets are coded as neutral. Table 8 provides the misclassification data for the positive and negative tweets in the contextual polarity categories (Categories 4 and 5). Here, tweets are typically coded in terms of the keywords’ typical meaning, for example, “it’s not good” is coded as a positive and “it’s not bad” is coded as a negative.

Table 6: Misclassification of Neutral Comments (% Misclassified)

	Fee Co. 1	Fee Co. 2	Fee Co. 3	Free Co. 1	Free Co. 2	Free Co. 3
Neutral Statements misclassified as:						
Positive	46.7	19.7	15.3	3.6	4.4	1.5
Negative	21.9	20.4	2.2	5.8	0.7	0.0

Table 7: Misclassification of Positive and Negative Comments in Categories 1, 2 and 3 (% Misclassified)

	Fee Co. 1	Fee Co. 2	Fee Co. 3	Free Co. 1	Free Co. 2	Free Co. 3
Keyword Present, Simple (Category 1)						
Positive tweets misclassified as:						
Neutral	15.6	25.0	34.4	9.4	3.1	21.9
Negative	0.0	0.0	0.0	0.0	0.0	0.0
Negative tweets misclassified as:						
Neutral	5.1	12.8	38.5	17.9	28.2	23.1
Positive	2.6	2.6	2.6	2.6	0.0	0.0

Table 7: Misclassification of Positive and Negative Comments in Categories 1, 2 and 3 (% Misclassified)

	Fee Co. 1	Fee Co. 2	Fee Co. 3	Free Co. 1	Free Co. 2	Free Co. 3
Keyword Present, Complex (Category 2)						
<i>Positive</i> tweets misclassified as:						
Neutral	10.6	14.2	17.7	8.0	8.8	10.6
Negative	16.8	4.4	0.9	1.8	6.2	1.8
<i>Negative</i> tweets misclassified as:						
Neutral	12.0	8.7	32.6	6.5	28.3	31.5
Positive	4.3	13.0	2.2	3.3	4.3	2.2
No Keyword Present (Category 3)						
<i>Positive</i> tweets misclassified as:						
Neutral	27.4	54.0	63.7	48.4	61.3	79.8
Negative	26.6	8.1	15.3	15.3	15.3	4.0
<i>Negative</i> tweets misclassified as:						
Neutral	26.1	54.5	59.1	21.1	64.8	79.5
Positive	35.2	23.9	4.4	21.1	11.4	3.4

Table 8: Misclassification of Positive and Negative Comments in Categories 4 and 5 (% Misclassified)

	Fee Co. 1	Fee Co. 2	Fee Co. 3	Free Co. 1	Free Co. 2	Free Co. 3
Negated Keyword (Category 4)						
<i>Positive</i> tweets misclassified as:						
Neutral	35.9	48.7	30.8	25.6	43.6	41.0
Negative	64.1	46.2	64.1	74.4	53.8	56.4
<i>Negative</i> tweets misclassified as:						
Neutral	17.9	33.9	51.8	19.6	25.0	32.1
Positive	69.6	53.6	41.1	78.6	73.2	67.9
Context Reversed Keyword (Category 5)						
<i>Positive</i> tweets misclassified as:						
Neutral	14.3	9.5	19.0	14.3	47.6	33.3
Negative	76.2	71.4	81.0	81.0	47.6	52.4
<i>Negative</i> tweets misclassified as:						
Neutral	26.9	26.9	38.5	11.5	7.7	23.1
Positive	53.8	50.0	53.8	76.9	84.6	76.9

DISCUSSION AND MANAGERIAL IMPLICATIONS

Overall, automated sentiment coding (as represented by the six companies used in the research) has limited reliability and appears to be accurately accomplished only for very simple statements in which a keyword is used to convey its typical meaning, for example, “Dryekkix is a good beer.” Statements without keywords or statements in which keyword meaning is reversed through negation or context are accurately coded much less frequently, with accuracy for the latter types of statements exceedingly low. Neutral statements appear to be problematic for some but not all companies.

The lack of accuracy is compounded by the types of misclassification errors. In statement categories in which there is relatively higher coding accuracy (Categories 1 and 2) misclassifications of positive and negative statements tend to err toward “neutral” and thus will, to a small degree, reduce the overall proportion of positive and negative statements reported in summary measures. This reduction, however, should not significantly distort the overall interpretation. The inability of most companies to accurately code statements without a keyword, and the misclassification of these statements as neutral, have significantly greater potential to distort the overall summary of tweet sentiment. Here, a sentiment summary would indicate consumers’ general neutrality toward the brand, when, in fact, either positive or negative sentiment was much greater. Finally, the very low level of automated sentiment coding accuracy for statements with contextual polarity, combined with the way in which these statements are miscoded, holds significant peril for brands using this information for strategic decision-making, as the miscoding errors will result in a sentiment analysis that is the exact opposite of the actual situation.

The Risk of Summary Sentiment Coding

We mentioned earlier that the results of automated sentiment coding are typically presented as summary measures, that is, marketers typically receive a report that notes the percentage of comments coded as positive, negative, and neutral. The lack of automated coding accuracy for many types of comments coupled with the types of observed misclassification errors should make managers very cautious about using overall summary measures for tracking brand-related sentiment. The research suggests that short- and long-term changes in the relative proportion of positive, negative and neutral statements may be as likely to reflect coding inaccuracy as actual changes in consumer sentiment. Moreover, given that some types of statements are coded with more accuracy than others, changes in period-to-period sentiment may simply reflect changes in the relative proportion of different types of statements being coded during a particular period rather than actual changes in the proportion of positive, negative and neutral statements.

The data presented in Table 9 illustrates this latter phenomenon. Each “Period” in the table reports two companies’ actual coding of 100 tweets selected from the tweet corpus used in the research. Tweets were specifically selected so that the correct coding and reporting should be

30% positive, 40% neutral, and 30% negative for every period. However, while every period's underlying percentage distribution is the same, we varied the proportion of tweets drawn from each of the tweet categories. The results are, we believe, striking. While the actual percentage of positive, negative and neutral tweets remains consistent across all periods (thereby indicating no movement in sentiment), the trend reported by Fee Co. 1 would be interpreted to indicate a significant rise in positive sentiment, nearly eliminating neutral and negative opinion. The trend indicated by Free Co. 1 would result in a different interpretation where positive sentiment is rising, but that there are still relatively equivalent levels of neutral and positive sentiment in the ending period. Finally, the automated sentiment reported is quite different across companies. A marketer using Fee Co. 1 would draw very different conclusions about current sentiment and sentiment trends versus the information reported by Free Co. 1 *even though the underlying data is exactly the same*. Unfortunately, given the percentages of positive, negative and neutral sentiment reported by each company, neither set of conclusions would be correct.

Table 9 : Company Classification of 100 Selected Tweets^a						
	Fee Co. 1			Free Co. 1		
	Period 1	Period 2	Period 3	Period 1	Period 2	Period 3
Sentiment Category						
Positive	47	49	82	29	38	48
Neutral	16	32	12	42	38	43
Negative	37	19	6	29	24	9
^a Numbers represent the percentage of the 100 tweets assigned to each sentiment category. Correct coding for all periods is 30% positive, 40% neutral, and 30% negative.						

Automated Sentiment Coding Versus in-House Coding

The data indicate that managers should be very cautious in their use of automated sentiment coding unless high levels of accuracy across a broad range of statement types can be independently verified. Until external coding accuracy is verified, we recommend that managers use third-party companies to collect comments while marketers use their own (or contracted) personnel to manually code comment sentiment. This would accomplish two things. First, it would ensure that accurate data is informing decisions utilizing sentiment analysis. Second, it would facilitate marketers' understanding of how trends in sentiment relate to trends in content. This latter outcome is important because it helps marketers better understand the aspects of their brand and behaviors that are contributing to positive and negative sentiment.

Selecting a Company for Sentiment Coding

We realize that the prior recommendation may not be feasible for all companies, and that some companies will decide that in spite of its limitations, automated sentiment analysis is their best option. Given the variability in coding accuracy across companies, what can marketers do to ensure that they have selected the “best” company for their sentiment monitoring? We recommend that both free and fee-based sentiment monitoring companies be “test driven” prior to selection. (Almost all fee-based companies provide a free test period.) Reflecting the results obtained in this research we recommend that marketers take advantage of this period to do the following for each of the companies being evaluated:

1. Create a list of product-related tweets using the category definitions provided in this research. We recommend approximately 30 neutral comments, as well as 20 positive comments, and 20 negative comments within each tweet category. Comments should be brand and category specific and should represent typical consumer comments for the brand or product category. Initial starting points for comment creation include existing brand and product reviews as well as searches for prior tweeted comments (Twitter search at <http://search.twitter.com> provides this service free of charge.)
2. Tweet 70 comments at a time. After each set of tweets has been sent then, similar to this research, managers should obtain automated sentiment coding accuracy from each company. (Be certain to retweet any comments missed by one or more of the companies.)
3. Continue until all tweets have been sent and coded.
4. Identify the company with highest overall accuracy and accuracy within each different type of tweet category.

The prior evaluation exercise is not overly labor intensive as the set of tweets need only be tweeted once and since each company will provide detailed information on the coding of each tweet.

This approach has several benefits. First, the creation of the set of tweets will provide systematic exposure to the already existing brand-related comments. Second, this research indicated that companies vary with regard to their accuracy across categories of statements. As a result, the prior procedure will help identify the specific strengths and weaknesses of each company as well as the overall “strongest” company for the types of brand-related comments likely to be encountered. Third, it will help to highlight one of the limitations of free automated sentiment coding companies. This research indicated that at least some free companies provide automated sentiment coding at levels equal to or exceeding that of fee-based companies. This is certainly a significant positive. Free companies, however, handle the set of tweets differently than do fee-based companies. Free companies typically provide analysis of only the last 70 to 100 tweets, while fee-based companies provide analysis of all current tweets plus historical data. (This is why the prior procedure recommended tweets be sent in sets of 70.) This limitation should be taken into account when identifying the strengths and weaknesses of each evaluated company.

LIMITATIONS AND FUTURE RESEARCH

Several limitations of the research should be noted, where each limitation points toward potential future research.

The first set of limitations relates to the corpus of comments used in the research. The comments provided for the automated sentiment analysis were simple, short, and contained only a single sentiment. This, we believed, provided a “best case” scenario for this first investigation of automated coding accuracy. There are, however, other types of comments not explored in this research that should be evaluated in future research. These include comments which use sarcasm and irony to express sentiment as well as statements which communicate sentiment in other ways, for example, using abbreviations and emoticons. In addition, not all comments express a single sentiment (i.e., “I usually love Pizza Hut but last night’s pizza was terrible.”). The accuracy of automated sentiment coding for these latter types of statements should also be a focus of further research.

The second set of limitations relates to the set of companies used. The six companies selected were all well-known companies. However, an exploration of an expanded number of companies would be beneficial in future research, as it is certainly possible that some companies may be able to exceed the coding accuracy obtained in this research.

The final set of limitations relates to the social medium used - Twitter. Brand comments appear not only on Twitter, but also in other social media venues, with blogs and product review sites perhaps being the most important from a brand management perspective. An evaluation of automated sentiment coding accuracy of comments appearing in these sources would be of great benefit to brand managers.

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PLACE BRANDS AND THE RELATIONAL BRANDING COMMUNICATION PROCESS

L. Jean Harrison-Walker, The University of Houston-Clear Lake

ABSTRACT

Using Hankinson's conceptual model of places as relational networks, an expanded model is introduced that more clearly reflects the relational nature of place brands by identifying the relevant communicational concepts at both the source (brand) as well as receiver (target audience) side of the relationship and provides greater detail on each of the elements of the model. According to the conceptual model presented herein, the core place brand consists of identity, personality, and positioning, while the corresponding audience elements are image, affect, and position. This conceptual model contributes to the extant literature in relational place branding by including both source and receiver constructs in the relational model of place brands and defining each of the six constructs involved in the Relational Brand Process.

INTRODUCTION

In general, place branding is defined as the practice of applying brand strategy and other marketing techniques and disciplines to cities, regions and countries (<http://www.palgrave-journals.com/pb>). Of particular relevance to place branding is the conceptualization of the brand as something that consumers can have a relationship with (Hankinson, 2004). Hankinson (2004) draws upon concepts from classical branding, the relational exchange paradigm, and the network paradigm to develop a conceptual model of a 'relational network brand.' In this model, the core brand consists of brand personality, brand positioning, and reality in which both personality and positioning must be firmly rooted (Hankinson, 2004). Hankinson (2004) contends that the ultimate success of a place branding strategy relies on the effective extension of the core brand through effective relationships with stakeholders. While Hankinson (2004) makes a decidedly significant first step toward understanding the relational nature of place brands, the model only identifies concepts on the source side of the relationship. Furthermore, only the two branding constructs of personality and positioning are included in his model.

The purpose of this paper is to develop and expand upon Hankinson's conceptual model of relational place brands. This paper first distinguishes place branding from the similar concepts of destination branding and nation branding. Second, the challenge that is unique to place branding is briefly reviewed. Third, the model of relational networks proposed by Hankinson is briefly explained. Next, a more developed model of the Relational Branding Communication Process as it applies to place is introduced. Finally, the relevant concepts in the expanded model that are associated with the source and the receiver are examined.

PLACE BRANDING BY ANY OTHER NAME

In general, place branding is defined as the practice of applying brand strategy and other marketing techniques and disciplines cities, regions and countries' (<http://www.palgrave->

journals.com/pb). Some researchers suggest, however, that more specific terms may be more appropriate depending on the benefit sought or the type of venue. For example, the term ‘destination branding’ may be used when places are treated as brands with the primary objective of attracting tourism (Morgan, Pritchard and Pride, 2002). Hanna and Rowley (2008) differentiate the terms ‘place branding’ and ‘destination branding’ by observing that the term “destination” occurs most frequently in the tourism literature, whereas the term “place” dominates in business and branding journals.

The appropriate terminology may also depend upon the type of venue or place under consideration. For example, city branding would be at the city level while national branding would be at the country level. Like destination branding, city or nation branding may be concerned with tourism development. Unlike destination branding, nation branding in particular also relates to the positive effects of branding the nation for the attraction of foreign investment (Kavaratzis, 2005).

For the purposes of the current paper, we will use the more general term ‘place branding’ to avert focus on any particular benefit or any venue level. The model developed in this paper is not dependent upon specific benefits or location, but rather should generalize to meet the needs of place marketers.

What Makes Place Branding Unique?

In a special issue of *Place Branding and Public Diplomacy* on culture Parkerson (2007, p.263) stresses that “places and place brands are inherently different from products and product brands.” The primary difference is that places, unlike new products launched onto the market, do not begin from a zero base (Hankinson, 2004b, p.7). The place already exists, complete with its own culture, population, facilities and infrastructure. Accordingly, the marketer cannot typically design the place brand but must develop a marketing strategy based on what is given.

Relational Place Branding

Of particular relevance to place branding is the conceptualization brands as relationships (Hankinson, 2004). According to Hankinson (2004), the effectiveness of place branding relies on the extension of a core brand through effective relationships with various stakeholder audiences (e.g., customer relationships, media relationships, service relationships, and infrastructure relationships). In more recent work, Hankinson (2004) draws upon concepts from classical branding, the relational exchange paradigm, and the network paradigm to develop a conceptual model of a ‘relational network brand.’ In this model, Hankinson (2004) suggests that the core brand consists of brand personality, brand positioning, and reality (in which both personality and positioning must be firmly rooted).

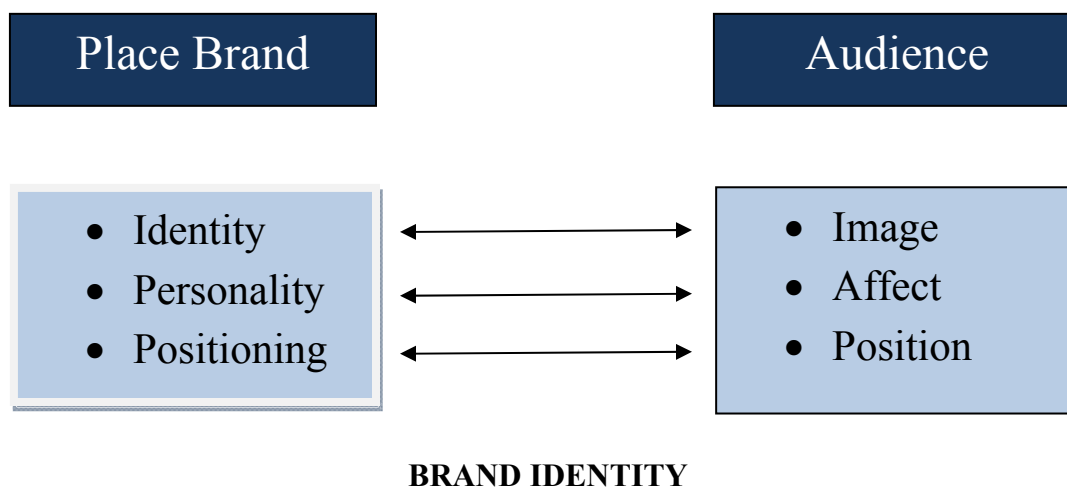
As noted by Morgan, Pritchard and Pride (2002, p.24), “branding is a mode of communication and communication is always a two-way process; it is something “done with and not to the consumer.” In Hankinson’s (2004) network model, double headed arrows are used to indicate a relational connection between the core brand and the four sets of stakeholders (as well as connections among the stakeholder groups). The conceptualization of a brand as a relationship cannot be overemphasized, and in fact calls for further development and explanation.

The Relational Branding Communication Process

Figure 1 shows the proposed Relational Branding Communication Process as it applies to place marketing. At the brand's core are identity, personality, and positioning. Identity was not specifically included in the Hankinson (2004) model. Rather, Hankinson (2004) included reality as a third core element. Although it is agreed that the core elements must indeed be firmly rooted in reality, reality is not seen as a unique element of the core brand but rather a critical strategic consideration. Accordingly, reality is not specified as an element of the core brand in the proposed model.

The Relational Branding Communication Process model further identifies the corresponding constructs on the receiver's end. As observed by DeChernatony and Dall'Omo Riley (1998), a brand is a multidimensional construct, the boundaries of which are, on the one side the activities of the firm [e.g. the core brand] and on the other side the perceptions of the receiving audience. Accordingly, on the receiving side are the corresponding elements of image, affect and position. All three of these constructs are presented in the proposed Relational Branding Communication Process model. Next, each of the source and receiver constructs is discussed in greater detail.

Figure 1
The Relational Branding Communication Process



Although Hankinson (2004) does not specifically include brand identity in his relational model, he does in fact contend that "the brand core represents the place's identity, the blueprint for developing and communicating the place's brand," (Hankinson 2004, p.115). Importantly, identity is quite distinct from personality and positioning. This becomes clear when one considers Keller's (1998) six elements of brand identity: names, logos, symbols, slogans, jingles and packages. In most place branding campaigns, an inordinate amount of time, energy and funding is spent on logos and slogans (Levine, 2008). Ashworth and Kavaratzis (2009, p.522) observe that all too often place marketers undertake "only a part of the branding process, namely the development of a catchy slogan and or the design of a new logo to be attached in promotional material." Examples abound. The Missouri Department of Tourism recently unveiled its new slogan "Where the Rivers Run" along with a new logo that turns the 'ss' in the middle of the

word Missouri into a river, accompanied by a rising sun (Baar 1997; Beirne 1999). South Dakota's slogan of "Great Faces. Great Places." follows an illustration of Mount Rushmore. A racetrack symbol woven through the state's name of Indiana uses the slogan "Restart Your Engines," while Kentucky's "Unbridled Spirit" includes a partial illustration of a racehorse. Finally, Las Vegas is touted as having one of the most popular slogans among adults: "What Happens in Vegas Stays in Vegas." Rhode Island, the smallest state in the nation, does not have a slogan but hopes to get one in 2010 as part of a \$70,000 project to brand the state. Countries also focus heavily on slogans, such as "Come and Say G'Day," to Australia, "Any Decent Doctor Would Prescribe Norway," "Cool Britannia," and "100% New Zealand." Given the amount of time, energy and funding being spent on the development of these identity elements, Levine (2008) reminds place marketers that a logo [and/or a slogan] is not a strategy."Yes, you need a professionally developed, graphic identity that reflects favorably on your...community. But it is only a small piece of the overall puzzle" (Levine, 2008, p.7). Given that identity plays such a major role in relational branding, it is the first element of the core brand identified on the place brand side of Figure 1.

BRAND IMAGE

From the target market's perspective, central to the concept of the brand is the brand image, which incorporates perceptions of quality and values as well as brand associations and feelings (Kavaratzis, 2005). Keller (1993) similarly defines brand image from the audience's perspective suggesting that brand image is characterized by a set of associations or attributes to which consumers attach personal value. Hankinson (2004) clearly distinguishes brand image from brand identity, defining brand image as what the consumer perceives and brand identity as what the firm tries to communicate. Accordingly, image is the counterpart to identity and therefore the first element on the audience side of the Relationship Branding Model in Figure 1.

Just as products and companies project images to their target audiences, places also conjure up images in the minds of their audiences. Baloglu and McCleary (1999) define place image as being a 'set of beliefs, ideas, and impressions that people have of a place or destination.' Similarly, Martin and Eroglu (1993, p.193) suggest that country image may be defined as "the total of all descriptive, inferential, and informational beliefs one has about a particular country." The beliefs, ideas, and impressions one has about a place may be based on facts, inferences, or stereotypes and much of this may depend upon the individual's personal familiarity with the place. Lack of familiarity may, in some case, be used to the marketer's advantage. For example, while most institutions have distinguishable images (Wilbur, 1988), the image of most nations is vague because there is a general level of ignorance of countries other than one's own (O'Shaughnessy and O'Shaughnessy, 2000). This would seemingly offer an opportunity for most nations to build their brand for projection to the world (O'Shaughnessy and O'Shaughnessy 2000).

BRAND PERSONALITY

Brand personality, the second element of the place brand in figure 1, is quite distinct from brand identity. Marketing practitioners and advertisers were the first ones to coin the term 'brand personality', well before the academicians studied and accepted the concept (Pandey 2009). In 1958, Martineau used the word to refer to the non-material dimensions that make a

store special, e.g. its character. King (1970) wrote that “people choose their brands the same way they choose their friends in addition to the skills and physical characteristics; they simply like them as people”.

Brand personality was defined in the academic literature by (Aaker 1997, p. 347) as “the set of human characteristics associated with a brand.” Aaker (1997) developed a robust and reliable brand personality inventory, which has been hypothesized to be a generalized brand personality construct and tested with a number of product categories in the US. The final scale contains 42 personality traits, grouped into five factors (Aaker 1997). However, Heere (2010) questions the usefulness and validity of the scale noting that despite the large number of brands that were used in developing the scale, the number of adjectives that used are limited and only cover a small part of the universe of adjectives. Heere (2010) suggests that the measurement of brand personality begin by asking brand managers to use a free listing technique to provide a list of personality objectives that they feel their brand is associated with. Then, stakeholders can be asked how well the brand represents each of the adjectives. This approach is particularly attractive as it is in keeping with a relational branding approach. That is, both the marketer and the audience are questioned in order to describe a brand’s personality, rather than simply one side or the other.

In recent years, the strategic importance of brand personality has become increasingly apparent (Pandey, 2009). Brand personality (1) creates unique and favorable associations in the consumer’s mind; (2) contributes significantly to brand preference and brand choice (Batra *et al.*, 1993; Biel, 1993); builds emotional ties to the brand, leading to trust and loyalty (Siguaw, Mattila, and Austin, 1999; Johnson, Soutar, and Sweeney, 2000); (4) provides an enduring basis for differentiation (Aaker and Fournier, 1995; Haigood, 1999, Halliday, 1996) which is difficult to copy (Aaker, 1996); and (5) enhances brand equity (Keller, 1993; Johnson, Soutar and Sweeney, 2000; Phau and Lau, 2000).

Specifically with regard to place marketing, Hankinson (2004) suggests that brand personality is characterized by functional attributes, symbolic attributes, and experiential attributes. *Functional attributes* include Museums, art galleries, theatres and concert halls; leisure and sports activities and facilities; conference and exhibition facilities; public spaces; hotels, restaurants, night clubs and entertainment; and transport infrastructure and access. *Symbolic attributes* include the character of the local residents; the profile of typical visitors (e.g., age, income, interests and values); and descriptors of the quality of service provided by service contact personnel. *Experiential attributes* include how the destination makes visitors feel (e.g., relaxed, excited or fascinated); descriptors of the destination’s feel (e.g., the city experience, vibrant or peaceful); the character of the built environment (e.g., historic, modern, green and spacious); and descriptors related to security and safety.

Affect

Affect is the counterpart to personality and therefore the second element on the audience side of the Relationship Branding Model in Figure 1. In the current study, affect is used as a general term to include both attitude and emotional attachment. Consumers who are emotionally attached to a brand are also likely to have a favorable attitude toward it (Park *et. al.*, 2010). Although the two constructs are similar, there are important differences that suggest both be included in the model. Attitudes reflect one’s evaluative reactions to an object and these reactions can develop without any direct contact with it (Thomson, MacInnis and Park, 2005).

Thus, a consumer might have a positive attitude toward an object without ever having had any experience with it at all (Thomson, MacInnis and Park, 2005). Since it is not only possible but likely for people to develop attitudes toward places they have never been to based on their second-hand knowledge and understanding of the place brand's functional, symbolic and experiential attributes, it is important to recognize that the personality associated with a brand place may indeed invoke positive (or negative) attitudes in its target audience.

Strong attachments, on the other hand, develop over time and are often based on interactions between an individual and the brand object (Baldwin et. al., 1996). These interactions encourage the development of meaning and invoke strong emotions in reference to the attachment object (Thomson, MacInnis and Park, 2005). When the brand is associated with a hedonic product (i.e., a product for which fun, pleasure, or enjoyment is a primary benefit), stronger emotional responses tend to be generated (e.g., Chandon, Wansink and Laurent, 2000; Hirschman and Holbrook, 1982). In other words, consumers find such products more lovable (Carroll and Ahuvia 2006). In fact, to the extent that such emotional attachment becomes passionate, the level of affect may be described as "brand love." Brand love is defined as 'the degree of passionate emotional attachment a satisfied consumer has for a particular trade name,' (Carroll and Ahuvia, 2006). Certainly, target audiences may develop an emotional attachment to a particular place and, to the extent that the attachment becomes passionate, the audience may love the place.

BRAND POSITIONING

Positioning has long been acknowledged as a core branding activity (Ries & Trout, 1981; Aaker and Shansby, 1982; DiMingo, 1988). Positioning is the act of designing an organization's offering and image to occupy a distinctive place in the target market's mind (Kotler, 2000). For example, Charmin is positioned as the soft bathroom tissue (Harrison-Walker 2009). Excedrin is positioned as the headache medicine (Harrison-Walker 2009). Nyquil is positioned as the nighttime cold medicine (Harrison-Walker, 2009). Grey Poupon is positioned as the expensive, top of the line mustard (Harrison-Walker, 2009). Each of these brands holds a distinct position in its product category and the organization's product, promotion, distribution and pricing strategies are designed to communicate and support the brand's unique position (Harrison-Walker, 2009). In other words, positioning is what marketers do. It is a branding strategy that, if successful, will lead to the desired perceptions in the minds of the target audience.

According to Dinnie (2008), establishing uniqueness is a key point in place positioning. For example, Switzerland is the country of choice when one needs personal banking services (Gilmore, 2002). The fact that this position is cemented within Switzerland's banking client secrecy laws means that other countries trying to promote themselves as a personal financial center would have difficulty entering the market and competing on this front (Gilmore, 2002). Personal banking is perceived as a distinct use associated with Switzerland (Harrison-Walker, forthcoming). Another example is Singapore's traditional position as the best entry point to Asia for Western multinationals (Quelch and Jocz 2005). This position was supported by the reality that its laws, institutions and educated English-speaking workforce made doing business from Singapore safe and easy (Quelch and Jocz 2005). At the city level, Miami positions itself as part of South America rather than where it truly belongs, North America; more specifically, Miami identifies itself as the financial capital of South America (Kotler and Gertner 2002).

Aaker and Shansby (1982) identify a number of ways in which a positioning statement can be conceived. The six approaches to positioning are: (1) by attribute, (2) by use, (3) by user, (4) by product category, (5) by price/quality, and (6) competitive positioning. In the above examples, Switzerland and Singapore are positioning by use, while Miami is positioning by product category (Harrison-Walker, forthcoming). Harrison-Walker (forthcoming) shows how each of the six approaches can be applied to the strategic positioning of nation brands.

Position

While brand positioning is something marketers do, the brand position is what is perceived by the receiving audience. Accordingly, position is the counterpart to positioning and therefore the third element on the audience side of the Relationship Branding Model in Figure 1. The characteristics of a good position for the brand are thought to be (1) perceived uniqueness (e.g. different from competitors), (2) prevalence (e.g. how many customers are aware of it), and (3) strength (Aaker, 1991). Note that each of these characteristics is assessed from the perspective of the target audience.

A brand's position evolves and, if managed effectively, becomes stronger over time (O'Shaughnessy and O'Shaughnessy, 2000). Furthermore, position implies a frame of reference, the reference point usually being the competition (Aaker and Shansby, 1982). Importantly, in order to be successful over the long term, the place brand must be perceived more favorably than competitive place offerings.

CONCLUSIONS AND IMPLICATIONS

There is an increasing interest on the part of cities, states, and nations in the application of strategic branding. Of particular intrigue to place marketers is the conceptualization of the place brand as something that consumers can have a relationship with. The current paper builds upon Hankinson's (2004) relational model of branding by incorporating matched sets of constructs from the sender and receiver's perspective. First, brand identity is added to the conceptualization of the core brand, which also includes personality and positioning. Second, the corresponding audience constructs of image, affect, and position are added to the model to demonstrate and emphasize the relational nature of the branding process. Finally, each of the constructs is explained in detail. A more advanced model of the Relational Branding Communication Process is presented (see Figure 1). By its very nature, this model suggests that relational branding should be measured from the perspective of the place marketer as well as the target audience based on the constructs relevant to each.

According to Freire (2005), places will always mean something to consumers; that is, places are embedded with meaning and will function as a brand even if not managed under a branding conceptual framework. However, it behooves place marketers to understand the constructs presented in the Relational Branding Communication Process model to (1) determine the extent to which the identify, personality, and positioning are being accurately and positively perceived by the target audience and (2) to assess the impact of the audience constructs on critical outcome variables such as brand loyalty, brand equity, willingness to pay a price premium, and word-of mouth communications.

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HEAVY VERSUS LIGHT USERS: A PRELIMINARY STUDY OF BEHAVIOR PATTERNS IN RETAIL SERVICES

Larry P. Pleshko, Kuwait University
Sarah Al-Houti, University of Alabama

ABSTRACT

The purpose of the study is to investigate differences in profiles between heavy and light users of four retail services: fast-food burger outlets, convenience stores, medical clinics, and health clubs. The findings indicate that heavy users, along with more visits to the services, have generally had experience with more brands in each of the retail service categories. Light users tend to concentrate their purchases in a smaller number of brands than do heavy users, indicating higher loyalty levels in light users. Few differences are evident between heavy and light users regarding satisfaction, perceived risk, or the size of buyer's choice sets.

INTRODUCTION

A heavy user is suggested to purchase a much larger volume than does a light user, regardless of the category (Twedt, 1964). This statement alone explains why researchers should take more interest to study this area further. It has been many decades since the earliest studies of heavy and light user segments, and still this area of research has not been fully explored. Many segmentation schemes are possible, most commonly lifestyles or demographics, but volume segmentation may provide similar insights into understanding consumption (Twedt, 1964; Clancy & Shulman, 1994). The 80-20 rule suggests that a large proportion of business is derived from the heavy users in relation to the remainder of purchasers, emphasizing the importance of the heavy-light user research for companies in general (Cook & Mindak, 1994; Pareto & Page, 1971). Even more reflective of the importance of volume segmentation is the now-common marketing practice which, in lieu of focusing on new customers, attempts to persuade current customers to purchase more (Finkleman, 1974).

Previous research has addressed many aspects of the heavy and light user dichotomy. Efforts have analyzed the influential factors that create a heavy user (Goldsmith, 2000), personal characteristics and demographic differences (Goldsmith & d'Hautevilie, 1998; Goldsmith et al., 1994; Goldsmith & Litvin 1999), and attitude structures related to advertising (Burnkrant et al., 1991; Jewell & Unnava 2004). Although, the conceptual development of the heavy and light user literature has resulted in many noteworthy findings, many related areas remain unexplored. For example, consumers' behavior patterns or the outcomes of these patterns in the context of heavy and light users segment have not yet been fully explored.

This study aims to extend the heavy and light user literature by addressing the differences between users in relation to the outcomes of consumers' behavior. Specifically, the focus will be

on the number of visits to outlets, the users' awareness of available service outlets, the number of service outlets with which users have experience, and the number of outlets considered prior to purchase. Also, the loyalty to a particular service provider, consumers' perceptions of risk, and global satisfaction affiliated with purchases are included. In addition, this study examines heavy and light users from four retail service categories which have not been previously studied in this context.

LITERATURE REVIEW

At the current time, there is no definitive methodology for distinguishing between heavy and light users. However, a clear distinction in the purchase volume between the two segments seems clearly evident (e.g. Goldsmith, 2000). Many options, all related to purchasing activity, exist for creating segments including volume, spending, experience, consumption time, and occasions. For example, buyers may be classified as heavy users if they spend more than others, buy more product units than others, have experience with more products than others, participate for longer periods than others, and purchase on more occasions than others.

The testing of demographic differences is a natural step in conceptually distinguishing between the segments. However, as argued by Goldsmith (2000), demographic differences are most likely to vary by product category. This is one explanation for the absence of demographic differences in a variety of research studies (Goldsmith et al., 1994; Goldsmith et al., 1998; Goldsmith et al. 1999). It seems intuitive that heavy (and light) users will be evident across a variety of age categories, in both genders, and across most of the income segments. However, we would expect more heavy use 'gamers' to be younger, more big-time investors to be older, most sanitary napkin users to be women, and so on. Therefore, demographics may provide little general long-term knowledge regarding heavy and light users, but may be useful to focus on which product category the various demographic groups will be using heavily.

Research has shown that psychographics may offer a better avenue of study for heavy and light users. Heavy users, when compared to light users, are more involved, more innovative, more knowledgeable, more likely to be opinion leaders, and are more sensitive to price variations in the products with which they affiliate (Goldsmith et al., 1994; Goldsmith et al., 1999; Goldsmith et al., 1998; Helsen & Schmittlein, 1994). Furthermore, attitude processing may differ between the two segments. Consumers who tend to have more experience with a product have a greater consistency between the cognitive, affective, and conative components of people's attitudes (Burnkrant et al., 1991).

It would seem obvious that, if heavy and light users are truly different, that behavioral or outcome-related distinctions would be evident. Research has shown that the two segments react differently to price promotions, with light users increasing their consumption and heavy users increasing their stockpiling (Chan et al., 2008). Also, given the attitude processing differences previously mentioned, it comes as no surprise that heavy users process advertisements differently than do light users (Jewell & Unnava, 2004). For example, heavy users tend to have more access to brand names during exposure to feeling advertisements than when exposed to attribute ads. The same can not be said about light users, indicating a need for repetitive exposures to ads.

Additionally, heavy chocolate users did not perceive store brands to be of inferior quality compared with manufacturer brands, a common perception among light users (Lybeck, et al., 2006). Also, heavy consumers of fish are shown to be better at judging quality than light users (BrunsØ et al., 2009).

As previously mentioned, the distinction between heavy and light users may depend on the product category or setting. In other words, do the findings in a study of women's shoes generalize to the sports industry? Notable past studies have examined fashion lovers, wine hobbyists, and travelers (Goldsmith et al., 1994; Goldsmith, 1998; Goldsmith et al., 1998; Goldsmith et al., 1999). Despite the difference in the products or service, it is evident that specific consumers are heavy users because of the intrinsic satisfaction or pleasure which a specific type of product or service brings to them. Therefore, heavy users (or light users) will not be heavy users for all categories in which they consume; only those for which they derive a special satisfaction.

Furthermore, a difference in countries (cultures) may play a role in the heavy-light user dichotomy, as it pertains to product categories. Note that travel admirers in Singapore presented similar results to wine hobbyists in Germany, France, and the US (Goldsmith et al., 1999; Goldsmith et al., 1998). But, differences between heavy and light users emerged in chocolate consumption and in fish consumption across countries (Lybeck, et al., 2006; BrunsØ et al., 2009). The studies offer that heavy users and light users differ across countries in their abilities and actions as consumers. Therefore, heavy users of the same product category in one country or culture may be different than heavy users in another country on a variety of factors.

The shopping environment may also have an impact on the differences between heavy and light users. There appears to be differences when considering a standard retail setting compared with an online setting. Studies have revealed that heavy and light users may switch roles within the same category under differing shopping environments (Kang et al., 2006). For instance, light users of traditional coupons became regular users when utilizing the electronic medium. In the case of heavy users of coupons, they were unwilling to take advantage of the e-coupons. Also, evidence has been provided for a light user segment which tends to purchased higher sales volume when migrating to the web (Ansari et al., 2008).

To summarize, the exigent theory on heavy and light users is unfinished. While demographics might be useful to pinpoint in which product categories the heavy and light users will be evident, they offer little in the way of a contribution to general theory. Psychographics are a more useful tool to determine theory related to this dichotomy, particularly as lifestyles may be a driving force behind consumption in many categories and cognitive processing appears to be different for the two segments. But what psychographic mechanisms are keys? Behavioral outcomes do support the existence of (at least?) two distinct segments defined by their volume of usage. But very little evidence has been provided in the behavioral area other than volume and a few claims regarding reactions to advertisements. An unaddressed aspect of this field of inquiry relates to the effects of marketing factors on this dichotomy. In other words, is it possible to *create* heavy users from otherwise light users?

THEORY AND HYPOTHESES

Past research has demonstrated that heavy users are more knowledgeable of the product category, and tend to search for information through various media outlets more than light users (Goldsmith et al., 1994; Goldsmith et al., 1999; Goldsmith et al., 1998; Helsen et al., 1994). Thus, it can be presumed that the heavy user segments are more aware of various retail service outlets due to their familiarity with the service category and their tendency to seek information in regards to the product or service. Given the plausibility that heavy users are more aware and knowledgeable of available retail outlets, naturally these consumers will have a higher number of brands that they would have considered before their last purchase, and would consider purchasing from in the future. Therefore, the following hypotheses are presented for testing.

- H1 Heavy users have a higher awareness of retail outlets than light users.*
- H2 Heavy users have considered more retail outlets before buying than light users.*
- H3 Heavy users would consider more retail before future purchases than would light users.*

Consumers who are less aware of available brand are likely to sample more variety (Hoyer & Brown, 1990; Macdonald & Sharp, 2000). Not only has past research demonstrated that less knowledgeable buyers are more willing to purchase from a variety of outlets, but also more experienced buyers have shown to be more loyal to a particular brand (Day, 1969; Kuehn, 1962). Thus, we might presume that when buyers initially enter the market they have little experience with the products. At that time they will begin to sample products over time from the available selection(s). After gaining more experience with the products they will eventually settle on a smaller number of brands from which to choose. An analogy might be made with heavy and light users. Initially everyone is a light user, testing a variety of products. After time some of these will become heavy users. These heavy users will narrow their selection possibilities to a smaller more select few, based on their greater experience, which they will continue to purchase from in large volumes. The light users on the other hand have less experience in general and are likely to purchase from a larger variety of retail outlets. Therefore, the following hypotheses are presented for testing.

- H4 Heavy users have experience with more retail outlets than have light users.*
- H5 Heavy users are more loyal than light users.*

When consumers make choices in the marketplace, they face uncertainty about the consequences of their decisions. The uncertainty creates an anxiety, also known as risk, which can result in consumers delaying purchases or taking actions to reduce risk (e.g. Stone & Winter, 1987). This perceived risk plays an important role at explaining a consumer's behavior, in fact, avoiding mistakes is often more preferred to the individuals than maximizing the utility of purchasing (Mitchell, 1999). Heavy users are more experienced, and thus should be more informed, than light users. Also, it has been proposed that heavy users are also more loyal.

Thus, heavy users should feel less anxiety related to their choice decisions when compared with light users. Therefore, the following hypothesis is presented for testing.

H6 Heavy users will have less perceived risk than light users.

Buyers continually consuming higher relative volumes of a specific product, or from a specific retail outlet, would most likely not do this unless their basic needs/wants were being met. In other words, if buyers did not like the product then it would not be purchased, especially not in larger quantities. Therefore, a basic level of satisfaction is necessary for repeat purchases to occur, both from a specific brand and from a category. The basic idea behind marketing thought suggests this relationship between satisfaction and use (Keith, 1960). If a buyer is unhappy with most of the fast-food burger outlets, then it is likely the buyer will switch to some other outlet category, such as chicken or Mexican food. Also, buyers with a lower perception of risk have been found to be more satisfied with their purchases (Montoya-Weis et al., 2003). Therefore, we provide the following hypothesis for testing.

H7 Heavy users will be more satisfied with their purchases than light users.

DATA COLLECTION

The data for the current study was gathered from a buyer group in a university town in the southeastern USA. The sampling frame is comprised of undergraduate business students, consumers who are frequent users of each of the four types of retail service businesses: health clubs, convenience stores, medical clinics, and fast food burger outlets. Information is accepted only from respondents who buy from the specific category. The data are from self-administered questionnaires. Twelve classes are selected for inclusion in the study from the offering at the university. Each separate class is assigned only one retailer type (i.e. convenience stores), with three classes each retailer type. This process results in the following number of usable respondents, totaling three hundred and thirty-nine: eighty-one for health clubs, ninety for convenience stores, ninety-seven for fast-food burger outlets, and seventy-one for medical clinics.

A plethora of service retailers are evident in each of the four categories selected for study. Therefore it is necessary to limit the number of service retailers somehow to a given market area. In each category the retailers are identified by speaking with the buyers and looking through the yellow pages to locate outlets within the range of the city limits. This was appropriate as the university sits near the center of the city itself. An 'others' category was included to catch those retailers not specifically listed on the questionnaire. This methodology resulted in the following numbers of service retailers (i.e. Burger King, 7-11) in each category: For health clubs there are sixteen clubs included on the questionnaire. For convenience stores there are twelve outlets. For medical services there are twelve clinics in the general area. Finally, six fast food hamburger outlets are included in the study.

The retailer categories themselves are selected for two reasons. First, it was necessary to find a type of business that was used by the target group under study: students. Second, multiple

retailer categories are necessary as we would expect to find differences based on retailer-types (Chaudhuri & Holbrook, 2002). Thus, the Murphy and Enis (1986) taxonomy was used as a guide to select the retail service categories for study: convenience stores (a convenience product), health clubs (a specialty product), fast-food burger outlets (a preference product), and medical clinics (a shopping product). Measurement The study includes eleven total indicators: two indicators of usage (TIMESNUM, USEDNUM), three choice-sets indicators (AWARENUM, CONSUM, RECSNUM), three indicators related to brand attachment/loyalty (MPB%, 2NDMPB%, 1B%), one indicator of perceived risk (RISKA), a single indicator of customer satisfaction (SATF_{LP}), and one indicator of heavy and light user type (USERTYPE). The details of each indicator are described below.

The number of times a buyer *purchases from each retail service* (TIMESNUM) is defined as the number of total purchase visits per period. Respondents were asked to indicate, by writing a number next to each of the retailers, how many times they purchased (visits) from that retailer each month. Then the numbers were summed for each respondent to arrive at a total. For example, if respondent #19 purchased from store A two times, store B three times, and store C five times, then TIMESNUM=10 for that respondent.

The main construct in the study is the categorical indicator *user type* (USERTYPE), which refers to the buyers levels of consumption. Expectations are that heavy users will be a much smaller number of the total users for a category than light users, oftentimes in the range of three or four to one (Cook & Mindak, 1994). The frequency distributions for TIMESNUM are used to classify the consumers into heavy and light user segments. For each of the retail service categories a two to one ratio of light users to heavy users is chosen as appropriate. This cutoff point for heavy users allows a large enough sample size in each group for statistical testing, given the small number of respondents in each category. Also, a two to one ratio offers a more liberal (larger numbers) definition of heavy users, which should result in a more difficult rejection of the null hypotheses in statistical testing. Therefore, all those buyers with the number of visits above the 66.6 percentile are classified as heavy users for each category. The remaining respondents are classified into the light user category. The exact cutoff point may vary slightly from the two-thirds target due to particulars of the sample frequencies.

The cutoff points for classification into light versus heavy users are as follows. For fast-food burger outlets the range of consumption is from one to thirty-three visits, with light users defined as those buying eight times or less per month and heavy users as those who consume nine times or more per month. For convenience stores the range is from one to forty visits, with light users defined as those buying twelve times or less per month and heavy users as those consuming thirteen times or more per month. For health clubs the range is from one to thirty visits, with light users defined as those using the club fifteen times or less per month and heavy users as those using a club sixteen times or more per month. For medical clinics the range is from one to twenty visits, with light users defined as those using a clinic three times or less over the past six months and heavy users as those using a clinic four times or more in the past six months. Table 1 shows the dispersion of users across the service categories after classification. Tables 2 to 5 reveal the TIMESNUM averages for the two groups across the four retail service categories.

Table 1: Classification Information

<i>User Group</i>	Heavy	Light	N
<i>Service Category</i>			
Convenience Stores	31	59	90
Fast-Food Outlets	32	65	97
Health Clubs	22	59	81
Medical Clinics	27	44	71

An estimate of experience, the number of *retail service brands previously used* (USEDNUM), is defined as the total number of stores that a respondent has purchased from in the past. This indicator of experience was measured by asking respondents to check a box next to all the brands that he/she had purchased from previously. Then the total checks were summed to arrive at the indicator of USEDNUM. For instance, if respondent #11 indicated that she had visited six out of the sixteen possible health clubs, then for respondent #11 USEDNUM=6.

Information on consumer choice sets was included as another indication of respondents' previous experience with the various retail service categories, as well as the specific retailers within each category (Narayana & Markin, 1975; Spiggle & Sewall, 1987). Three indicators were used for the choice sets: the size of the *awareness set* (AWARENUM), the size of the *consideration set* (CONSNUM), and the size of the *reconsider set* (RECSNUM). Each of these three types of choice sets was measured by having respondents indicate, by checking a box next to the company name, those retail service brands which they were aware of (AWARENUM), considered before the last purchase (CONSNUM), and would consider purchasing from in the future (RECSNUM). By summing the total for each respondent with regard to each choice set, we arrived at the total numbers for AWARENUM, CONSNUM, and RECSNUM. For instance, if respondent #5 indicated that she was familiar with four retail fast-food burger outlets, then AWARENUM for respondent #5 would equal four.

Three indicators of buyer attachment (loyalty) are included: the percent of purchase from the most purchased brand, the percent of purchase from the second most purchased brand, and the percent which purchases only one brand (Pleshko 2006). The *most-purchased-brand percent* (MPB%) is defined as the percentage of a respondents' total visits, given that the store is the most used by that respondent. Thus, for respondent 15 who uses store A primarily, but also visits stores B and C: $MPB\% = \text{timesA}/(\text{TIMESNUM})$. The *second-most-purchased-brand percent* (2NDMPB%) is defined as the percentage of a respondents' total visits, given that the store is the second most used by that respondent. Thus, for respondent 17 who uses store A primarily, but also visits stores B secondly and C thirdly: $2NDMPB\% = \text{timesB}/(\text{TIMESNUM})$. The *purchase-only-one-brand percent* (1B%) is an indicator of brand insistence for users regarding the service retailers. This is defined as the percentage of respondents, whether heavy or light users, who only purchase from one service retailer, given the category (Heiens et al 2006). So, for example, if in banking services twenty percent of the females only does business at one bank, then $1B\%_{FEM} = 0.20$.

Perceived risk (RISKA) is defined as the amount of anxiety evident in a purchase situation. Risk is generally defined as some combination of two factors, (i) uncertainty in the outcome and (ii) the amount at stake (consequences) in that decision (Cunningham, 1967; Hoover et al., 1978). Consistent with research conducted by Hoover et al. (1978), the indicator of perceived risk (RISKA) utilized in the current study was created by adding together both the uncertainty score and the average score of three consequences questions. Given that the scales were seven points and anchored by 'very much risk' and 'no risk at all', this resulted in a possible range of the risk scale from a low of two to a high of fourteen.

The study includes one indicator of *consumer satisfaction* (SATF_{LP}), which pertains to satisfaction with the last purchase. Each of four questions is measured using consumer ratings on a scale from very satisfied [7] to very dissatisfied [1]. The four satisfaction items are factor analyzed using principal axis analysis for each type of retailer, as is common in other studies on satisfaction (Pleshko et al 2008). In each of the four retail consumer groups the four items exhibited a single dimension. The overall indicator of SATF_{LP} is constructed by summing the four items into an overall score. Across the sample SATF_{LP} has a possible range from four to twenty-eight. For health clubs, SATF_{LP} has a mean of 20.45, a standard deviation of 4.6, and a coefficient alpha of 0.917. For medical clinics, SATF_{LP} has a mean of 21.43, a standard deviation of 5.4, and a coefficient alpha of 0.949. For convenience stores, SATF_{LP} has a mean of 19.18, a standard deviation of 4.5, and a coefficient alpha of 0.834. For fast-food outlets, SATF_{LP} has a mean of 20.65, a standard deviation of 4.1, and a coefficient alpha of 0.887.

ANALYSIS/RESULTS

The relevant analysis for testing mean differences for two groups is the T-test. The averages of the various indicators, the test statistics, and the findings for the four retail service types are shown in Tables 2 to 5. In general, it can be seen in the four tables that heavy users have more experience with each of these categories than do light users as is revealed by larger means for USEDNUM and TIMESNUM (as by definition). Also, the size of the choice sets, when different, is larger for heavy users than for light users. Finally, when evident, light users seem to be more attached, showing higher loyalty levels and consuming fewer brands than do the heavy users.

Specifically, for the fast-food outlet sample, it can be seen that heavy users use more outlets (H4+), visit more times (H4+), and reconsider more outlets for future purchases than do the light users (H3+). On the other hand, the light users exhibit a larger percent of purchase of the most purchased outlet (H5-) and have a larger percent of outlet-insistent users (H5-) than do the heavy users of fast-food burger outlets. No significant differences are found for awareness number (H1), number of outlets considered (H2), perceived risk (H6), the purchase percent for second most purchased outlet (H5), or satisfaction (H7). See Table 2 for the relevant details.

Table 2: Descriptions and Statistical Tests for Fast-Food Outlets

	<i>User Type</i>	Heavy Users	Light Users			
	<i>Variable</i>	(HU)	(LU)	t	'p'	Finding
	Size (N)	32	65	n/a		
<i>H4</i>	TIMESNUM	14.65	4.03	9.65	0.000	HU>LU
<i>H4</i>	USEDNUM	4.43	2.87	6.11	0.000	HU>LU
<i>H1</i>	AWARENUM	5.87	5.60	1.67	0.098	
<i>H2</i>	CONSNUM	2.34	2.26	0.34	0.729	
<i>H3</i>	RECSNUM	4.37	2.93	4.32	0.000	HU>LU
<i>H5</i>	MPB%	47.67	57.81	2.53	0.012	LU>HU
<i>H5</i>	2NDMPB	24.17	25.92	0.76	0.448	
<i>H5</i>	1B%	0.00	16.90	3.61	0.001	LU>HU
<i>H6</i>	RISKA	8.62	8.83	0.42	0.671	
<i>H7</i>	SATFLP	21.38	20.29	1.23	0.221	

Specifically, for the convenience stores sample, it can be seen that heavy users use more outlets (H4+) and visit more times than do the light users (H4+). On the other hand, the light users exhibit a larger percentage of purchases from the most purchased store (H5-) and have more outlet-insistent users (H5-) than do the heavy users of convenience stores. No differences are found for awareness number (H1), number of stores considered (H2), the number of stores considered for future purchases (H3), the purchase percent for second most purchased outlet (H5), perceived risk (H6), or satisfaction (H7). See Table 3 for the relevant details.

Table 3: Descriptions and Statistical Tests for Convenience Stores

	<i>User Type</i>	Heavy Users	Light Users			
	<i>Variable</i>	(HU)	(LU)	t	'p'	Finding
	Size (N)	31	59	n/a		
<i>H4</i>	TIMESNUM	19.06	5.83	9.42	0.000	HU>LU
<i>H4</i>	USEDNUM	5.22	3.13	4.79	0.000	HU>LU
<i>H1</i>	AWARENUM	10.06	9.22	1.70	0.092	
<i>H2</i>	CONSNUM	2.58	2.76	0.38	0.699	
<i>H3</i>	RECSNUM	7.38	6.61	0.92	0.359	
<i>H5</i>	MPB%	45.21	57.83	3.04	0.003	LU>HU
<i>H5</i>	2NDMPB%	24.92	24.46	0.18	0.854	
<i>H5</i>	1B%	0.00	16.90	3.44	0.001	LU>HU
<i>H6</i>	RISKA	7.25	6.63	1.28	0.202	
<i>H7</i>	SATFLP	19.35	19.08	0.27	0.788	

Specifically, for the health clubs sample, it can be seen that heavy users use more health clubs (H4+) and visit more times than do the light users (H4+). On the other hand, the light users exhibit a larger percentage of outlet-insistent users (H5-) than do the heavy users of health clubs. No differences are found for awareness number (H1), number of clubs considered (H2), the number of clubs considered for future purchases (H3), perceived risk (H6), percent purchase of the most purchased brand (H5), the purchase percent for second most purchased outlet (H5), or satisfaction (H7). See Table 4 for the relevant details.

Table 4: Descriptions and Statistical Tests for Health Clubs						
	<i>User Type</i>	Heavy Users	Light Users			
	<i>Variable</i>	(HU)	(LU)	t	'p'	Finding
	Size (N)	22	59	n/a		
<i>H4</i>	TIMESNUM	21.13	5.01	14.82	0.000	HU>LU
<i>H4</i>	USEDNUM	1.31	0.76	3.77	0.000	HU>LU
<i>H1</i>	AWARENUM	5.22	5.69	0.70	0.482	
<i>H2</i>	CONSNUM	2.18	2.37	0.70	0.483	
<i>H3</i>	RECSNUM	2.54	2.28	0.82	0.413	
<i>H5</i>	MPB%	94.91	98.06	1.37	0.173	
<i>H5</i>	2NDMPB%	5.09	1.52	1.39	0.175	
<i>H5</i>	1B%	68.20	93.20	2.34	0.027	LU>HU
<i>H6</i>	RISKA	7.37	7.75	0.77	0.442	
<i>H7</i>	SATFLP	21.13	20.19	0.81	0.417	

Specifically, for the medical clinic sample, it can be seen that heavy users use more clinics (H4+), visit more times (H4+), and are aware of more clinics (H1+) than do the light users. On the other hand, the light users have more perceived risk (H6+), exhibit a larger percentage of purchases from the most purchased clinic (H5-), and have more brand-insistent users (H5-) than do the heavy users of medical clinics. No differences are found for number of clinics considered (H2), the number of clinics considered for future purchases (H3), the purchase percent for second most purchased outlet (H5), or satisfaction (H7). See Table 5 for the relevant details.

The results offer support for some of the hypotheses and not for others. Strong support can only be offered for H4 as stated. Eight out of eight possible statistical tests are significant and in the direction hypothesized. Therefore, the findings suggest that heavy users have more experience than light users. Strong support is also offered for H5, but in the opposite direction as stated. Seven out of twelve possible statistical tests are significant, but contrary to H5. Therefore, support is offered to suggest that light users are more attached (loyal) to their preferred outlets than are heavy users.

Regarding the other hypotheses, little or no support is offered. Only one out of four statistical tests is significant and supportive regarding H1. Therefore, little evidence suggests that heavy users are aware of more brands than light users. In regard to H2, none out of four statistical tests are significant. Thus, it seems that heavy users and light users consider the same

number of service retail outlets before purchasing. Also, only one out of four statistical tests is significant and supportive regarding H3. Therefore, little evidence suggests that heavy users will consider more brands in future purchase decisions when compared to light users. Regarding H6, only one out of four statistical tests is significant and supportive. Therefore, little evidence suggests that heavy users experience less perceived risk than do light users. Finally, regarding H7, none out of four tests are significant. Thus, it seems that heavy users and light users exhibit equivalent levels of satisfaction from their purchases.

Table 5: Descriptions and Statistical Tests for Medical Clinics

	<i>User Type</i>	Heavy Users	Light Users			
	<i>Variable</i>	(HU)	(LU)	t	'p'	Finding
	Size (N)	27	44	n/a		
<i>H4</i>	TIMESNUM	6.25	1.75	6.5	0.000	HU>LU
<i>H4</i>	USEDNUM	1.77	1.11	3.92	0.000	HU>LU
<i>H1</i>	AWARENUM	4.66	3.31	3.45	0.001	HU>LU
<i>H2</i>	CONSNUM	1.88	1.72	0.71	0.479	
<i>H3</i>	RECSNUM	3.33	2.79	1.16	0.247	
<i>H5</i>	MPB%	70.61	84.47	2.52	0.014	
<i>H5</i>	2NDMPB%	20.58	14.02	1.52	0.131	LU>HU
<i>H5</i>	1B%	25.90	68.10	3.74	0.000	
<i>H6</i>	RISKA	8.04	9.23	2.37	0.020	LU>HU
<i>H7</i>	SATFLP	20.46	22.02	1.15	0.250	LU>HU

DISCUSSION

The purpose of the study was to determine if there are major differences in purchase-related factors across a variety of service categories between heavy and light users. Although many differences were evident in the statistical testing, little support is offered for most of the hypotheses. In each category, two findings stand out.

First, the results indicate that heavy users have experience with more stores and purchase more often than do light users. These findings are not surprising. It would seem plausible in these categories that the consumers gain experience by trying new outlets. Thus, due to the larger volume of usage, heavy users would logically test more outlets than would light users.

Second, the findings suggest that light users exhibit more attachment (loyalty) to the specific outlets than do heavy users. In actuality, this finding in regards loyalty refers to the most purchased outlet. It seems that two possible actions are evident when compared to heavy users: (i) light users focus a much larger percentage of their purchases on the most-purchased brand or (ii) light users purchase only one brand. These actions may be attempts to reduce risk (e.g. Roselius, 1971). However, risk was significantly higher for light users in only one category. These actions also could be due to the fact that, as light users, they are not all that excited or involved with the category and therefore stay with the one brand that they find

acceptable. Heavy users might also exhibit loyalty in similar amounts, just differently. Although no evidence is provided for this, it may be that heavy users also have favorites, but just not a single brand as with the light users. Maybe the heavy users have a profile of favorites. This is an idea which should be investigated in the future.

LIMITATIONS

An important factor which might impact many of the null findings pertains to the methodology used to place buyers into heavy and light user groups. Much of the literature seems to point to an 80-20 split as being appropriate. However, this study used a 2-1 split, with the result being larger numbers of users classified as heavy users. This would lead to some light users being included in the heavy user category, with the result being a movement towards the middle of each concept being tested for the means of each group; similar to a statistical regression problem. However, an advantage to the 2-1 split is that the significant differences are probably more trustworthy.

The readers must wonder if the current findings are indicative of general tendencies or simply a characteristic of this limited student-based study of four retailer-types in a single university town. The sample size is definitely an important limitation. While the three hundred thirty nine respondents might be enough for a single category study, it may be insufficient for a multi-category study. Additionally, although students are common users of each of these services, it would be important to include other demographic or psychographic segments in future studies. Another possible improvement would be to include a wider variety of service retailer categories, such as banking or automotive or coffee shops.

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PURSUIT OF HAPPINESS BY CONSUMPTION: SPENDING TIME VS SPENDING MONEY

Lee Yoonjae, Seoul National University
Song Sangyeon, Dongduk Women's University

ABSTRACT

Both time and money can be considered as resources, but many studies have shown that they have different characteristics and impacts on consumer behavior. In this study, the authors have focused on the difference between spending time and spending money as currency. We suggest that spending time activates eudaimonic orientation on subjective well-being. Consumption of time induces people consider the meaning of the purchase. And that leads people to pursue eudaimonic happiness. In Study 1, people had been primed with time consumption or money consumption as currency, and study confirmed that the group primed with spending time showed higher eudaimonic orientation compared to spending money primed group. Moreover, from the experiment, we can suggest people consider target product and spending time as currency as one but people can separate spending money.

Study 2 and Study 3 examined asymmetric impact on purchase satisfaction between spending time and spending money as resources. Spending time activates eudaimonic orientation; spending money fails to do so. In addition, spending time prompt people to consider currency and target product as a whole; on the other hand, spending money does not have such effect. In this way, people, in evaluation of their purchase of hedonic products that evoke less practical meaning and more guilt than utilitarian product, tend to report higher overall satisfaction for the target product when they spend money, rather than time. Finally, Study 3 focuses on personal involvement. Personal involvement with the target product will encourage people to seek personal meaningfulness, importance, and relevance; hence they are more likely to be satisfied when they have spent more time rather than money.

INTRODUCTION

People usually consume money to purchase the products they want; the money is obtained by consumption of time, such as time spent in work. However, when people spend money, time spent for the money is not taken into account. In other words, consumption of time is overlooked when spending money. Therefore, if one is to remind the customers of their time spent in consumption of money, it is possible to affect their pattern in purchase.

Time and money are fundamental resources in life. These two are closely related, yet they have different effect on customer behavior. Various existing research projects have focused on the value of time and money as resource, and also on mutually distinct effect of those two resources (Zauberman & Lynch, 2005; Okada & Hoch, 2004; Malkoc & Zauberman, 2006; Mogilner et al., 2008; Liu & Aaker, 2007; Carstensen et al., 1999; Williams & Drolet, 2005;

Trope & Liberman, 2003; Vohs et al., 2006; Soman, 2001; Hoch & Ha, 1986; Hsee, 1995, 1996; Friedman & Neumann, 1980; Hoskin, 1980).

This research focuses on the premise that consumers have different goals in pursuit of happiness depending on resources utilized in purchase (Study 1), and consequently they have different level of satisfaction from the products acquired by trade (Study 2, Study 3). Researches on subjective well being present two types of happiness orientation. Hedonic happiness orientation, which is the first type to be presented, is designed to pursue enrichment of positive emotion and minimization of negative emotion (Diener, 1994). The other is Eudaimonic happiness orientation, which is designed to pursue people's meaning of life (Telfer, 1980). This research suggests that in spending time and money, level of eudaimonic orientation activation is different. This indicates that consumption of time on the one hand and money on the other has distinct effect on people's happiness orientation. Time inevitably includes experience, and when one is requested to spend some time for volunteer work, one tends to give high importance to emotional value(Liu & Aaker, 2008). If one is to consider time as currency, one shall consider experience and required effort. In sum, this research concludes that if people utilize time as if spending money, they would pursue eudaimonic value of subjective well being, which is the meaning of time. Moreover, when people use time as currency, time would be understood as medium of exchange and such understanding cause people to consider the purchase and the currency separately. In addition, less consideration on the meaning of purchase occurs due to decrease of eudaimonic orientation. That is to say, difference in degree of eudaimonic orientation depending on the type of currency may induce different evaluation of the exchange.

While consumption of hedonic products provides more positive emotion and experience value compared to utilitarian products(Barta & Ahtola, 1991), it also results in feelings of guilt(Kivetz & Simonson, 2002). This research, in study 2, confirms satisfaction in cases of acquiring hedonic and utilitarian products.

Okada(2005) explains, based on terms of possibility of justification, that people are more willing to spend more time compared to money to purchase hedonic products, and that people are more willing to spend more money compared to time in purchase of utilitarian products. Such explanation is grounded upon the confines of pre-purchase step of justification that value of time tends to be ambiguous. However, caution is needed as actual after-purchase evaluation might have different results. Previous research on the mind-set which is activated by time and money suggests that time causes experience and emotional meaning to be salient(Liu & Aaker, 2008); in consumption of hedonic products, due to the fact that it is accompanied by feelings of guilt, it may be predicted that satisfaction may decrease when time is spent in purchase of hedonic products.

In research on the mind-set defined by money, it is argued that spending money in terms of cognitive functions activate rational mind(Pham, 2007) and cools off emotional status(Van Boven & Loewenstein, 2003). In spending money, one's mode of decision making-process is determined by the mind, not by heart (Shiv & Fedorikhin, 1999). This indicates that in case of money, it is easy to differentiate between the money spent and the product being purchased; in case of time, it is difficult to differentiate between the time spent and the product acquired. That is to say, in case of feelings of guilt related to purchase of hedonic products(Kivetz & Simonson,

2002), that purchased with money satisfaction may be high as the product and the money spent can be differentiated; if purchased with time, as no differentiation may be made between the time spent and the product acquired, satisfaction may be low. In study 2 findings are as follows; when purchasing hedonic products with money, distinction between the product being acquired and the currency being used may be separated; this results in evaluation of satisfaction on a higher mark compared to time being used, as no feelings of guilt may be involved. In case of utilitarian products, people were more satisfied when meaningful consumption of time was made in the purchase.

In study 3, the authors suggest that if one is to define involvement as meaningfulness of the product to oneself, in case of high-involvement products, satisfaction increases when time is spent; in case of low-involvement products, satisfaction increases when money is paid.

TIME AND MONEY AS RESOURCE

Various studies on value of time and money tend to focus on the fact that time has more ambiguity compared to money, resulting difference in mind-set and in their effect.

People have a general understanding that time is a more loosely defined resource compared to money (Zauberman & Lynch, 2005). Study by Okada & Hoch (2004) tried to discover the difference of outcome in consumption of two resources, focusing on ambiguity of time. People tend to spend time on more high risk, high return ventures, while on the other hand money is spent in less risk averse, and low return work.

Such phenomenon may be incurred by ambiguity of time. Ambiguity of time in turn induces accommodation and rationalization easier (Okada & Hoch, 2004). In case of Okada (2005), it is contended that people are more willing to spend more time than money in purchase of hedonic products. This is due to the fact that while opportunity cost for money is to define, opportunity cost for time tend to be unclear; hence people are more willing to spend time on hedonic products for a more convenient justification. Consequently, it is possible to say that people are more willing waste time than money.

Ambiguity of time as a resource occurs due to hardship in evaluation of its opportunity cost. Money is easily tradable to other merchandise in the market, highly fluid and interchangeable in character and convenient to store such as in bank accounts. In contrast, it is almost impossible to trade time with currency, and time tends to disappear with passing of that time period. Moreover, it is impossible to store time for future usage as in the case of money. In case of money, one can find viable alternatives, but for time such alternatives do not exist. Hence, because of aforementioned reasons, it is likely that opportunity cost of time have ambiguous character (Okada & Hoch, 2004). In terms of currency, time is more of a ambiguous currency (Soman, 2001), leaving a lot of possibility for interpretation (Hoch & Ha, 1986).

Hsee (1995, 1996) argues that, while commenting on elasticity justification, ambiguity of time fortifies justification. People, when asked to evaluate their time usage tend to take a more opportunistic view, and they were more willing to detach themselves from loss of time and disown time from their personal asset. In addition, sunken cost due to consumption of time is

more likely to be ignored than those from consumption of money; hence people are more willing to invest time in risky adventures.

When people consider opportunity cost, it seems that they tend to forgo opportunity cost for time or disregard importance of time consumption when not informed of time consumption (Neumann & Friedman, 1980; Hoskin, 1983). In other words, systematic underweight evaluation of time occurs in assessing opportunity cost (Thaler, 2004). Such ambiguity of time resource supplements pre purchase justification. That is to say when acquiring hedonic products, if asked to choose between time and money for purchase prior to actual purchase, people will choose to spend time (Okada, 2005). However, in this research, authors shall enquire into time as currency in purchase, and evaluation after the purchase. Such effects cannot be discerned from experience rather than from ambiguity of time, and are more apt to be affected by special characteristics of time consumption in pursuing meaningful activities.

Some other streams of research exist on mind-set from time and money. Liu & Aaker (2008) suggest that when asking for donations, if asked for time prior to being asked for money, people will donate more in whole. This can be interpreted as that when asked for their time, connection between donation and happiness was strengthened, resulting in a more intense emotion towards donation. That is to say, people, when reminded of time, consider emotional values more importantly in their decision making process.

In another research, it was found that people, when asked to think about time in a expansive manner and also in a more constrained manner, activate distinct mind-sets (Malkoc & Zaubermann, 2006). It was also found that this also induces people to think of different types of goals (Mogilner et al., 2008). When considering expansive period of time, approach goals were activated; in consideration of limited periods of time, avoidance goals were found to be activated. Liu & Aaker (2007) also found that when considering expansive periods of time, long-term goals were activated; while in considering limited periods of time short-term goals were pursued. Carstensen et al. (1999) also suggested that educational goals were more likely to be activated in relation to expansive periods of time.

Image of time, as perceived by the public is deeply related to its emotional meanings (Carstensen et al., 1999; Van Boven & Gilovich, 2003). Consumption of time entails experience, and such experience comes with feelings and emotions (Schwarz & Clore, 1996), which in turn gives more importance to related meanings. Moreover, when definition of time becomes more salient; directly emotional meaning also becomes more salient as well (Liu & Aaker, 2007). Hence, it may be assumed that when reminded of time, people will pursue more meaningful activities centered on a more eudaimonic orientation.

Furthermore, while money is intimately related to economic utility, time leads people to think of their long-term goals (Loewenstein et al., 2003; Vohs et al., 2006). Vohs et al. (2006) stipulated that when reminded of money, people activate measurable mind-set designed to maximize utility. In contrast to consumption of time, consumption of money is separated from the purchase target. In the same manner, it can be found that in Liu Aaker (2008) research when asked for donation of money people consider maximization of utility through their donation, resulting in decreased intended donation total compared to the group asked for time. That is to say, consumption of time includes experience (Schwarz & Clore, 1996), which in turn makes

consumption of time and the target impossible to separate. Consequently, utilizing time for a certain activity naturally entails arousal of emotions, and this affects people's prerogative to acquire positive meaning. In sum, consumption of time induces people to pursue a more meaningful and long-term goal related activities (Schwarz & Clore, 1996; Liu & Aaker, 2007, 2008; Pham, 1998; Van Boven & Gilovich, 2003).

Such effects of time consideration may be confirmed by priming time on individuals. When primed of their time, people processed information in a top-down manner. In other words, they placed heavier weight on high-level goals compared to low-level goals (Trope & Liberman, 2003). The authors of this research would like to argue that consumption of time increases the level of eudaimonic orientation activation; hence that if consumption of time is primed, eudaimonic orientation activation level - activities which induce people to pursue more meaningful activities - may be increased.

STUDIES ON HAPPINESS

Diner (1984), in defining subjective well-being, conceptualized happiness as both high level of positive affect and low level of negative effect. Kahneman et al. (2003) also accepted such view and conducted their research on terms of affective viewpoint. However, happiness also has its cognitive factors as well as its affective factors (Deci & Ryan 2006). This viewpoint focuses on the meaning of happiness in life. These two perspectives on happiness are termed Hedonic perspective in case of the former, and eudaimonic perspective in case of the latter.

Ryff (1989) evaluated psychological well-being in terms of eudaimonic perspective; in terms of psychological happiness in points of self-acceptance, personal growth, relatedness, autonomy, relationship, environmental mastery, purpose in life. Waterman et al. (2008) presented Personally Expressive Activities Questionnaire (PEAQ) Measure, which included both eudaimonic and hedonic perspectives on happiness. Waterman et al. (2008), Telfer (1980) contends that hedonic and eudaimonic perspective are not totally independent of one another and that they have certain co-relationship to one another.

This research predicts that consumption of time will activate meaning - centric eudaimonic orientation based on existing studies on time and money. On this coin, it was assumed that consumption of time was inseparable from purchase target and consequently that meaning shall be pursued in a more influential manner compared to cases of consumption of money. To confirm such contentions, this research will enquire how different effects of consumption of time and money may be in activation of happiness-pursuing orientation.

The authors predict that the motivation to pursue meaning will be activated when time is used to purchase or to acquire a certain target. Hence, in Study 1, priming on money and time respectively was conducted. Through this study, it was found that when time was primed, people will pursue eudaimonic happiness compared to cases when money was primed.

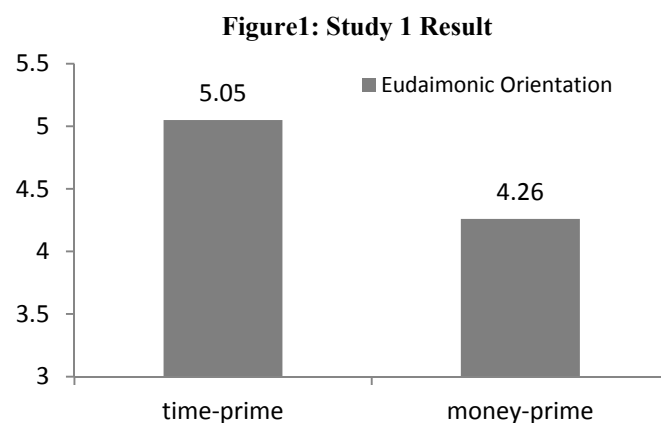
In Study 2, different customer satisfaction on purchase of hedonic and utilitarian products by either consumption of money or time shall be determined. Consumption of money shall have distinct character of being separated from the target, while consumption of time shall be impossible to separate from the target. Hence, feelings of guilt involved in purchase of hedonic

products may be decreased when the product is purchased with money, resulting in higher satisfaction; while when the products are bought with time, the satisfaction may be comparatively low. In case of utilitarian products, when purchased with time shall have higher satisfaction due to fact that eudaimonic happiness is activated; when purchased with money such satisfaction may decrease.

In Study 3, this research endeavored to confirm that satisfaction through transaction by consumption of either time or money may differ due to personal involvement to the target product. That is to say, in case of high-involvement products, this would have more personal meaning and hence when time is spent, pursuit of eudaimonic happiness is activated, resulting in higher satisfaction.

STUDY 1: MOTIVATION ON PURSUIT OF HAPPINESS IN TERMS OF TIME CONSUMPTION AND MONEY CONSUMPTION PRIMING

In Study 1, it was assumed that consumption of money and time will result in activation of different motivation on pursuit of happiness. When time consumption is primed, more emotional meanings were to be pursued; hence more eudaimonic motivation on pursuit of happiness was to be found. This research primed consumption of time and money by sentence construction. In case of time consumption priming group, they were to write sentences including 'time' or 'time spending'; money consumption priming group participants were told to compose sentences with 'money' or 'money spending'. After some filler tests, PEAQ(Personal Expressive Activities Questionnaire) test presented by Waterman et al.(2008) was adapted to better represent the actual purchase situation. To evaluate eudaimonic orientation, statements such as 'this purchase makes me feel alive', 'this purchase makes me feel deeply involved', 'this purchase is meaningful to me' were presented. The enquiry involved 27 undergraduate students and the results are as following [figure 1];



The data were analyzed by t-test. It was confirmed that time consumption prime group had a higher pursuit of eudaimonic values compared to money consumption prime group($t(25)=2.11$, $p<.05$). This indicates that when time consumption is primed level of eudaimonic orientation activation is higher than when consumption of money is primed.

STUDY 2: TIME AND MONEY RESOURCE INPUT TO HEDONIC AND UTILITARIAN PRODUCTS

The authors predict that when money is paid in purchase of hedonic products, satisfaction in such trade shall be higher than in cases when time was paid in return. Hedonic products are hard to define in terms of utility, and they tend to have higher symbolic values rather than utility. Consumption of money shall have higher satisfaction in cases of hedonic products purchase which have hedonic enjoyment values compared to purchase of utilitarian products with utility.

Participants were divided into two groups and types of payment (time vs. money) was set as between variable. Meal at an upscale restaurant was presented as the hedonic product, while indoor bookshelf was presented as the utilitarian product. However, it is rare to exchange time for products in real life. Such instances may only be found in exceptional circumstances in online games where people actually buy game currency with real money or acquire game currency by spending time. Therefore a scenario to remind people of the time spent to purchase was constructed instead of direct exchange between time and the products.

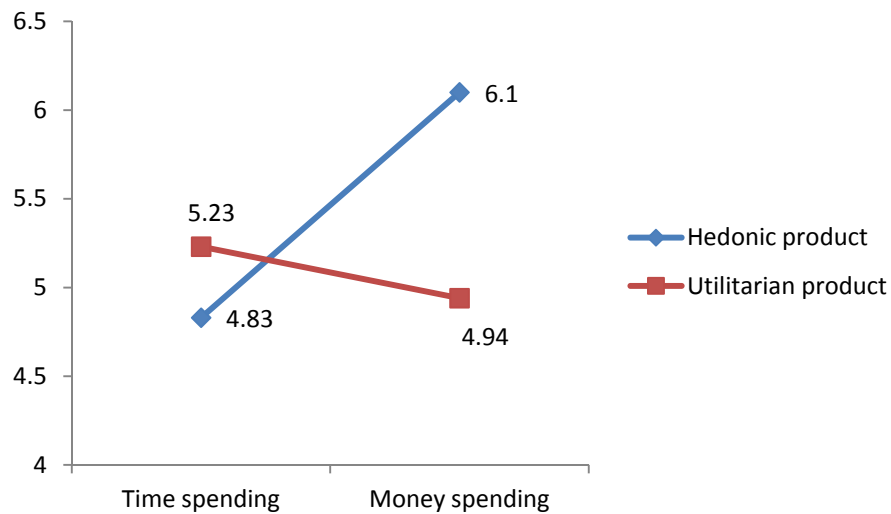
The scenario was presented to 52 undergraduate students and their satisfaction was measured. The scenario consisted of product attribute (2, hedonic products/utilitarian products) and input resource (2, time/money); product attribute was measured as a with-in factor, while input resource was measured as a between factor.

Analysis of the manipulation checks revealed that both the utilitarian product and hedonic product manipulations were successful. And then the data were analyzed using a 2 X 2 repeated measures analysis of variance(ANOVA). The results are as shown in [figure 2]. The main effect of product attribute was significant($F(1,51)=4.30$, $p<.05$), showing that participants were more satisfied with hedonic product($M_{\text{hedonic}}=5.45$, $M_{\text{utilitarian}}=5.09$). More importantly, a predicted interaction between product attribute and input resource was significant($F(1,51)=10.89$, $p<.01$). For the time spending, satisfaction was higher for the money spending group than for the time spending group. For the utilitarian product, there was no difference in the two conditions.

In sum, the results suggest that higher satisfaction may be acquired by consumption of money rather than time in purchase of hedonic products. In addition, no meaningful deviation was to be found in purchase of utilitarian products, as both consumption of time ($M=5.23$) and money ($M=4.94$) showed no noticeable difference in satisfaction.

Hence, it was possible to conclude more satisfaction may be incurred by consumption of money in purchase of hedonic products. Such conclusion was unable to be presented by existing research on ambiguity of time and mind set brought on by time and money. This research utilized after purchase evaluation scenario in place of pre purchase evaluation. It was found, based on the aforementioned scenario, that satisfaction of the transaction was affected by strengthening of eudaimonic orientation in after purchase time period and the attribute of time that it is impossible to isolate currency and the target.

Figure2: Study 2 Result



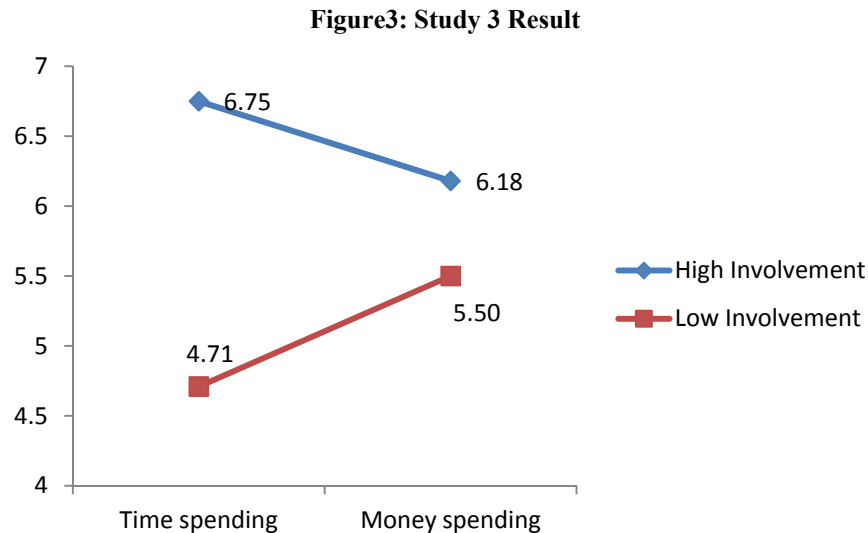
STUDY 3: INPUT OF TIME AND MONEY RESOURCES IN TERMS OF INVOLVEMENT

In Study 3, the assumption was that higher satisfaction may be found in cases of spending time to high involvement product compared to consumption of money in such cases. In contrast, it was to be found that in cases of low involvement products, consumption of money would result in higher satisfaction when compared with time consumption. In sum, it was predicted that if more time is spent on highly personalized products, satisfaction would increase due to improved emotional values. This prediction was based on the premise that as a result of eudaimonic orientation activation, people would search for emotional values in transaction of products; this in turn would result in higher satisfaction for time consumption on high involvement products. In case of low involvement products, as they have low emotional value, higher satisfaction may result in consumption of money rather than time.

A scenario on purchase of the smartphone was distributed to 29 participants who were both undergraduate and graduate students. The group was divided in two in terms of level of involvement by mean-split. Next, after presenting the group with a scenario on purchase of the smartphone the group was divided into two by setting mode of consumption, namely time and money, as the between variable. Finally, satisfaction on the purchase of the product was measured.

The data were analyzed using a 2 X 2 repeated measures analysis of variance (ANOVA). The results are as shown in [figure 3]. The main effect of product involvement was significant ($F(1,28)=24.97$, $p<.01$), showing that participants more satisfied with high involvement product ($M_{\text{Hinvolvement}}=6.43$, $M_{\text{Utilitarian}}=5.13$). And the interaction effect between product involvement and input resource was significant ($F(1,28)=6.12$, $p<.05$). Satisfaction shown in instances of time consumption to high-involvement products is significantly higher ($M=6.75$) than in cases money consumption ($M=6.18$). Likewise, it was found that in cases of

low involvement products, instances of money consumption had higher satisfaction ($M=5.50$) compared to time consumption ($M=4.71$). Higher satisfaction may result in cases of time consumption to high-involvement products, and also in cases of money consumption to low-involvement products.



In sum, this research found that in case of high-involvement products, higher satisfaction may be achieved by time consumption in purchase of such products, while in case of low-involvement products, higher satisfaction may result when the products are bought with money.

CONCLUSION: PURSUIT OF HAPPINESS BY CONSUMPTION OF TIME AND MONEY

Existing studies on the field have dealt with ambiguity of time resource and the consequences of stimulation of emotional mind-sets related to time resources. This research, based on such findings, confirmed the effects of time and money consumption on after-purchase satisfaction evaluation. Moreover, it was also found that consumption of time resource induces consideration of target product and currency simultaneously. Consequently, it was also discovered that people, when spending time as a resource instead of money, prefer utilitarian products to hedonic products; and also that high-involvement products were preferred to low-involvement products.

This research confirmed distinctive effect of time and money when used as currency on purchase evaluation. Such conclusion may have practical implication to advertisement frame in terms of marketing; the authors encourage future research in regards to such possibility.

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MODELING SATISFIED AND DISSATISFIED CUSTOMERS IN A B2B SETTING

Gregory M. Kellar, Wright State University
Michael W. Preis, University of Illinois at Urbana-Champaign
James W. Hamister, Wright State University

ABSTRACT

In this paper we propose a simulated approach to model empirical customer satisfaction data in a B2B setting for medium technology offerings. The model is compared to empirical customer satisfaction response data to examine fit. Our model suggests that customer satisfaction response in this setting should be characterized as separate distributions for satisfied and dissatisfied customers. Research and managerial implications are discussed.

INTRODUCTION

Establishing long-term business relationships, a critical component of effective supply chain management, requires understanding customer satisfaction in a meaningful way. While the B2C satisfaction construct is well-studied in the literature, B2B customer satisfaction has received less attention (Patterson, Johnson, & Spreng, 1997; Szymanski & Henard, 2001). Increasing customer satisfaction is expected to increase repurchase intentions, a likely precondition for long-term business relationships. This paper builds on this stream by exploring the implication of modeling separate response distributions for satisfied and dissatisfied customers in medium technology industries in a B2B setting. We develop a series of simulations based on survey data that will allow researchers to explore sensitivity of parameter estimates.

The characterization of customer satisfaction as separate distributions has important implications for the study of customer satisfaction and for marketing practitioners. If customer satisfaction is a single construct then the goal of maximizing average customer satisfaction levels is appropriate. Conversely, if customer satisfaction is a two-factor (or multifactor) construct as theorized here, implications for theory and practice are profoundly different: dissatisfied customers imply separate managerial actions than do satisfied customers and should be modeled separately. Dissatisfied customers are more visible to researchers and managers when the response distributions are disaggregated as we suggest in this paper.

The paper is organized as follows. First we review the relevant literature on customer satisfaction. Next we develop a series of simulation models to best characterize demand distribution in an empirical sample including theoretical discussion. In the concluding section we discuss research and managerial implications of our work, limitations, and suggested future research.

LITERATURE REVIEW

Importance of Customer Satisfaction

The nature and composition of customer satisfaction are important research topics. Increased customer satisfaction is believed to increase repurchase intentions and enhance long-term financial performance (Mittal, Anderson, Sayrak, & Tadikamalla, 2005). Satisfying customers increases repurchase intentions and loyalty (Kellar & Preis, 2011). On the other hand, dissatisfied customers are more likely to defect from business relationships and potentially sour relations with additional customers and potential customers through negative word-of-mouth (East, Romaniuk, & Lomax, 2011). Dissatisfied customers may in fact be more likely to disseminate their evaluations than are satisfied customers (citation). Therefore satisfying customers tends to be an emphasized aspect of business strategy, and customer satisfaction measures often play a central role in organizational balanced scorecard systems of measurement (Kaplan & Norton, 2007).

Long-term business relationships increase performance through several mechanisms such as value creation, cost minimization, and customer acquisition. Long-term business relationships allow firms to combine capabilities in unique value-creating ways that neither firm could accomplish independently (Ghosh & John, 1999). An example of this is a small appliance retailer partnering with a large manufacturer to develop training and service procedures for the manufacturer's products. The retailer doesn't have the technical skills to develop the training program on its own and is therefore dependent on the manufacturer for support. The manufacturer lacks the customer contact capability to directly service their product in the field, yet the availability of service is critical to overall marketing success for their appliances. Neither firm will invest the resources necessary to develop the service training program absent an expected long-term business relationship. The second benefit of long-term relations is cost minimization through transaction cost economizing (Williamson, 2008). This branch of economics posits that governance forms are established in order to minimize transaction-related costs. Relational contracting is generally less expensive to execute than more formal and detailed contracting approaches by economizing on legal and monitoring efforts. Long-term business relationships also reduce the marketing and promotional costs of customer acquisition (Star, 2007), although even highly satisfied customers may defect under certain conditions such as a better price offering (Naumann, Haverila, Sajid Khan, & Williams, 2010).

Models of Customer Satisfaction

Customer satisfaction can be viewed as an attitudinal response following a transaction or series of transactions with a supplier (Fournier & Mick, 1999) and has been modeled in a variety of ways. The confirmation/disconfirmation paradigm, whereby customers have a range of preexisting expectations of product or service offering criteria, and judge satisfaction based on the extent to which the purchase experience met or didn't meet those expectations (Patterson et al., 1997). When expectations are exceeded, customers are highly satisfied, while when expectations are not met customers are dissatisfied. This model implies that customer satisfaction is anchored around a set of expectations which may be set in a variety of ways such

as experience with the product or brand and advertisements. While firms strive to meet or exceed expectations, customers' expectations are likely to increase over time as firms deliver better products and services due to competitive pressures, and performance knowledge becomes more widely distributed through such mechanisms as product reviews posted on the internet (Zhu & Zhang, 2010). Additional satisfaction models include equity (reasonable performance levels given price) (Oliver & Swan, 1989) and experienced-based norms (expectations are based on prior product experience and informational sources such as product reviews) (Woodruff, Cadotte, & Jenkins, 1983).

The American Customer Satisfaction Index (ACSI) (Fornell, Johnson, Anderson, Jaesung, & Bryant, 1996) reports overall satisfaction levels by brand, firm, or industry. ACSI reports scaled scores (on a 0 to 100 scale) for more than 225 companies in 45 industries, as well as for government services (ACSI, 2011). East et al. (2011) argue that ACSI is incomplete since it does not capture dissatisfaction fully and lacks input from lost customers. Researchers often model customer satisfaction as an overall emotion or judgment constructed of multiple components, i.e., a multi-attribute model. Accordingly, for B2C transactions in consumer markets, Mittal, Ross, and Baldasare (1998, p. 34) say that "a consumer can be both satisfied and dissatisfied with different aspects of the product." Crosby and Stephens (1987) suggest that in the B2C area, there are three components of overall satisfaction: satisfaction with the product itself, satisfaction with the vendor's performance, and satisfaction with the relationship with the salesperson.

The composition of customer satisfaction differs in relative weights or attributes between B2B and consumer markets (Patterson et al., 1997). Depending on the product application, product attributes, distribution, and price differ in importance to industrial buyers (Kauffman, 1994). Kauffman (1994) also found that products are evaluated differently based on market position (differentiated versus undifferentiated). Environmental factors impact customer satisfaction in a service-acquisition context (Wood, 2008). Homburg and Rudolph (2001) show that the buyer's position in the firm leads to different components of customer satisfaction.

Composition of Customer Satisfaction Differs by Context

The implicit assumption that customer satisfaction is a uniform construct across markets, product characteristics, and product categories is being challenged (Preis & Kellar, 2003). Yi (1990) proposes that the characteristics of a product offering influence how consumers evaluate satisfaction. For example products and industries may be differentiated by level of technology, and classified as "high-tech," "medium-tech, or "low-tech." A definition provided by Gardner *et al.* (2000, p. 1056) states "high-technology products are those that employ turbulent technology in their use, manufacture and/or distribution, and are seen to require significant changes in usage patterns." In contrast, they define low-technology products as "those that employ familiar and accepted technology and whose acceptance and use are generally understood." Prior work has established that the customer satisfaction construct should be modeled differently by level of technology employed (Kellar & Preis, 2003; Preis & Kellar, 2003).

Customer satisfaction as measured by researchers tends to be skewed as has been noticed by several researchers. Peterson (1992) found that most self-reported customer satisfaction measures are highly skewed towards the highest performance level ("highly satisfied" for example) in B2C settings. A number of reasons were put forward to explain this phenomenon, but complete understanding is still elusive. Unless carefully worded, surveys can frame

satisfaction from either a positive or negative perspective, skewing response levels, for example by asking “how satisfied are you...?” instead of asking “how satisfied or dissatisfied are you...?” The most critical customers may be those with significant experience with the product category and the highest perception of performance risk for those products (Johnson, Garbarino, & Sivadas, 2006). Response bias, whereby more satisfied customers are more likely to respond to surveys, was discounted as an explanation since response rates and response levels were uncorrelated in several studies Peterson (1992) examined. Peterson (1992) suggests that analyzing mean response level is incorrect since the mean is a biased measure of central tendency for skewed variables, although Hurley and Estelami (1998) suggest with proper adjustments, means may be utilized if the underlying response distribution is not excessively skewed. Skewed distributions in customer satisfaction data are problematic in B2C settings, as noted above.

The research reviewed above is based on a theory that satisfaction and dissatisfaction are opposite extremes of a single bipolar construct. The two-factor theory of customer satisfaction is based on the premise that satisfaction and dissatisfaction represent different constructs and customers can be both satisfied and dissatisfied simultaneously. This is similar in nature to Herzberg’s two-factor theory to explain job satisfaction (Herzberg, 1959). Herzberg (1959) called those factors which must be present in order to avoid job dissatisfaction *hygiene factors* and factors that cause job satisfaction *motivators*. In a two-factor framework the opposite of satisfaction is the *absence of satisfaction* and not dissatisfaction. Similarly, the opposite of dissatisfaction is the *absence of dissatisfaction* and not satisfaction. Satisfied and dissatisfied customers may both be in a zone of ambivalence in which they are neither highly satisfied nor highly dissatisfied. “Czepiel, Rosenberg, and Akerele (1974) claimed that consumer satisfaction has dual factors: “For any level of satisfaction, these facets may be of two types; maintainers which must exist in order for dissatisfaction to be avoided, and satisfiers which truly motivate and contribute to satisfaction”” (Yi, 1990). A bimodal distribution is not fully described by a mean and standard deviation. Sales predictions based on mean values show inconsistent results.

THEORY DEVELOPMENT

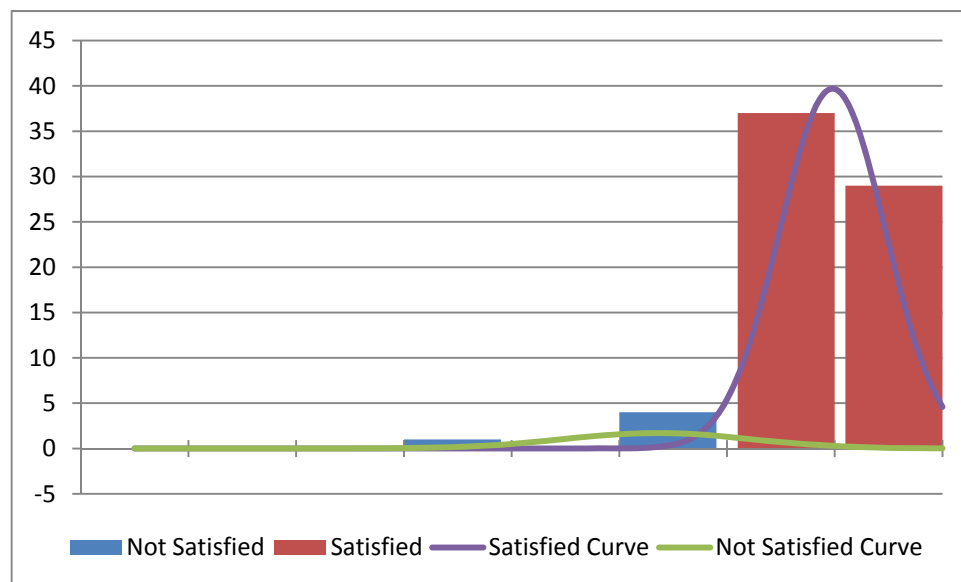
Building on the two factor framework any sample of customers can be characterized as containing two groups: one being satisfied or not and the other being dissatisfied or not. Thus any sample of customers is likely to contain some customers from each classification. Further we theorize that the distribution of satisfied customers and the distribution of dissatisfied customers can each be represented graphically by appropriately shaped normal curves and the addition of the two normal curves will result in a distribution closely approximating the sample distribution. For example, the normal curve representing the satisfied customers would have its mean somewhere near the high end of the satisfaction scale and the normal curve representing the dissatisfied customers would have its mean somewhere near the low end of the satisfaction scale. The curve resulting from the addition of the two normal curves will be bimodal. This bimodal curve will reflect the bimodal nature of many customer satisfaction distributions.

Next we turn to demonstrating how the two factor theory of customer satisfaction can be applied to understanding and modeling a sample of B2B buyers.

An Empirical Example

Kellar and Preis (2011) demonstrated that customer satisfaction for products from medium-technology industries differs from satisfaction for products from industries utilizing other levels of technology and should be modeled separately. We restrict our attention to medium-tech industries, as well. Utilizing a sample of 71 observations obtained from members of the National Association of Purchasing Management (now the Institute for Supply Management) we will model the sample using two normal curves, one representing satisfied customers and the other representing dissatisfied customers. Satisfaction with the product, satisfaction with vendor performance, satisfaction with the relationship with the salesperson and overall satisfaction are measured. All measures of satisfaction demonstrate a bimodal distribution. For example, vendor performance has a mode of 3 for customers expressing dissatisfaction and a mode of 6 for customers expressing high levels of satisfaction. The sample of overall satisfaction ratings is depicted in Figure 1. As can be seen from this graph, the sample is bimodal, with modes of 5 and 6. The mean of the sample is 6.31 and the standard deviation is 0.709.

Figure 1: Graph of Survey Data Superimposed with Fitted Curves



We utilized a computer to simulate the observed data. A program was written in Matlab to create two normal curves, simulating the distribution of observations in the sample. With only one point (the point with the lowest satisfaction rating) assigned to the low satisfaction category (all other data points are assigned to the high satisfaction category), all possible combinations of means and standard deviations (in 0.01 increments) for the pair of normal curves are compared to the original dataset. The sum of the absolute values of differences (absolute errors) between the number of observed data points for each survey response level and the number of data points simulated for each response level by the normal curves determined by the means and standard deviations is calculated. The process then repeats itself with the two points having the lowest satisfaction points being assigned to the low satisfaction category. This process continues until the best fitting model is found. In particular, the model with the lowest sum of the absolute errors

is selected. The pair of normal curves that best fits the sample data is shown superimposed on the observed data set in Figure 1. Simulated data sets that are randomly generated emphasize the goodness of fit of the pair of curves. In particular, with a sample size of 71 the sum of the absolute value of the differences between the original data set and simulated data sets range from 2 to 6 with a mode of 4. As shown in Figure 1 the fit of the two normal curves to the observed data is very close and within the range of expected normal variation of samples. We can therefore conclude from this exercise that customer satisfaction response is best model with two separate distributions in this case: one distribution representing satisfied customers and a separate distribution representing dissatisfied customers.

CONCLUSIONS AND LIMITATIONS

This characterization of customer satisfaction as a two-factor construct has important implications for the study of customer satisfaction and for marketing practitioners. If customer satisfaction is a single construct then the goal of maximizing average customer satisfaction is appropriate. Conversely, if customer satisfaction is a two-factor (or multifactor) construct as theorized here, implications for theory and practice are profoundly different: dissatisfaction should be minimized at the same time that satisfaction is maximized. Each situation is likely to require different managerial actions. Better understanding of the factors, the circumstances under which each is created, the relative importance of the two factors in multiple situations (e.g., B2B and B2C) and in multiple circumstances (e.g., high-tech, medium-tech, low-tech, etc.), the components of each factor—both common components, if any, and unique components, and improved scale development are all important areas of future research. Treating satisfied and dissatisfied customers as distinct segments furthers our understanding of why customer satisfaction exhibit a positivity bias (Peterson & Wilson, 1992). It is also worth noting that the curve of dissatisfied customers occurs at higher average satisfaction levels than might be expected, which contributes to our understanding of why prior research has found higher defection rates from “satisfied” customers than expected (Naumann, Haverila, Sajid Khan, & Williams, 2010).

Our simulation study was based on parameters observed from a single empirical survey of B2B customers in firms in medium technology industries. Our study may not generalize to different industries, different levels of technology or to the consumer segment. . Further research is needed to test the applicability of these findings in other situations. Future research should examine whether the two-factor model of overall customer satisfaction has multiple components, as has been shown to be the case for the expectancy-disconfirmation model. Research should also focus attention on whether the satisfaction or dissatisfaction segments correlate with repurchase intentions.

Our study establishes that customer satisfaction can be modeled as two separate distributions: satisfied customers and dissatisfied customers. The treatment of customer satisfaction as a single distribution, often described by mean response level, can lead to flawed interpretations of customer perceptions. Our approach is more closely aligned with the marketing approach of segmenting customers into groups for separate analysis and is aligned with the two-factor theory of customer satisfaction.

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THE READING MOTIVES SCALE: A USES AND GRATIFICATIONS STUDY OF WHAT DRIVES PEOPLE TO READ

R. Nicholas Gerlich, West Texas A&M University
Kristina Drumheller, West Texas A&M University
Marc Sollosy, West Texas A&M University

ABSTRACT

The Uses and Gratifications literature contains numerous scales measuring people's motives for media-related activities such as watching television, using the Internet, listening to radio. In this study the Reading Motives Scale was developed and tested. Factor analyses were performed in order to reduce scale items into relatively homogeneous factors with descriptive names. These factors were then used to better describe user motives for consuming the particular medium, and in numerous cases to predict that particular behavior. Exploratory and Confirmatory Factor Analyses were performed to analyze the data, along with t-tests assessing inter-group differences, and a regression against self-reported reading activity. Marketing applications and implications are provided.

READING MOTIVATIONS: USES AND GRATIFICATIONS OF AVID READERS

While books have been around far longer than television, radio, and the Internet, reading motivations have been overlooked and underrepresented in uses and gratifications research. Technology has begun to impact how books are consumed. E-readership is up 70% (Richtel & Miller, 2010), with e-books representing 7% of book sales (Hyatt, 2011) with projections of e-books representing 22.5% of all book sales by 2015 (PWC, 2011).

There are numerous theoretical and practical reasons for studying uses and gratifications of reading books, the most significant of which is reader motives.. "The uses and gratifications paradigm has proven helpful in identifying a variety of motives regarding media use and viewing patterns that reflect the utility, selectivity and intentionality of audience activity" (Ebersole & Woods, 2007, p. 24). These patterns are identified as either an instrumental orientation, which reflect more intentional media choices, or a ritualized orientation, which reflect less intentional choices (Rubin, 1993).

Choice of media consumption is highly personal, and thus dependent upon a variety of factors. As with other media, it can be assumed that book choices are volitional and thus based on particular user goals. There is a paucity of research examining reader motivations, and thus a great need to more fully understand this phenomenon. Metzger and Flanagin (2002) focused on ritualized and instrumental media orientations between new media (i.e., e-mail, Internet, and

web) and traditional media (i.e., books and magazines, newspapers, telephone, and television) and found the use of traditional media to be more ritualistic, but even the authors acknowledged that the clustering of media could “obscure the degree of audience activity for the traditional media cluster” (p. 347). It is difficult to draw conclusions about any one media form because multiple media forms were included in this one study..

The purpose of this paper is to breaking out an individual media form, specifically reading motivations. This will likely present a clearer picture of motivations than grouping multiple media formats that have limited similarities. We start by examining the cultural and historical influence of books and then address the current direction of uses and gratifications with the intention of linking the medium and theory.

LITERATURE REVIEW

The National Endowment for the Arts has noted that Americans are reading less and comprehending less. This may be the result of numerous forces, including time poverty, cost, and interest. By virtue of this, the societal implications are great (2004; 2007). Also relevant to this is the finding that “the number of books in a home is a significant predictor of academic achievement” (NEA, 2007, p. 11). Proficiency in reading is also positively related to one’s job and resulting income level. While cause and effect cannot necessarily be inferred, the relationship is not one to be ignored. Education is antecedent to employment, which results in income. Books thus play a very important role in our lives, and ignoring the importance of reading is detrimental at both personal and societal levels.

Beyond this, though, is the fact that books and reading enrich lives. Said noted that “the book was, and to many people still is, a site of extraordinary human richness and significance” (2001, p. 12). Books, Said concluded, can influence our lives in both positive and negative ways depending on intent and motivations. In spite of this, books remain a virtually overlooked in the field of communication research.

One study did, however, examine repeated exposure to media, including books, and found that despite the low likelihood of re-reading a book due to time constraints, “most of the participants can think of books they would like to reread and remember rereading books during childhood” (Hoffman, 2006, p. 392). The reason for repeat exposure to media, including books, is likely due to the familiarity of the text or content, and thus the ability to predict the gratifications obtained.

The roles of personal norms and values, as well as needs and wants, have been studied in great depth. Blumler and Katz (1974) and other early media effects research envisioned uses and gratifications research less in light of what media do to users and more toward what users do with media (Palmgreen, Wenner, & Rosengren, 1983). Uses and gratifications research is built upon the assumption that users actively and volitionally select media based on “our psychological and social environment, our needs and motives to communicate, our attitudes and expectations about the media, functional alternatives to using the media, our communication

behavior, and the outcomes or consequences of our behavior” (Rubin, 2002, p. 527). Blumler (1979) and Abelman (2006) also report that users often make media selections that match their preexisting norms and values. This would be especially true among avid readers.

Rubin (1983) created the oft-cited Television Viewing Motives Scale (Rubin, Palmgreen, & Sypher, 1994), which was adapted from Greenberg’s (1974) Viewing Motivation Scale, first for children and adolescents and later for adults. The TVMS has also been adapted for other media, including the Internet (e.g., Armfield, Dixon, & Dougherty, 2006). The TVMS and its subsequent variants have led researchers to a variety of derived gratifications including Rubin’s initial factors: learning, habit/pass time, companionship, escape, arousal, and relaxation (Rubin, 2002, p. 531). The number and nature of factors derived has varied across studies, though.

A key perspective in uses and gratifications research has been the focus on audience control over their reading and viewing choices (Levy & Windahl, 1984). Specifically, the fact that audiences choose their media based on their own goals speaks of the need to study this phenomenon under the perspective of motives. While news and entertainment have been the focus of most uses and gratifications research, examining reading motivations can strengthen audience activity research.

Like watching TV, listening to radio or using the Internet, reading is a discretionary activity. While many entertainment choices (such as TV or radio) occur “rather mindlessly” (Zillman, 1985, p. 228), reading is much more intentional than passively flipping through channels. Books are more often purchased and read because of the person’s specific interest in what the book has to offer, or on someone’s recommendation. Although television viewing motives have been studied extensively with a well-established scale, little or no work has been done to study book reading motives. Our primary research question in this study is thus to isolate reading from other media-related activities and ask:

RQ: What are the motives readers have for reading books?

While we are interested in advancing uses and gratifications research into the medium of books, we also question whether readers seek and obtain gratifications similar to those of users of other media such as television, radio, and the Internet. We thus propose a scale that captures the motives of readers, and perform both an exploratory factor analysis and confirmatory factor analysis of this scale such that they can serve as a foundation for future research.

METHOD

In Spring 2011, data were collected using an online survey created with the Qualtrics survey software. The survey was administered to individuals 18 or older who self identified as avid readers, exemplified by the fact that the average number of books read per year was 17.3. Participants were solicited via the authors’ Facebook accounts and a communication electronic mailing list attempting to reach a wide variety of demographics. A total of 283 usable surveys

were submitted (roughly one-third male, two-thirds female), although missing data in some instances trimmed the number to 263. The average age was in the low-30s, and about 80% of respondents identified as Caucasian. The sample was a highly educated one, with slightly over one-half reporting holding an undergraduate degree or higher. About one-half of respondents indicated having an annual household income of \$50,000 or higher.

The Survey of Reading Preferences was deployed using the Qualtrics online research suite. The online survey functioned equally well from desktop or mobile devices; the Facebook and email appeals could thus be launched anywhere rather than having to wait until returning to a desktop computer. The survey consisted of the Reading Motives Scale (RMS), which is our 25-item adapted version of the Television Viewing Motives Scale (Rubin, 1983; see Rubin, Palmgreen, & Sypher, 1994). Basic demographic information was collected (age, gender, ethnicity, education, etc.); participants were also asked to indicate how many books they read, on average, each year.

We began with the nine areas of uses and gratifications identified in Rubin's adapted scale for reading: relaxation, companionship, habit, pass time, entertainment, social interaction, information, arousal, and escape. The literature shows the Television Viewing Motivation scale is considered to be reliable, as are other adapted versions. Since reading and watching television are two very different activities (i.e., one that is solo vs. one that can easily be done in a group), it was necessary to make adaptations to some of the items. Words that did not fit reading behavior were altered, and two items that were specific to television viewing were eliminated.

The resulting Reading Motives Scale (RMS) is our adaptation of Rubin's (1983) Television Viewing Motives Scale (TVMS), which was derived from Greenberg's (1974) seminal work. In the online format, the scale took about 4 minutes to complete. All statements were written in the affirmative voice, presented as 5-level Likert statements (Strongly Disagree to Strongly Agree). The use of different response categories is found throughout the literature (Babrow, 1988), as is random or systematic ordering of the statements. The items in our RMS appeared in the same order as they did in Rubin's adaptation.

RESULTS

A principal component analysis (PCA) was conducted on the 25 items comprising in the Reading Motives Scale (RMS) utilizing orthogonal rotation (VARIMAX). The sample exceeds the recommend ratio of 10 responses per variable (10:1) as recommended by Hair, et al (2010) with 283 usable responses. The Kaiser-Meyer-Olkin measure verified the sampling accuracy for the analysis, KMO=.890 as strong (Field, 2009). Bartlett's test of sphericity $X^2(300) = 5227.92$, $p < .001$, indicates that correlations between items are sufficiently large of PCA.

Four factors emerged from the analysis: factor 1 - relaxation, factor 2 - escape, factor 3 - pass time, and factor 4 - sharing / learning. After rotation, the first factor accounted for 24.4% of the variance, the second factor accounted for 15.1% of the variance, the third factor accounted for 13.7% of the variance, and the fourth factor accounted for 13.6% of the variance. Table 1

displays the items and loading factors for the rotated factors, with loadings of less than .50 omitted to improve clarity.

Table 1: Factor Loadings for the Rotated Factorsa					
Question Number	Question	Component			
		1	2	3	4
1	I read books because it relaxes me	.802			
2	I read books because it allows me to unwind	.807			
3	I read books because it is a pleasant rest	.750			
4	I read books to keep me company		.597		
5	I read books when there is no one else to talk or be with				
6	I read books because they make me feel less lonely		.553		
7	I read books just because they are there				.662
8	I read books because I just like to	.766			
9	I read books because it is a habit, just something to do				.526
10	I read books when I have nothing better to do				.812
11	I read books because it passes the time, particularly when I am bored				.855
12	I read books because it gives me something to do to occupy my time				.761
13	I read books because it entertains me	.810			
14	I read books because it is enjoyable	.844			
15	I read books because it amuses me	.778			
16	I read books so I can talk with others about the stories			.731	
17	I read books so I can share stories with other family members or friends			.738	
18	I read books because it helps me learn things about myself and others			.717	
19	I read books so I can learn how to do things which I haven't done before			.734	
20	I read books because it is thrilling			.521	
21	I read books because it is exciting	.547		.553	
22	I read books because it peps me up				
23	I read books so I can forget about work, school or other things		.692		
24	I read books so I can get away from the rest of the family or others		.818		
25	I read books so that I can get away from what I am doing		.820		
Extraction Method: Principal Component Analysis.					
Rotation Method: Varimax with Kaiser Normalization.					
Rotation converged in 7 iterations.					

The PCA on the initial 25 items did result in dropping 2 of the items: number 5 - I read books when there is no one else to talk or be with, because it did not load at the .50 level or above on any factor; and number 21 - I read books because it is exciting, because it cross loaded on factors 1 and 3 with values of .547 and .553 respectfully.

Given that RMS is a scale modified and adapted from Greenberg's (1974) original Viewing Motivation Scale (VMS), the authors subjected the output from the PCA to a first order CFA model to test for factorial validity. The measurement theory can be represented by a model showing how well the measured variables converge to represent the constructs (Hair et al., 2010).

The initial model from the survey contains 4 factors and 25 items. The reliability and validity of the model's constructs were evaluated using CFA in AMOS. Maximum likelihood estimation was utilized for the analysis

The initial specification of the model returned a normed X2 of 6.300 at the .000 level of significance indicating that the fit of the model can be improved.

CMIN					
Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	56	1694.719	269	.000	6.300
Saturated model	325	.000	0		
Independence model	25	5415.236	300	.000	18.051

Further support for lack of fit is represented in the values of .629 for GFI, .721 for CFI and .616 for PNFI. All of these levels are below the acceptable level of .90 (Hair et al., 2010). Additionally, the return value for RMSEA of .141 is above the acceptable level of .07 for a model with greater than 12 observable variables and a sample exceeding 250 (Hair et al., 2010).

RMR, GFI				
Model	RMR	GFI	AGFI	PGFI
Default model	.145	.629	.552	.521
Saturated model	.000	1.000		
Independence model	.448	.222	.157	.205

Baseline Comparisons					
Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.687	.651	.723	.689	.721
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures			
Model	PRATIO	PNFI	PCFI
Default model	.897	.616	.647
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

RMSEA				
Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.141	.135	.148	.000
Independence model	.254	.248	.260	.000

An examination of the Average Extracted (AVE) indicates that two of the constructs; 2 and 3, fall below the accepted minimum of .50 for convergent validity with returned values of .488 and .445 respectfully.

	Factor 1	Factor 2	Factor 3	Factor 4
AVE	.651	.488	.445	.515

The model was re-specified a number of times, removing items that hindered the overall goodness of fit of the model. The final respecification returned a normed X2 of 2.724 at the .000 level of significance.

CMIN					
Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	29	133.455	49	.000	2.724
Saturated model	78	.000	0		
Independence model	12	2710.464	66	.000	41.068

The normed X2 coupled with returned values of .919 for GFI, .968 for CFI and a REMSEA of .081 satisfy the requirements of 3 satisfactory indicators as per Hair et. al. (2010).

RMR, GFI				
Model	RMR	GFI	AGFI	PGFI
Default model	.100	.919	.870	.577
Saturated model	.000	1.000		
Independence model	.539	.299	.172	.253

Baseline Comparisons					
Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.951	.934	.968	.957	.968
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

RMSEA				
Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.081	.064	.097	.001
Independence model	.389	.376	.401	.000

An examination of the Average Variance extracted (AVE) indicates that all 4 constructs exhibit convergent validity with values greater than .50 (Hair et al., 2010). They all improved from their initial specification. Additionally, the construct reliability for each construct exceeds the .7 indicator of good reliability.

	Factor 1	Factor 2	Factor 3	Factor 4
AVE	.881	.714	.782	.718

	Factor 1	Factor 2	Factor 3	Factor 4
Construct Reliability	0.96	0.88	0.93	0.90

Regression was calculated where Number of Books Read (DV) was regressed against the summated factor scores for the 4 factors (IVs) identified in the PCA analysis. The regression results indicate that the four factors explain 14.7% ($R^2 = .147$ and an $R^2_{adj} = .134$) of the variance in model

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
dimension01	.383a	.147	.134	14.249	.147	11.215	4	261	.000
a. Predictors: (Constant), Sum_FAC4, Sum_FAC3, Sum_FAC2, Sum_FAC1									

Relaxation (Sum_FAC1) and Pass Time (sum_FAC3) exhibited strong correlations with a $\beta = .315$ at the .01 and $\beta = .132$ at the .05 respectfully. The remaining factors, escape and sharing/learning, exhibited no significance. Multicollinearity does not appear to be a concern with no factor's tolerance level less than .602 or a VIF greater than 1.662

Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-10.073	4.608		-2.186	.030		
	Relaxation	5.377	1.257	.315	4.277	.000	.602	1.662
	Escape	-.454	1.170	-.027	-.388	.698	.666	1.501
	Pass Time	2.405	1.189	.132	2.024	.044	.769	1.301
	Sharing / Learning	.024	1.142	.001	.021	.983	.778	1.286
a. Dependent Variable: # of Books per Yr.								

An independent samples t-Test was run to determine if any differences exist between mean scores of males and females on the summated factor scores. As indicated in the following table there appears to be a significant difference in the mean scores of Relaxation (Sum_FAC1) and Escape (Sum_FAC2) and no significant difference in the mean scores of Pass Time (Sum_FAC3) and Sharing/Learning (Sum_FAC4).

Male vs. Female			
	Male	Female	T - statistic
Relaxation	83	180	-2.732*
Escape	83	180	-2.818*

Passing Time	83	180	0.229
Sharing / Learning	83	180	-1.247
Sig. p<.05*			

An independent samples t-Test was run to examine any difference between Age, where the mean age of 31.9 years of age was utilized, based upon the existing sample, and the constructs. As indicated in the following table there appears significant differences between the two age groups with regard to Sharing/Learning, but not among the remaining constructs.

Age			
	>=31.9	<31.9	T - statistic
Relaxation	94	165	1.399
Escape	94	165	-0.970
Passing Time	94	165	1.077
Sharing / Learning	94	165	-2.820*
Sig. p<.05*			

An independent samples t-Test was run to examine any difference between Education level, where a value <4 = an undergraduate degree or higher and >=4 = all else. As indicated in the following table there appears to be a significant difference between the means scores of both groups and the Relaxation factor, but not among the remaining constructs.

Education Level			
	All Else	Undergraduate Degree or higher	T - statistic
Relaxation	119	144	-2.555*
Escape	119	144	-0.448
Passing Time	119	144	-1.418
Sharing / Learning	119	144	-0.086
Sig. p<.05*			

A correlation matrix of the four constructs and the number of books read per year was calculated. The results indicate strong correlation between all four constructs with three of the constructs; Relaxation, Escape, and Passing Time, significant at the .01 level and Sharing / Learning significant at the .05 level.

Correlations						
		# of Books per Yr.	Relaxation	Escape	Passing Time	Sharing / learning
# of Books per Yr.	Pearson Correlation	1	.365**	.175**	.274**	.137*
	Sig. (2-tailed)		.000	.004	.000	.025
	N	266	266	266	266	266
Relaxation	Pearson Correlation	.365**	1	.513**	.476**	.380**
	Sig. (2-tailed)	.000		.000	.000	.000
	N	266	266	266	266	266
Escape	Pearson Correlation	.175**	.513**	1	.301**	.435**
	Sig. (2-tailed)	.004	.000		.000	.000
	N	266	266	266	266	266
Passing Time	Pearson Correlation	.274**	.476**	.301**	1	.208**
	Sig. (2-tailed)	.000	.000	.000		.001
	N	266	266	266	266	266
Sharing / learning	Pearson Correlation	.137*	.380**	.435**	.208**	1
	Sig. (2-tailed)	.025	.000	.000	.001	
	N	266	266	266	266	266
**. Correlation is significant at the 0.01 level (2-tailed).						
*. Correlation is significant at the 0.05 level (2-tailed).						

DISCUSSION

Our adaptation of the TVMS scale allowed us to determine some of the gratifications sought by avid readers. The four factors we found yield great insight into exactly why people read books. Of these factors, the Relaxation factor explained the most variance, indicating these scale items were very effective in measuring the construct. Furthermore, this same factor yielded the highest construct reliability coefficient.

Thus, while all four factors are indicative of reading motives, the sample tested herein shows relaxation to be the most compelling motive for reading. Based on these results, the implications for marketers are that a primary focus of promotional activities should be on stressing the relaxation afforded through reading. While the other three factors (escape, pass time and sharing/learning) also play a role in reading motives, it is relaxation that this sample of readers exhibits as their primary motive.

Though looking for individuals who self identified as “avid readers,” we did not expect our sample to be necessarily comprised of heavy readers, yet our sample did read an average of nearly 1.5 books per month. An interesting application of the RMS would be to assess possible differences between different groups of readers (e.g., low, moderate, high), as well as non-readers. In other words, why do some people not read?

An area ripe for future research is among the differences noted by the t-tests. That significant differences occur between the genders, education levels and age groups shows that

motivations for reading vary widely. Marketers would benefit from such study in that better appeals could be made to target audiences for books.

Also of interest is the regression equation with the four summated factors as independent variables. This regression equation showed Relaxation and Pass Time to be significant predictors of the number of books this sample reads in a given year. While these two constructs may seem complimentary, they are in fact different. Pass time can be related to alleviating boredom, whereas Relaxation is more of an active use of leisure time. Thus, there are two distinct primary drivers, or motives, pushing this group toward reading books. While Relaxation explained the most variance in the factor analysis, Pass Time still proved to be an important predictor of reading activity.

One possible limitation of the study is that the RMS might have missed motives. While our scale is derived and adapted directly from the TVMS, it is possible that reading and television viewing are not at all perfectly analogous activities, in spite of both being media-related. While one is solitary and the other has the potential for a group activity, it is possible there may be some motives for watching TV that do not apply to reading, and vice-versa. Although our exploratory research indicated that the RMS scale was inclusive, further testing must be done to confirm this conclusion.

This study could be criticized on the grounds that it captures the inputs of but one sample of 283 individuals, but every effort was made to not have a solely convenient student sample. It is thus important that this instrument be tested again among different groups of participants in order for us to be able to draw more definitive conclusions. Still, the results reported above do offer some degree of conclusion validity.

It also is certainly possible that the person who purchases a book has very different reading motives from someone who borrows a book from a friend or a library, which this study did not seek to differentiate. The reading motives and experience may be quite different without the monetary cost. Finally, although we are pleased with the diverse sample, with the relative simplicity of the factor analysis and high degree of variance explained, we recognize that internal validity is not a certainty. As mentioned above, other categories of readers, including “light” readers as well as those consuming books via various formats (e.g., audio, print, and e-books), should be sought to ensure a more inclusive sampling of readers.

An interesting extension of this research would be to compare and contrast readers of traditional books with those who have made the transition to e-books. The significant growth of this product category (and the resulting book sales) demonstrates that the activity of reading is taking on an entirely new dimension. Are these readers motivated in the same ways as those who continue to read the printed page? While no effort was made in this study to distinguish among these categories of readers, it is possible that differences exist between the groups. Future research needs to be done along this dimension as well.

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SYSTEM OPTIMIZATION, HUMAN NATURE, CUSTOMER VALUE

Jim Turner, Xavier University

ABSTRACT

Self interest, customer value, and psychology are integrated via a systems perspective. Using a perspective based on evolutionary psychology and cultural anthropology, social responsibility, a pro-social predisposition, and an ethical foundation are shown to complement the economics of self interest in the creation of a stable social order. The basis of a pro-social model is explored as a more rational and moral model replacing the hedonistic economic model.

INTRODUCTION

Information is filtered and organized by the mind producing order from chaos. "[I]nformation filters leave out some information and alter other information"(Pfeffer & Salancik, 1978 p.6). Whether this process is one of distilling Platonic essences, building paradigms (Kuhn, 1962); or simply selective perception"(Pfeffer & Salancik, 1978), the result is a perceived reality which is contingent upon the filtering process.

SUPERSTITIOUS LEARNING

"... people in organizations focus on what they have been trained to notice and on things relevant to their jobs" (Pfeffer and Salancik, 1978, p. 81). Sometimes, however, training creates paradigms that function as absolutes, as limits. When one successfully performs a task in a particular manner, one implicitly assumes the elements of the process all contributed positively to success, especially if the result is obtained repeatedly. Skinner (1948) calls this superstitious learning. Particular elements of the process may have contributed nothing or in fact may have impeded its success. Temporal relationships, even success or failure, are poor indicators of causality.

Management requires understanding context and the associated set of filters. The filters illustrated here are not new by any means. They are as old as humanity. Their real strength may be that they represent a better understanding of the roots of human collaboration. Understanding the human motivational complex has long been approached through a filter of cynicism -- resulting in an understanding based on hedonism and self interest. These stories illustrate other motivations.

TWO STORIES

Old Man

Kohn (1993) relates a story (purely fictional) about an old man who lives next door to an elementary school.

Each day an elderly man endured the insults of a crowd of ten-year-olds as they passed his house on their way home from school. One afternoon, after listening to another round of jeers about how stupid and ugly and bald he was, the man came up with a plan. He met the children on his lawn the following Monday and announced that anyone who came back the next day and yelled rude comments about him would receive a dollar. Amazed and excited, they showed up even earlier on Tuesday, hollering epithets for all they were worth. True to his word, the old man ambled out and paid everyone. "Do the same tomorrow," he told them, "and you'll get twenty-five cents for your trouble." The kids thought that was still pretty good and turned out again on Wednesday to taunt him. At the first catcall, he walked over with a roll of quarters and again paid off his hecklers. "From now on," he announced, "I can give you only a penny for doing this." The kids looked at each other in disbelief. "A penny?" they repeated scornfully. "Forget it!" And they never came back again (Kohn, 1993 p. 71-72).

Carothers relates a story that must surely have occurred in our distant past. In his scenario, a clan of early *Homo sapiens* has returned from the hunt. Even though they have learned the value of cooperation, they had not yet progressed to specialization. Og was a highly team spirited individual and one of the leaders the others turned to in times of stress.

As Og was preparing to eat his portion of game, he realized that everyone had set about the same task, they were all beginning the preparation of a grain mixture fried on a hot stone to be eaten with the fresh kill of the hunt. While it was something he had always enjoyed, in fact he liked it even more than he liked the hunt, others were bemoaning the extra time it took, especially after a long day at the hunt. Gradually an idea took shape. Why couldn't one individual prepare the bread while the others were hunting the game? The evening meal would certainly be earlier, leaving time for story-telling and socializing; and it would certainly be more pleasant without the complaints of those who didn't really like to bake bread.

THE "C" WORD

The problem Og recognized was that he knew it would require a commitment greater than he had ever made before. After all, if he felt sluggish and out of sorts on the hunt, he could always rely on the others to pick up the slack. The group might not even notice that he did a little less than usual. If he decided to be the bread maker, he would not have the group to carry him on the days he was not up to par. The responsibility would rest squarely with him to have the bread ready when the hunters returned from the hunt. It was quite a commitment, quite a responsibility.

After several days of thought, Og decided the improvement for all was worth the extra responsibility. After a particularly successful hunt, and a meal with the normal amount of

complaining about being tired and having to bake bread in the dark, Og seized the opportunity to explain his plan. Moving to the center of the clan, Og stepped tall on a rock and made his proposal. Og would henceforth bake bread for the entire clan. This would allow the hunters more time to commit to the hunt and would relieve them of the bother of baking bread in the dark -- not to mention, Og bakes the best bread.

Once the others accepted, Og was committed -- ethically, morally committed. The commitment gradually grew even larger. Unforeseen from atop the rock, it was a relatively short time before most of the clan members had forgotten how to make their own bread. The obligation had become stronger and more important than ever (Carothers, 1993).

These stories tell us about a new approach to management and its implications for marketing. Two of the most important lessons for management are:

- 1) human nature must be understood beyond the simplistic models of "economic man" as espoused by Smith (1776), and the "stimulus-response man" of Skinner (1958). Management has often sought to treat employees as though the only employee connection to the organization and its products was through economics and that employee motivation was a result of management's manipulations. "Management seems to assume that machines and workers are alike in that both are normally passive agents who must be stimulated by management in order to go into action. In the case of machines, management turns on the electricity. In the case of workers, money takes the place of electricity" (White, 1955 p. 3).
- 2) a producer has a moral commitment to those he serves. Even though standing on the rock may have been the first attempt at marketing, the real lesson from Og's story is that a producer has accepted the responsibility of producing a product to satisfy the needs of customers and to recognize changes as they occur in those needs and in the environment. In fact, the producer and his customers and suppliers are part of the same clan, i.e., the same team, the same environment the same system.

This may be a major change in how producers see themselves *vis-à-vis* their customers and their employees. The traditional approach to management emphasizes internal stakeholders (shareholders, managers, employees) and focuses on providing benefits (rewards) for them. This drives an attitude of "satisficing," i.e., providing a minimally acceptable product or service that can be exchanged for the benefits desired. "Each party is expecting from the other, a condition of conflicting predispositions of protective self-interest. The exchange process often becomes a bargaining contest, a relationship that is at best "contractual" (Stahl and Bounds, 1991). This, of course, leads to differing aims between the producer and the consumer.

"Changing the firm's predisposition from expecting to providing also changes *what* the firm provides. The providing of a minimum is replaced by the intent to provide the best net value" (Stahl and Bounds, 1991 p.42). This change in focus requires producers to clearly identify the needs of consumers and then to accept the responsibility of providing for that need. "This describes a covenant view of the relationship between firms and customers based on *bona fide* provisioning, not bargained exchange" (Stahl and Bounds, 1991 p.45).

WHAT'S IN IT FOR ME?

In 1776, Smith, a moral philosopher, published his thoughts on the interdependency of mankind. While he quite correctly identified the division of labor as the key to the continual improvement of the standard of living of mankind, he was more concerned with the moral weakness of selfishness. How can selfish human beings cooperate? How do selfish individuals produce improvements in their mutual standard of living? His solution was to suggest that if each individual seeks what is best for him/her (selfishness) the greatest total good, and therefore the greatest common good, will obtain. With surplus to exchange, commerce ensues and everyone benefits. Social organization, he believed, is a result of human selfish desires manifest as a disposition to “truck, barter, and exchange” (Smith, 1986 (1776), p. 120).

Smith interpreted the human propensity to barter as the result of self-interest alone. Selfishness combined with economic inducement is, for Smith, the basis of commerce and the source of our increasing standard of well-being. With this as a foundation, is it any wonder that *Homo sapiens* are viewed as fundamentally economic beings?

The only problem with Smith's concept is that he was wrong. *Homo Sapiens* is a social animal. Working in collaboration, toward a common objective, much more accurately defines the human condition than greed. Working together – cooperating -- is a prerequisite to the division of labor (Hirshleifer (1977). How can anyone see people working together, recognize division of labor and specialization (which of necessity require cooperation), see people living in communities, and congregating just to be together and yet suggest that selfishness and competition drive the human character and somehow derive the common good?

When Og began baking bread, he did it as much for the common good as for his own benefit. He understood quite well that seeking what might be good for him without considering the common good was impossible. He also understood that his aim was not to see how much of the hunt he could barter for, but rather to ensure the bread was provided for the clan. His job was to work with the hunters in such a manner that all lived better. He was not in competition with clan members, but rather he was a part of the clan doing his best to retain the respect and trust of the others, and to optimize the lot of the entire clan. "Competition, which is the instinct of selfishness, is another word for dissipation of energy, while combination is the secret of efficient production" (Bellamy, 1888 p 178).

AIM

An organization must have an aim (other than self love), just as Og's aim was to provide the bread for the clan. An organization's effectiveness, by whatever measure, must derive from its interaction with its environment. The basis of this interaction should follow directly from the organization's aim. A system must be managed with an aim (Deming, 1993). The aim is an essential component for every organization. An organization's aim is an ethical commitment to do something for someone – better in some way than they could do it for themselves. The aim must be externally focused and it must be couched in terms of doing something for the customer, i.e., "all functions of a business must understand customers and their needs, and translate that understanding into well-coordinated strategies that create value and satisfaction for those customers" (Stahl and Bounds, 1991 p. 567). The success of the organization, its profit, even its survival, will be a function of how well it accomplishes its aim, how important the aim is to the customers, and the sacrifices required of the customers in exchange for the satisfaction.

CUSTOMER SACRIFICE

Producers must recognize the sacrifices made by customers in exchange for the product. These will include the purchase price, the inconvenience of going to the vendor, the difficulties of dealing with sales people, the loss of perceived control when outsourcing instead of making, the uneasiness associated with changing to an unproved source, etc. All customer sacrifices must be understood and minimized in an ongoing effort to provide best net value to our customers.

SYNERGY

Synergy must exist throughout the system; i.e., the sacrifices required must be less than the perceived gain, measured for the entire system. As Pfeffer and Salancik said, "The key to organizational survival is the ability to acquire and maintain resources. ... Organizations must transact with other elements in their environment to acquire needed resources, ..." (Pfeffer and Salancik, 1978 p. 2). While Pfeffer & Salancik's focus (1978) would seem to be more traditional, more contractual than "provisioning," the relationship or reciprocity model espoused here focuses on the creation of value for customers as the only imperative. The more a supplier is able to become a part of its customers' system (and to make the customer a part of the supplier's system) the more its survival and success is assured. The more producers are able to focus on the creation of value for customers, on satisfying customer needs with a minimum of customer sacrifice, the more likely they are to survive, and to thrive. The more producers focus on taking care of the goose, and in fact, the less they focus on getting the golden egg, the more likely their system will be to prosper. The less we "demand" of the world in return for our services and the more we focus on "provisioning," the more we and our entire system will benefit.

This is, of course, the genesis of the open systems model of organizations. The customer buying Og's bread is part of Og's clan; Og must develop a relationship with that customer based on inclusion. The customer must understand that Og's commitment to him/her is based on moral principles and that profit, the motive of selfishness, is not Og's principle motivation. In fact, in this model, profit is a measure of synergy he has created within the system of customers and suppliers (and the impact of environmental factors). Assuming the system functions as Og conceived it, profit (synergy) will result. Benedict defined synergy as "social-institutional conditions which fuse selfishness and unselfishness, by arranging it so that when I pursue selfish gratifications, I automatically help others, and when I try to be altruistic, I automatically reward and gratify myself also, i.e., when the dichotomy or polar opposition between selfishness and altruism is resolved and transcended" (Maslow and Honigmann, 1970). If sufficient synergy is not obtained, the system must be re-engineered or it will die.

Providing customer value means much more than simply delivering value in an accounting sense. It means building a relationship wherein we acknowledge that we are members of the same team -- accept that we are mutually vulnerable, inter-dependent. Understood in this perspective, we can learn to work together with long-term agreements based on trust and mutual benefit. This requires leadership, but "leadership is hard because we are caught in a management paradigm, thinking of control, efficiency and rules instead of direction, purpose" (Covey, 1989 p 102).

SOCIAL EXCHANGE

Blau (1964) combined similar concepts into the development of social exchange theory. Blau in effect created a relationship continuum ranging from close kin on one end to complete strangers on the other. Blau saw exchange and cooperation as occurring quite differently along the continuum, following the relationship differences. Exchanges within family or close clan relationships are characterized by trust and willing cooperation -- the reciprocal altruism described by Trivers (1971). It is generally expected that if each individual cooperates, i.e., acts altruistically, all will benefit. On the other end of the scale, exchange is characterized by close accounting and negotiated contractual equivalencies. This end of the scale is characterized by skepticism and formality. Altruism is then the basis of ethical and moral codes (Lieberman, 1991). Altruism and skepticism (distrust) together form the basis for moral action and analysis.

Having spent millions of years evolving behaviors (and attitudes) that enhance survival, humans spent the overwhelming majority of that time living in extended family groups, i.e., clans. The moral rule that developed in this setting to enable cooperative behavior would follow the same genetic logic as developed by Hamilton in the theory of kin selection. This rule would resemble reciprocal altruism much more closely than measured economic exchange. The hypothesis that altruism is genetically based was supported by Rushton (1986). In a study of 573 pairs of twins he determined that genetics is the strongest factor in predicting both altruistic behavior and aggressive tendencies.

Reciprocal altruism manifests itself as prosocial behavior. Organizational citizenship behaviors are, after all, selfless acts that, when reciprocated, forge and maintain cooperative structure. As Smith, Organ & Near (1983) put it, "Citizenship behavior may represent just one manifestation of a broader disposition toward prosocial behavior" (p. 656).

AN EXPERIMENT

Individuals, regardless of our prehistoric psychological heritage, will act largely according to their own best interest. The logic of the group is, however, still very strong. John von Neuman, created game theory based on the assumption that people will always act rationally, i. e., based on the logic of self interest. In an informal experiment to test this premise (Poundstone, 1993) von Neumann asked a secretary to type a manuscript and offered to pay her \$75. Because he claimed to need the manuscript ASAP, he offered an additional \$25 if she could recruit another secretary to help in the project. (In 1950 these amounts were not insignificant.) The real objective was to see how she would divide the money.

Thinking along the same lines as Adam Smith, he concluded she would have two options: 1) give her helper the full \$25, or 2) split the \$25 with her helper. In either case the \$75 was hers from the beginning and should not have entered the considerations. What she did came as a complete surprise: she split the \$100 50/50 with her helper. Would not the selfish individual of Adam Smith have claimed a more generous portion? The logic of the group prevailed. The imperative to treat peers as equals is more powerful than economic incentives. It is difficult to defect against one's group.

The logic of the group sometimes extends well beyond the group itself. Heroics, sacrifices, and acts of 'altruism' only make sense when interpreted in terms of the benefits to the whole group (Trivers, 1971; Kohn, 1990).

The open system model suggests that synergy is not something to be found only within the strict boundaries of an organization but rather is something that must be found in our relationships with our suppliers and our customers. It becomes the task of management to optimize the whole, to carefully construct relationships in such a manner as to remove incentives for individuals, or elements, to act against the whole, to create synergy by structuring organizations to facilitate the natural tendency to collaborate and to minimize or eliminate those situations where an individual has the temptation or even the opportunity to act against the interests of the group.

PEOPLE

We must develop a better understanding of people; as academics we must include models based on more complete understandings of psychology. For far too long Adam Smith's notion that we are all born (and taught) to be selfish has predominated in our business and organizational relationships. "If any assumption drives our culture ... it is the belief that all problems can be solved if only we find a big enough carrot to dangle in front of people" (Kohn, 1992, p. 236). Disregarding for a moment the obvious question of how selfishness as the basic characterizing personality trait could exist in a social animal, let's go back to before the time of Org.

A CHRONOLOGY

Perhaps 300,000 years ago, using only rudimentary stone tools, *Homo sapiens'* diet included large animals –horses, wildebeest, and rhino. How is it that primitive man, using stone tools, could successfully hunt large animals? Teamwork wasn't only learned, it was bred in! Evolution prepared humans to live as social animals because that's what it took to survive. Millions of years of evolution had brought them together to survive.

Thirty thousand years ago mankind developed improved tools and weapons and, for perhaps the first time, had some likelihood of surviving without the group. This was also at the time of cave art. Truly, this must have been the freedom that allowed the individual to emerge (Solso, 2003). For all our adulation of the individual, we must keep in mind that without the group to identify with and to be separate from, the individual could not exist. Without the group, individualism is meaningless.

Ten thousand years ago humans developed agriculture. Now we could not only defend ourselves, but we could literally put down roots. Six thousand years ago non-family organization appeared.

Two hundred years ago Adam Smith described man as being driven by purely selfish motives. This inaccurate understanding of human nature has filtered even our interpretation of more legitimate perceptions of human nature. People want to belong and be a part of the team. The need for affiliation, however, was interpreted as simply another tool for management to use to manipulate workers -- like an extra string on a puppet.

Beyond the walls of the organization, however, marketing seemed to mean, "see how much we can get by with"; "it's us against them." In selling it becomes how much product can we push? Sales trainers sometimes describe selling as a competition with customers; "if you sit down with a prospect and you leave without an order, you didn't sell a line, you bought one!" A

car salesman says the most common bragging phrase signaling a good sale is, "Boy, did I knock him in the head!" Same team?

WHAT'S GOOD FOR GM

In 1979 a marketing executive from an automobile manufacturer proclaimed at a press conference that the trouble experienced by the US auto industry was caused by fickle consumers; "for years marketing research indicated the public wanted style -- "now they say they want quality!"

Ford Motor Company, under Lee Iacocca, made a "bottom line" decision to continue producing Pinto automobiles that had a tendency to burst into flames when struck from the rear, burning the occupants to death. Ford decided to defend the suits in court rather than recall the Pintos and fix the problem because it was cheaper! Same team? Ford thought they were in the business of making money, not of providing for the needs of their customers. Today, it appears GM may be repeating the same mistake.

AFFILIATION

The need to belong is fundamental. The connection must be to the group and to the purpose, not simply a naked cash nexus. Of course it is a saw that cuts both ways. Understanding that an organization is dependent on its customers is not so hard to swallow; but if the system truly has synergy, the organization and its customers must understand that they are dependent upon each other, part of a system. If a supplier is a part of a system, any change to the supplier will affect the total system. If the supplier becomes more efficient, the whole system must benefit. On the other hand, if the supplier becomes financially weakened, or goes broke and must be replaced, the whole system suffers.

Management must begin with the purpose of the organization. Leadership and direction are about purpose. It is our purpose that impels us to continue our work to satisfying our customers' needs. "To be truly market driven, a company's marketing strategy has to be developed, enthusiastically accepted, and actively implemented by the entire organization" (Stahl and Bounds, 1991 p. 569). It is the purpose and its accomplishment, however, that drives all strategy and makes a viable organization.

Management must be based on an understanding of people applied both inside and outside the formal organization -- across the entire system. Relationships must be built throughout the system that will help all to see their inter-connectedness and the benefits that accrue to all by virtue of collaboration.

Cognizant that individuals will sometimes act in out of self interest, organizational design must limit the opportunities to defect against the group and foster alignment of individual and group objectives.

Management must be carried out through structures that enhance collaboration and membership throughout the entire system, structures that allow people to take pride in the work they do for others, structures that provide each individual more in benefits than he/she sacrifices (synergy).

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