New Approaches to Psychographic Consumer Segmentation: Exploring Fine Art Collectors Using Artificial Intelligence, Automated Text Analysis and Correspondence Analysis

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Abstract

Purpose:
While the motivation for collecting art has received considerable attention in the literature, less is known about the characteristics of the typical art collector. This article explores these characteristics to develop a typology of art consumers using a mixed method approach over several studies.

Design:
This is achieved by analyzing qualitative data, gathered via semi-structured interviews of art collectors, and quantitatively by means of natural language processing analysis and automated text analysis, and using correspondence analysis to analyze and present the results.

Findings:
The study's findings reveal four distinct clusters of art collectors based on their 'Big Five' personality traits, as well as uncovering insights into how these types talk about their possessions.

Implications:
In addition to contributing to the arts marketing literature, the findings provide a more nuanced understanding of consumers that managers can employ for market segmentation and target marketing decisions in other markets. The article also offers a methodological contribution to the literature on correspondence analysis by demonstrating the 'doubling' procedure to deal with percentile data.

Originality:
This paper demonstrates a unique mixed methods approach to analyzing unstructured qualitative data. It shows how text data can be used to identify measurable market segments for which targeted strategies can be developed.

Keywords:
Psychographic consumer segmentation; Artificial intelligence; Correspondence analysis; Automated text analysis; Quantitative analysis of qualitative data

Introduction

Outside of standard sociodemographic or self-reported measures, deeper consumer psychographic characteristics are often hidden from marketing managers. However, marketing managers informed of reliable psychographic characteristics can more likely predict how consumers will behave in the marketplace and thus be able to build targeted marketing campaigns. Advances in artificial intelligence technologies now enable marketers to evaluate and segment consumer markets without the need for self-reported surveys. Using these new methods, this paper explores the psychographic characteristics of fine art collectors (i.e., art consumers) through their conversations regarding the art they own. These collectors are then classified into four segments that have important strategic implications for marketers of fine art in particular. The approaches used can also inform marketing decision makers in general.

Following Arnould, Price and Moisio (2006), fine art collection is a valuable research context to explore psychographics, as it is a business environment that presents relatively low barriers to entry while displaying much subjective variety in what collectors' value. As such, the motivations for collecting fine art, such as paintings, sculptures and sketches, have long held the attentions of economists, sociologists and consumer psychologists. Economists suggest that people collect art because it represents an investment, and have rigorously studied fine art's financial valuation and appreciation over time (Mei and Moses, 2002; Pesando, 1993; Worthington and Higgs, 2004). Sociologists argue that fine art collecting provides cultural capital (i.e., value on a cultural level) to collectors, which can be exchanged for other kinds of capital like money, but also social capital in the form of status and friendship (Bourdieu, 1986). Consumer psychologists have approached fine art collection mostly from the perspectives of aesthetic experience, or the mental state that is induced through the contemplation of a visual object (Kubovy, 2000). Art and aesthetics cannot be separated by virtue of the experiential and ephemeral interaction individuals have with a piece of fine art (Venkatesh and Meamber, 2006). In other words, the value of fine art extends past the physical object to the experience induced by the art (Reber et al., 2004). However, rather than further investigating the motivations for collecting, this article contributes to the literature by exploring the minds of fine art collectors, specifically in terms of their personalities. The collection of art has received attention in the recent consumer research literature (e.g. Belk, 1995; Chen, 2009; Parsons, 2010). However collection as a form of consumer behavior is not limited to art alone, and almost anything can be "collected", including baseball cards, wines, beer cans, antiques and t-shirts. We believe that the findings of this research may be mirrored in other collection activities, and if they are not, that this would still lead to interesting questions and opportunities for further investigation.

Who the collectors are is something we know less about, with the exception of art pieces acquired by the rich and famous and those publicized widely through the media. Even when such high-profile art works are purchased, insight into *who* the art collector is, is still lacking. For example, who was it that paid $300 million for Paul Gauguin's "Nafea Faa Ipoipo (When Will You Marry?)" early in 2016? And there is certainly a lot less known about the ordinary collector. Are they intro- or extroverted? Are they open to experience or not? Just how conscientious, agreeable and emotional are they? Do art collectors generally have similar personalities or are they very different from each other? Is it possible to group art collectors into smaller, more homogeneous categories according to their personality traits? Thus, the research questions that this paper aims to answer are: What is the personality of a typical art collector? And, if indeed there are differences in the personalities of art collectors, can these be used meaningfully to distinguish between different market segments, and then to target these segments? While psychographic market segmentation is indeed nothing new, the approach suggested here can add another tool to the marketing decision-maker's toolbox, offering a different way to carry out segmentation based on consumer personality. This can obviously be done for art collectors, as we will demonstrate here, but also for other consumers who collect, and at an even broader level, when- and wherever respondents offer up large volumes of data that can be gathered in text format.

To answer these questions, the article proceeds as follows. First, it examines issues and controversies concerning psychographic market segmentation before discussing literature on fine art collectors and their behavior with specific reference to psychographic segmentation. Then, the article details a semi-structured interview method for our empirical exploration that involves interviews with 25 informants in which they discussed their fine art collecting behavior. Next, we subjected the transcripts to three analyses: (1) an artificial intelligence natural language processing algorithm that identified the "big five" personality traits of each collector; (2) a correspondence analysis of these five personality traits that identified four distinct segments of informants; and (3) an automated text analysis tool that further investigated some important psycholinguistic characteristics of the informants. The article concludes by discussing research and practical implications and contributions, acknowledging the limitations, and suggesting avenues for future research.

Psychographic Market Segmentation

Marketing scholars (Kassarjian, 1971; Odekerken-Schröder et al., 2003; Sandy et al., 2013), have long been interested in the notion of personality, which can be defined as an individual's consistent responses to their environmental stimuli (Kassarjian, 1971). Marketers' interest in consumer personality springs from both an interest in the behavior of the individual, as well as a desire to group consumers with like personalities into more homogenous groups for purposes of market segmentation and target marketing. Psychographics is one of the main attributes on which consumers can be segmented along with demographics, geographics and behavioral attributes. Psychographics can provide researchers and managers with more descriptive insights into consumers and their lifestyles (Lesser and Hughes, 1986), and can even be used to help predict future behavior (Sandy et al., 2013). In his seminal work on the subject, Wells (1975) defines psychographic research in marketing as a form of quantitative research, delimiting of demographics, that is intended to assign psychological dimensions to consumers. He goes on to add that this offers unique insights and different outcomes, and, because it is "quantitative rather than discursive", facilitates larger, more representative samples of respondents enabling multivariate statistical analysis of findings (p. 197).

Self-report methods like surveys and questionnaires are often employed to measure psychological and psychographic variables (Furnham and Avison, 1997; Sandy et al., 2013; Schwarz, 1999; Sin and Tse, 2002). For example, a number of studies have looked at the relationship between personality and preference for different types of art using self-report measures. In a small sample study of the impact of personality on subjects' preferences between surreal and representational paintings, Furnham and Avison (1997) studied the effects of the so-called 'Big Five' (Goldberg, 1990) personality dimensions (i.e., extroversion, agreeableness, openness, conscientiousness and neuroticism, hereinafter referred to as 'traits'), as well as a tolerance for ambiguity and sensation seeking as personality traits on preferences. They found that sensation seeking positively predicted a preference for surrealist art, while none of the 'Big Five' traits was a strong predictor of predilection. Participants were asked to view 20 slides depicting paintings before completing a questionnaire containing items from MacDonald's (1970) Tolerance of Ambiguity Scale, Zuckerman et al.'s (1979) Sensation Seeking Scale, and McCrae and Costa's (1987) Five-Factor Inventory Scale.

Noting that the term aesthetic does not always equate with beauty, a classic example of which would be *Myra* by Marcus Harvey (a 1990s portrait of serial child killer Myra Hindley), Rawlings, (2003) explored the impact of personality traits on subjects' liking for "unpleasant" artwork. A multiple-item questionnaire was developed and distributed to a sample of 188 students. Rawlings (2003) found that, particularly male respondents, who scored high on sensation seeking (Zuckerman, 1979), unusual experiences (Mason et al., 1995), and psychoticism (Eysenck et al., 1985), preferred unpleasant works. Chamorro-Premuzic et al., (2009) used Goldberg's (1990) 'Big

Five' personality inventory to survey a very large sample of participants to predict art preferences among four different graphic art types. Their major finding was that the personality trait "openness to experience" was the strongest, and the only consistent, predictor of art preference.

In a small sample of art collectors required to complete the well-known Myers-Briggs Type Indicator, Gridley (2004) showed that the majority of respondents reflected the trait of intuition over sensation. This corresponds to the finding that artists and those knowledgeable in visual art, display disproportionately high scores on the 'Big Five' personality trait of openness to experience (Amabile et al., 1993; Eysenck, 1972). Most of the results thus far indicate that individuals, and especially art collectors, exhibit some common traits, such as openness to experience, which means that it might be possible to classify art collectors into more homogenous groups to understand them better.

There are several benefits to using self-report questionnaires and surveys including speed, convenience and an increased chance of reaching the intended sample (McDonald, 2008). However, along with the benefits of using self-report questionnaires and surveys there are some disadvantages that can impact the results. One of the main criticisms of using self-report measures is the potential of social desirability bias (McDonald, 2008; Paulhus, 1991). The wording of the questions and statements can also impact the answers provided by participants potentially influencing the answers (Schwarz, 1999). More realistically however, it has simply become more difficult to obtain data from consumers by means of self-report questionnaires and surveys. The advent of email has meant that mail surveys have not only become more expensive, but also result in even lower response rates than in the past, as consumers view these as "junk mail". While researchers can resort to email, the response rates to unsolicited email surveys are still abysmally low, particularly when potential respondents use spam-blocking software. The fact that most consumers nowadays use smartphones that have built-in caller identification, rather than land lines, means that unsolicited telephone interviews can simply be ignored, and even blocked. However, many consumers are willing to voluntarily provide information: mostly in the form of online content in reviews and blogs. While we were fortunate enough in the research described here to have had access to a dependable panel of informants for depth interviews, the same techniques could have been applied similarly to text data gathered from online sources.

An Empirical Demonstration: Segmenting Fine Art Consumers

Background

Almost all the research to date that has attempted to tie personality to visual art preferences and behavior has relied on some form of personality trait scale to assess the personality or closely related traits of individuals (see for example, Loveland et al., 2016). The research presented here is different in that it does not use personality scales to identify traits among art collectors; rather it uses their own words, obtained in in-depth interviews, to gauge the extent to which they exhibit particular personality traits or not, and then to group them according to these traits. Our study relies on Goldberg's (1990) 'Big Five' personality dimensions as a theoretical lens, which is one of the most widely used personality models (Costa and McCrae, 1992; Norman, 1963). The 'Big Five' traits are:

- *Intro-/Extroversion* - a person's tendency to seek stimulation in the company of others.
- *Agreeableness* - a person's tendency to be compassionate and cooperative toward others.
- *Conscientiousness* - a person's tendency to act in an organized or thoughtful way.
- *Emotional Stability* (i.e., neuroticism) - the extent to which a person's emotions are sensitive to their environment.
- *Openness to New Experiences* - the extent to which a person is open to experiencing a variety of activities.

Method and Sample

Following the Creswell and Creswell (2017) admonitions on semi-structured interviews, a purposive sample of fine art collectors was compiled. These were defined as individuals who intentionally and regularly engage in the acquisition, keeping, and exchange of fine art. Moreover, all informants self-identified as fine art collectors and in the process of the interview gave their definition of art. A list of local fine art collectors was compiled, and these individuals were asked to participate in interviews discussing their fine art collection. After initial informants were contacted and interviewed, a snowball approach was taken to recruit additional art collectors to participate in an interview.

Interviews pertaining to collector behavior and their collections were either conducted by telephone or in person. Interviews lasted an average of 37 minutes with the shortest being 15 minutes and the longest being 60 minutes. A semi-structured interview guide was developed and used in all interviews (see Appendix for details). To establish rapport, this began with general questions about how long informants had been collecting fine art and what areas of fine art they were most interested in. Questions then turned to market behavior, fine art evaluation, giving and receiving, influencers and, finally, dreams and aspirations with regard to fine art. At 27 interviews, responses to the questions had sufficiently repeated themselves over a variety of informants, and it was therefore assumed that theoretical saturation had been achieved (Creswell and Creswell, 2017).

Stage 1 Analysis: Using automated text analysis to gauge personality traits

The interview transcripts were subjected to an automated text analysis using a module of IBM Watson artificial intelligence software that analyzes textual data. Automated text analysis refers to various techniques powered by advanced algorithms that can answer questions from a variety of disciplines by processing textual data (Humphreys and Wang, 2017). Similar to the cognitive process that others would go through, IBM Watson uses natural language processing to understand, interpret and respond to the way in which individuals use language to communicate, rather than employ programmed or coded instructions in the way that conventional computer programs do. Since we are interested in identifying personality traits, we used IBM Watson's Personality Insights application (IBM, 2017) that applies linguistic analytics to infer individuals' personality traits from their own words in textual format. As Watson requires at least 1000 words for a "decent" analysis, two informants of the original 27 (i.e., informants 2 and 5) were excluded, leaving us with 25 informants in the sample for further analysis.

An individual's language reflects characteristics such as their personality traits, thinking style, and emotional state (e.g. Cohn, Mehl and Pennebaker, 2004; Pennebaker, Mehl and Niederhoffer, 2003). The frequency with which certain kinds of words are used can provide clues to personality, values and thinking style and by analyzing these words it is possible to predict aspects of personality (Fast and Funder, 2008; Golbeck et al., 2011; Hirsh and Peterson, 2009; Yarkoni, 2010). IBM Watson's Personality Insights reports percentile scores for the 'Big Five' personality traits. For example, if a respondent scores 87 on the Conscientiousness trait, this means that 87% of the population would score lower than the individual on that trait. Table 1 shows a summary of the results of this analysis, including informants' descriptive statistics.

Table 1: Descriptive and Personality Statistics

Informant	Age	Gender	Openness	Extra-version	Conscient-iousness	Agreeab-leness	Emotional Stability
1	30s	M	9	62	3	95	96
3	60s	M	54	22	17	52	79
4	30s	M	50	12	11	41	85
6	40s	M	28	23	9	68	91
7	20s	M	7	73	5	96	95
8	50s	F	60	9	38	33	78
9	60s	M	46	41	19	64	71
10	50s	M	38	24	43	61	74
11	60s	F	30	60	14	85	79
12	40s	F	48	22	33	58	76
13	30s	M	12	16	3	75	99
14	40s	M	19	47	4	91	95
15	40s	F	76	11	35	23	56
16	50s	M	23	40	18	81	87
17	50s	F	28	27	21	69	84
18	60s	M	37	33	16	79	67
19	60s	F	9	86	8	99	84
20	20s	F	12	25	20	92	99
21	30s	F	32	12	21	54	92
22	20s	M	14	28	3	77	99
23	30s	F	31	14	10	52	94
24	40s	F	58	27	40	32	54
25	40s	M	33	17	26	62	91
26	50s	M	6	57	7	94	97
27	20s	F	16	26	10	75	95
Mean			31	33	17	68	85
Std. Dev.			19.1	20.8	12.3	21.3	12.9

Stage 2 Analysis: Using correspondence analysis to create personality segments of fine art consumers

While personality trait statistics can be informative and useful to marketers on their own, we further analyze this data to identify segments among the respondents to this study according to their five personality traits. We employ correspondence analysis (Greenacre, 2007; Hoffman and Franke, 1986) that produces both numerical and graphical output from variations and associations of a number of statistics. Correspondence analysis traditionally uses counts arranged in a two-way frequency table that summarizes, in this case, the participants (in rows) and the Big Five traits (in columns). However, the personality traits data in Table 1 is in percentile-, and not count-form. Therefore, a transformation was needed before further analysis could be conducted. We used the "doubling" procedure (Bendixen, 1991; Greenacre 2007; Hoffman and Franke 1986) in order to produce a more appropriate solution for this type of data.

The doubling technique involved creating two complementary personality (i.e., column) variables for each of the original personality variables, and then computing scores on these "new" variables such that the lower endpoint for the scale is zero and the upper endpoint is its complement. This was done as follows: First, Subtract 1 from the percentile scores for the original five personality variables. The scores for these variables are now labelled - "Openness (+)"; "Extroversion (+)"; "Conscientious (+)"; "Agreeable (+)"; "Emotion (+)". These are referred to as the high (or +) poles for the variables. Then, second, subtract the scores on the variables - "Openness (+)"; "Extroversion (+)"; "Conscientious (+)"; "Agreeable (+)"; "Emotion (+)"- from 99. This provides the complementary set of scores to the high poles. These variables are labelled "Openness (-)"; "Extroversion (-)"; "Conscientiousness (-)"; "Agreeable (-)"; "Emotion (-)" and are referred to as the low (or –) poles. The procedure followed in this application ensures that each participant is given equal weight in the correspondence analysis solution (Greenacre, 2007). The data was analyzed using the SPSS correspondence analysis routine with the symmetric method of normalization. This procedure results in three perceptual maps and a number of tables of statistical measures that can be used to interpret the results of the correspondence analysis.

The relevant results for the correspondence analysis of the doubled data matrix are shown in Tables 2 and 3, and in the perceptual maps in Figures 1, 2 and 3. The interpretation of the correspondence analysis is set out in the steps below that involve the assessment of the statistical measures reported in Tables 2 and 3, followed by a visual inspection and subjective interpretation of the perceptual maps in Figures 1, 2, and 3.

Step 1: Selecting number of dimensions. For this problem, the maximum number of dimensions needed to capture 100% of the inertia (i.e., variability) in the percentile data is nine, since the maximum number of dimensions = minimum [(number of rows -1), (number of columns -1)]. Inspection of the "proportion of inertia" columns of Table 3 reveal that the first and second dimensions explain 74.3% and 18.10% of the total inertia, respectively. Thus, a two-dimensional solution will explain 92.4% of the total inertia, and we therefore select and report a two-dimensional solution in further analysis below.

Table 2: Correspondence Analysis Inertia Report

Dimension	Singular Value	Inertia	Chi Square	Sig.	Proportion of Inertia	
					Accounted for	Cumulative
1	0.346	0.120			0.743	0.743
2	0.171	0.029			0.181	0.924
3	0.089	0.008			0.049	0.973
4	0.055	0.003			0.019	0.991
5	0.038	0.001			0.009	1.000
Total		0.161	1993.1	$p < 0.001$[a]	1.000	1.000

a. 216 degrees of freedom

Step 2: Interpretation of the new solution. Table 3 reports the two-dimensional solution of the informants' doubled personality traits. All traits contribute significantly to inertia (i.e., all traits have total contributions to the dimensions above 0.5; Hair et al., 2009, p. 605). In order to interpret which personality traits contribute significantly to the total inertia of the dimensions, Bendixen (1991) provides a rule of thumb: as there are 10 personality traits in the doubled table, each trait should contribute at least 10% (0.10) to the inertia of the dimension to be deemed significant. Therefore, the "significant" personality trait points can be identified by an inspection of the magnitude of the contributions of trait to inertia of the dimensions. Applying this rule, Dimension 1 is significantly influenced by Openness (+) (0.179), Extroversion (+) (0.128), Agreeableness (+) (0.105), and Agreeableness (-) (0.223). Dimension 2 is significantly influenced by Extroversion (+) (0.359), Extroversion (-) (0.168), and Agreeableness (-) (0.300). These provide the poles of the two axes in Figure 1 and the traits' co-ordinates are those reported in Table 3's "score in dimension" columns.

Table 3: Two-Dimensional Correspondence Analysis Solution

Personality Trait	Mass	Score in Dimension		Inertia	Contribution of				
					Trait to Dimension Inertia		Dimension to Trait Inertia		
		1	2		1	2	1	2	Total
Openness (+)	0.061	1.009	-0.299	0.023	0.179	0.032	0.912	0.040	0.951
Extroversion (+)	0.064	-0.833	-0.980	0.026	0.128	0.359	0.577	0.396	0.973
Conscientiousness (+)	0.033	1.006	-0.494	0.018	0.097	0.047	0.643	0.077	0.720
Agreeableness (+)	0.136	-0.517	-0.082	0.013	0.105	0.005	0.934	0.012	0.946
Emotion (+)	0.169	-0.188	0.236	0.004	0.017	0.055	0.535	0.414	0.949
Openness (-)	0.139	-0.440	0.130	0.010	0.078	0.014	0.912	0.040	0.951
Extroversion (-)	0.136	0.390	0.459	0.012	0.060	0.168	0.577	0.396	0.973
Conscientiousness (-)	0.167	-0.199	0.098	0.004	0.019	0.009	0.643	0.077	0.720
Agreeableness (-)	0.064	1.098	0.174	0.029	0.223	0.011	0.934	0.012	0.946
Emotion (-)	0.031	1.027	-1.286	0.021	0.094	0.300	0.535	0.414	0.949
Active Total	1.000			0.161	1.000	1.000			

Figure 1: Correspondence results of doubled personality-traits

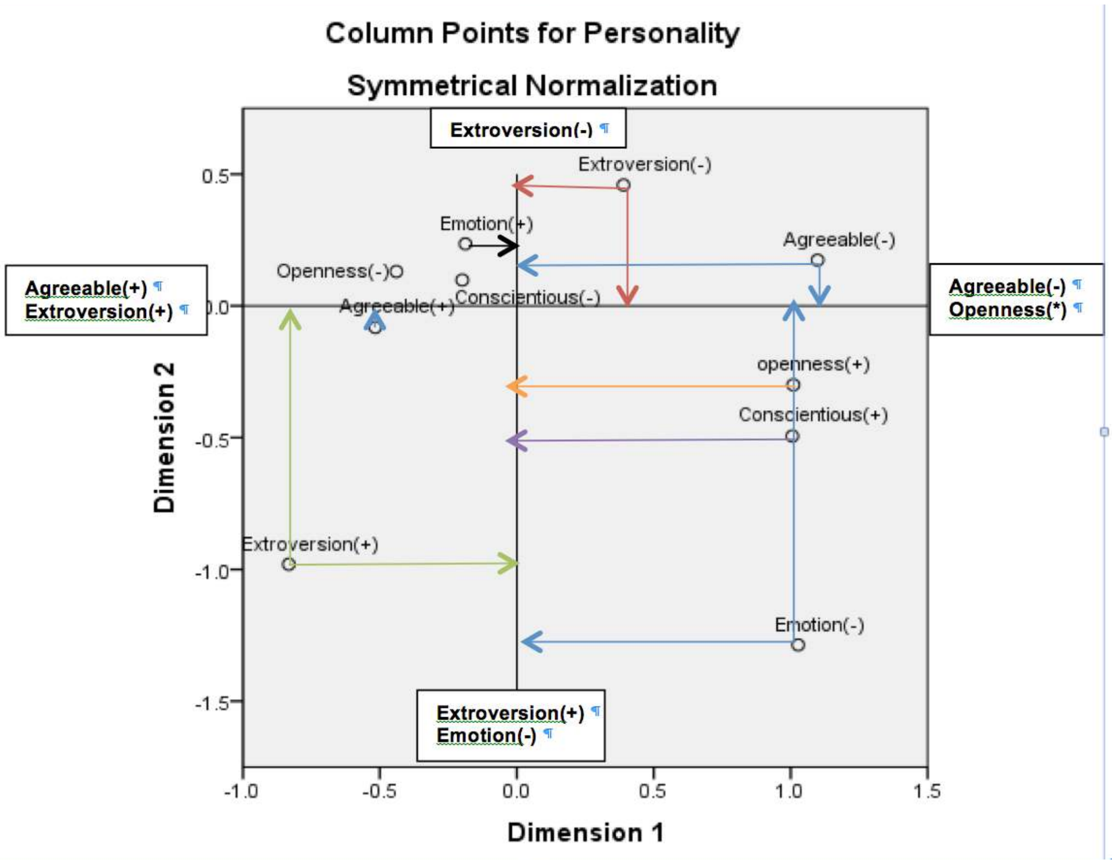


Figure 1 graphically illustrates a plot of the doubled personality traits in two-dimensional space, that is, there are two points for each trait - the positive pole and the negative pole. Using this figure, we can visually assess the distribution of the participant percentile scores for each of the five personality trait variables, as well as better understanding the nature and extent of the correlation between the personality trait variables. Imagine an arrow joining the negative (i.e., the lowest value) to the positive (i.e., the highest value) poles of a personality trait through the origin (i.e., the mean value). The shorter the distance between the origin and the positive pole of the trait, the higher the average score is for the trait. For example, visual inspection of “Emotional Stability” suggests its sample mean will be relatively high compared to the sample mean for “Extroversion” since the former’s “line” is shorter than the latter’s. It can therefore be inferred that the “average” participant in the sample is highly emotional and agreeable, but less conscientious, less open to experience, and more introverted than extroverted.

Furthermore, the length of the lines joining the two poles of a personality trait provides an indication of the variability in the percentile scores for that trait, such that the longer the line, the more variability there is in the scores. From a visual inspection of the lines for the five personality traits it is appears that “Conscientiousness”, and “Emotional Stability” have the lowest variability in percentile scores, with the variability in percentile scores for the other three personality traits being similar.

Additionally, the angle between two lines provides an indication of the strength of the correlation between the trait scores - the smaller the angle, the higher the correlation. When the angle is 0 degrees, the correlation is equal to 1. When the angle is 90 degrees, the correlation is 0. Should the lines be opposite in direction, the correlation between the scores is negative. From a visual inspection of the plot in Figure 1, it can be concluded that the scores on "Extroversion" and "Emotional Stability" are negatively correlated. Next, we use this analysis to generate clusters or segments of the informants.

Step 3: Clustering informants into segments. First, from a visual inspection of the informant plot in Figure 2, where each point is an informant's row profile (see Table 4), there are four distinct clusters. Second, using a four-cluster specification, a cluster analysis objectively determined the position of each informant in the personality trait space. Specifically, the informants' row profile scores from Table 4 were subjected to the SPSS hierarchical clustering procedure using Ward's (1963) method, specifying a four-cluster solution. This analysis resulted in four clusters or segments: *Segment A* comprises three participants (P8, P15, and P24); *Segment B* contained eleven participants (P3, P4, P6, P9, P10, P12, P17, P18, P21, P23, and P25); *Segment C* describes seven participants (P1, P7, P11, P14, P16, P19, and P26); and *Segment D* involved four participants (P13, P20, P22, P27). The overlaying of the personality trait profiles (Figure 1) and the participant profiles (Figure 2) is portrayed in the joint display in Figure 3.

Table 4: Row Profiles of the Participants

	Personality Trait									
Informant	Openness(+)	Extroversion(+)	Conscientious(+)	Agreeable(+)	Emotion(+)	Openness(-)	Extroversion(-)	Conscientious(-)	Agreeable(-)	Emotion(-)
1	0.016	0.123	0.004	0.190	0.192	0.184	0.077	0.196	0.010	0.008
3	0.107	0.042	0.032	0.103	0.158	0.093	0.158	0.168	0.097	0.042
4	0.099	0.022	0.020	0.081	0.170	0.101	0.178	0.180	0.119	0.030
6	0.055	0.044	0.016	0.135	0.182	0.145	0.156	0.184	0.065	0.018
7	0.012	0.145	0.008	0.192	0.190	0.188	0.055	0.192	0.008	0.010
8	0.119	0.016	0.075	0.065	0.156	0.081	0.184	0.125	0.135	0.044
9	0.091	0.081	0.036	0.127	0.141	0.109	0.119	0.164	0.073	0.059
10	0.075	0.046	0.085	0.121	0.147	0.125	0.154	0.115	0.079	0.053
11	0.059	0.119	0.026	0.170	0.158	0.141	0.081	0.174	0.030	0.042
12	0.095	0.042	0.065	0.115	0.052	0.105	0.158	0.135	0.085	0.048
13	0.022	0.030	0.004	0.149	0.198	0.178	0.170	0.196	0.051	0.002
14	0.036	0.093	0.006	0.182	0.190	0.164	0.107	0.194	18.000	0.010
15	0.152	0.020	0.069	0.044	0.111	0.048	0.180	0.131	0.156	0.089
16	0.044	0.079	0.034	0.162	0.174	0.156	0.121	0.166	0.038	0.026
17	0.055	0.053	0.040	0.137	0.168	0.145	0.147	0.160	0.063	0.032
18	0.073	0.065	0.030	0.158	0.133	0.127	0.135	0.170	0.042	0.067
19	0.016	0.172	0.014	0.198	0.168	0.184	0.028	0.186	0.002	0.032
20	0.022	0.048	0.038	0.184	0.198	0.178	0.152	0.162	0.016	0.002
21	0.063	0.022	0.040	0.107	0.184	0.137	0.178	0.160	0.093	0.016

22	0.026	0.055	0.004	0.154	0.198	0.174	0.145	0.196	0.046	0.002
23	0.061	0.026	0.018	0.103	0.188	0.139	0.174	0.182	0.097	0.012
24	0.115	0.053	0.079	0.063	0.107	0.085	0.147	0.121	0.137	0.093
25	0.065	0.032	0.051	0.123	0.182	0.135	0.168	0.149	0.077	0.018
26	0.010	0.113	0.012	0.188	0.194	0.190	0.087	0.188	0.012	0.006
27	0.030	0.051	0.018	0.149	0.190	0.170	0.149	0.182	0.051	0.010
Mean	0.061	0.064	0.033	0.136	0.165	0.139	0.136	0.167	0.783	0.031
Std. Dev.	0.039	0.042	0.025	0.044	0.035	0.039	0.042	0.025	3.587	0.026

Figure 2: Correspondence result of informants' personalities profiles

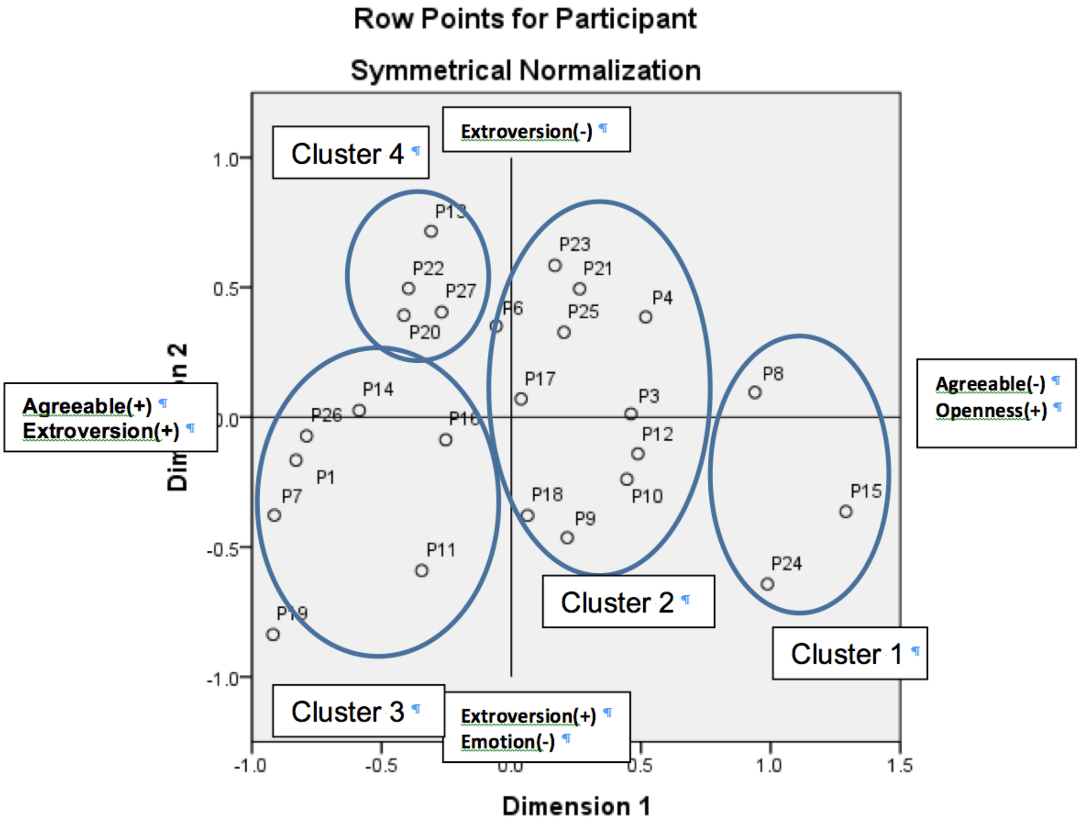
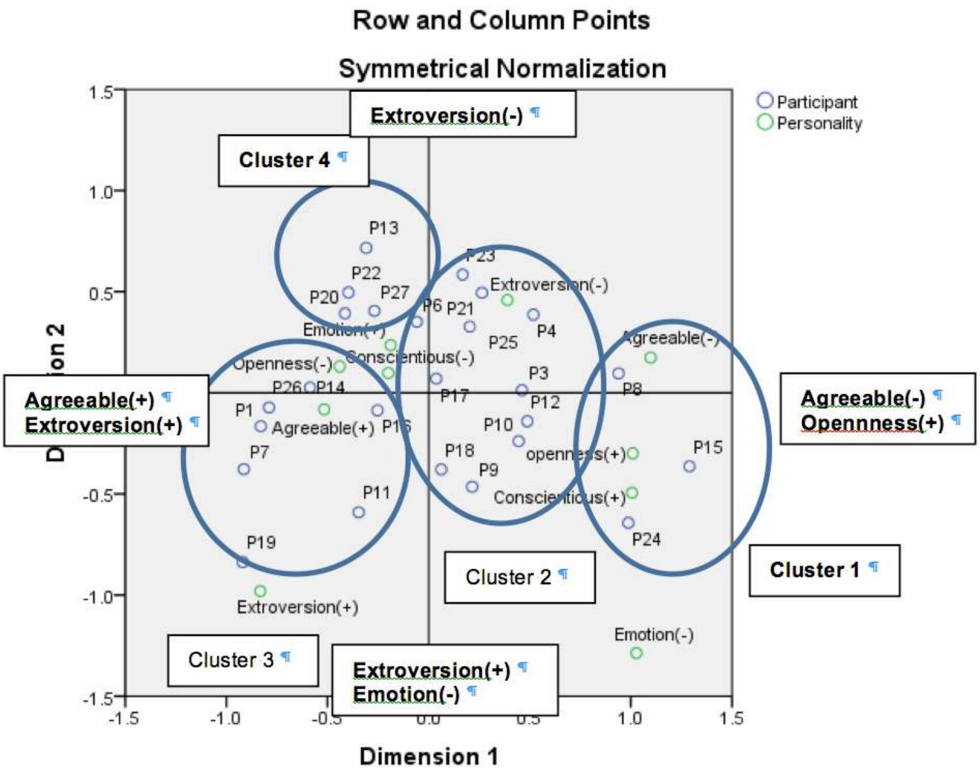


Figure 3: Correspondence results of doubled personality-traits and informants' personality profiles



Based on the analysis above, an interpretation of these segments can now be made, bearing in mind that: (1) Dimension 1 of the perceptual map is the main dimension to focus on, but Dimension 2 enhances the ability to understand the relationship between the column (personality traits) and row (participant) points; (2) the origin is interpreted as the sample mean for the personality trait variables, and this is used as the reference point in the visual interpretation; (3) and the poles of the dimensions and how the projection of these points “line-up” along the dimensions. The segments can thus be described as follows (and we have hopefully chosen appropriate names for these): *Open introverts* (segment A) are “well” above average with respect to openness to new experiences and conscientiousness, but they are below average on extroversion, agreeableness, and emotion stability. *Average Joes* (segment B) tend to be close to the mean of the informants on all five personality traits. *Closed Extroverts* (segment C) tend to be above “average” on extroversion, agreeableness, and emotional stability, but below “average” on openness to new experiences and conscientiousness. *Agreeable Introverts* (segment D) are above average on agreeableness and emotional stability but below average on extroversion, openness to new experiences, and conscientiousness. Now that we have identified the informants’ personality traits and categorized them into four segments (i.e., clusters), we are able to investigate other important psycholinguistic characteristics.

Stage 3 Analysis: Understanding psycholinguistic characteristics of personality segments of fine art consumers

Linguistic Inquiry and Word Count

The Linguistic Inquiry and Word Count (LIWC) software was developed by the psychologists Pennebaker and Francis (1996) out of a curiosity for the words people use and the emotions that they would reflect. The software was first developed to understand why writing is psychologically beneficial for people who have experienced periods of upheaval in their lives. The program consists of a text processing function and supporting dictionaries created to represent different psychological states (Pennebaker, 2011). The software reads a piece of text and counts the number of words that reflect different psychological states of emotions, thinking styles, social concerns and parts of speech (Pennebaker et al., 2015). LIWC can be used to show that the words that people use reveal more than just the emotions underlying the text, but can also reveal insights into the social status, motives and gender of the author of the text (Pennebaker, Mehl and Niederhoffer, 2003).

There are four main dimensions that LIWC can provide scores on namely, authenticity, clout, tone and analytical thinking:

- *Analytical thinking*: This dimension captures the degree to which people use words that suggest formal, logical, and hierarchical thinking patterns (Pennebaker et al., 2014).
- *Clout*: This dimension reveals the relative social status, confidence, or leadership that people hold through their word choice. People with higher status consistently use fewer first-person singular (“I”), and more first-person plural (“we”) and second-person (‘you”) singular pronouns (Kacewicz et al., 2014).
- *Authenticity*: This dimension reflects people who reveal themselves in an authentic or honest way through their words of choice. Among the characteristics revealed by high authenticity scores people tend to be more personable, humble, and vulnerable.
- *Tone*: This dimension assesses whether a text expresses a negative or positive emotional tone. Scores for words expressing positive emotions and scores for words expressing negative emotions are combined into a single summary variable, with a score over 50 meaning positive and below 50 meaning negative (Cohn, Mehl, and Pennebaker, 2004).

LIWC has been used to analyze a variety of texts such as classical literature, personal narratives, press conferences, and transcripts of everyday conversations (Pennebaker and Graybeal, 2001) and in marketing specifically, customer-firm interactions (Packard, Moore and McFerran, 2018).

Using the same content from the interview data referred to above, the LIWC analysis reveals significant differences among the segments identified above (see Table 5). Open Introverts (mean =

45.9) used significantly more analytic language than the other segments (F(3,24) = 9.562, $p <$ 0.001), particularly Closed Introverts (mean=16.1). Closed Extroverts (mean = 47.0) and Open Introverts (mean = 45.5) used language that had significantly more clout (F(3,24) = 7.375, $p =$ 0.001) than the other two segments, especially Agreeable Introverts (mean = 17.0). Agreeable Introverts (mean = 78.4) used significantly more authentic language than the other segments (F(3,24) = 9.232, $p < 0.001$), particularly Open Introverts (mean = 30.6). Not surprisingly, individuals in all segments used a relatively positive tone in their interviews to talk about their fine art collecting behavior (F(3,24) = 0.950, $p = 0.435$), and there were no significant differences between the segments on the dimension of tone. These results indicate overall that there are different psycholinguistic profiles across the segments. This has deeper research and managerial implications that are explored in the next section.

Table 5: Psycholinguistic Characteristics of Fine Art Consumer Segments

			Segment Means				ANOVA	
Variable	Mean	Std. Dev.	Open introverts	Average Joes	Closed Extroverts	Agreeable Introverts	F(3,24)	*p* value
Analytic	26.0	12.08	45.9	28.4	16.1	21.4	9.562	*p* < 0.001
Clout	35.8	14.69	45.5	33.0	47.0	17.0	7.375	0.001
Authentic	55.6	17.84	30.6	58.3	49.0	78.4	9.232	*p* < 0.001
Tone	78.0	10.27	81.6	74.1	80.5	81.5	0.950	0.435

General Discussion

Marketers have long sought to find ways of gaining insight into customer behaviors in order to segment markets in more insightful ways than simple demographic or geographic data. In their efforts to do so they have usually had to resort to self-report surveys of customers reporting their activities, interests and opinions (e.g., Darden and Perreault, 1975). In the three analyses reported above, this paper shows how quantitative psychographic market segmentation can be obtained from the transcripts of conversational qualitative depth interviews using tools such as artificial intelligence platforms, automated text analysis tools such as LIWC, and statistical tools such as correspondence analysis. This approach provides insights to marketing research and practice that are discussed below, along with the paper's limitations and avenues for future research.

Implications for High Involvement Consumption Behavior

While the setting for this research was the collection of art by consumers, the approach followed here would be applicable in most other high involvement purchasing and consumption situations (Zaichkowsy, 1985). For example, nowadays consumers talk extensively online in reviews and commentaries on a spectrum of high involvement offerings ranging from meals in fine restaurants, to travel adventures, to experiences of their surgeries such as knee replacements and chemotherapy. While this paper has used the collection of art as the domain to be studied, the approaches followed here could be pursued in a multiplicity of other areas. Specifically, with regard to the collection of art, while the motivations for collecting fine art have received considerable scholarly attention, there is less known about 'who' the art collector is, particularly concerning 'ordinary' art collectors. This article contributes to closing this gap by identifying the personality profiles based on the 'Big Five' personality traits of art collectors and developing groupings of homogenous categories (clusters) of art collectors. This not only adds to a more nuanced understanding of art collectors in the literature but also offers a number of implications for practice, as outlined in the following section.

This study sought to answer the following research question: What is the personality of a typical art collector? Specifically, this research suggests that art collectors can be described with respect to their 'Big Five' personality traits. To answer this question, the paper outlines a study in which in-depth transcribed interviews with art collectors were subjected to an automated text analysis using Watson's personality insights service. The data obtained in this way was then used in a correspondence and clustering procedure to identify homogenous groups of consumers with common personality traits. The findings reveal that the 'typical' art collector is highly emotional and agreeable, but less conscientious, less open to experience, and more introverted than extroverted. This is a deviation from the literature, which suggests that openness to new experiences in particular is a common personality trait of art collectors. The findings also reveal some correlations between personality traits, more specifically, a negative association between "Extroversion" and "Emotion". According to Eysenck's (1972) seminal work on the Big Five, individuals who score low on neuroticism (or high on emotional stability) are less easily upset and are less emotionally reactive. They tend to be calm, emotionally stable and less vulnerable to stress. For art collectors in particular, high emotional stability might allow individuals to seek stimulation in the company of others and thus gain greater enjoyment or value from art.

For marketing practitioners our findings point to four distinct clusters of art collectors that can be used to segment the arts market, to describe the characteristics of each identified customer segment, and to devise effective marketing and positioning strategies. In addition, this article provides a new and innovative way for managers to segment markets in general, thus expanding practitioners' market segmentation toolbox. While the focus here was on the personalities of art collectors as described by the 'Big Five' traits, the tools used here can be applied to any text corpus, including the words of individuals and groups in society, business, community leaders and politicians to uncover individuals' values, needs, personalities, the overall sentiment of, and the emotions expressed in a conversation or piece of text. This, in turn, enables decision makers to get a better understanding of those involved and hopefully, to craft better strategy or policy accordingly.

Methodological Contributions

The paper provides two methodological and two substantive contributions to market segmentation research. First, this paper outlines a method of extracting quantitative psychographic characteristics from qualitative interview data for the purposes of segmentation. It utilizes an artificial intelligence algorithm to naturally process the language contained in the interview transcripts to generate personality profiles for further segmentation using correspondence analysis. After identification, these segments can be further comparatively analyzed using not only automated text analysis tools (e.g., LIWC, DICTION, WordStat, see Humphreys and Wang 2017) as demonstrated above, but also more traditional analysis methods using sociodemographic or behavioral data. Thus, this paper contributes to the mixed methods literature (Fakis et al., 2014; Harrison, 2013) by demonstrating a method that can provide answers using a series of qualitative and quantitative techniques empowered by advanced computing.

Second, this paper shows how correspondence analysis can be used in marketing research when data are not in the form of simple counts or frequencies, which is common with nominal variables, but rather in the form of percentiles. This kind of correspondence analysis uses a "doubling" procedure that results in positive and negative poles of data in percentage form, as described in detail above. Thus, the paper provides a step-by-step analytical process that can be used by other researchers facing the same data constraints, which are common when employing advanced computing methods, including artificial intelligence or automated text analysis, to observe psycholinguistic or other variables in qualitative data. While the doubling technique has been described and used previously, this paper is the first as far as we know to outline a step-by-step procedure for doing this that can be followed by any researcher.

Table 6: A Summary of the Methods Used in the Study Implications for Practice

What it is?	Artificial Intelligence and Machine Learning tool on IBM's Watson cloud platform	A statistical technique to analyze data in rows and columns in tables	Dictionary-based automated text analysis software
What it does?	Derives scores on the Big Five personality traits of the author of a piece of text	Establish correspondence between the data in rows and columns	Matches words in text against pre-defined dictionaries and counts these according to categories
What is required?	Access via any online device to the free website	Available on most modern statistical software packages such as SPSS, JMP	Licensed software available for purchase
What is the input?	At least 1,000 words of text on any subject by a single author that can be copied and pasted into the platform	Row and column data	Words by a single author in a word processing file (e.g. .doc, .docx, .txt) or in a spreadsheet
What is the output?	Percentile scores on each of the Big Five personality traits for the author of a corpus of text.	Tables and multidimensional plots of rows versus columns in >1 dimension	Spreadsheet data with documents in rows and scores of the documents on various dimensions in columns
What questions it answers?	What are the personality traits of the author of a corpus of text?	What is the inertia of the rows and columns in a data table?	How does the author of a corpus of text score on various LIWC dictionary categories?
What can users learn?	How different authors of text can be compared to each other on the Big Five personality traits	How the data in the rows and columns contribute to the dimensions of a two-dimensional map, and how the rows and columns are similar/different to each other	How different authors of text can be compared to each other on the various LIWC dictionary categories

Third, this paper reported the results of comparative psycholinguistic characteristics in the third analysis. These insights can aid in the further collection of new qualitative data. For example, the Closed Introvert segment did not speak analytically about their fine art collection or associated behaviors. Researchers can use insights like these to alter further interviews or interactions with other consumers by tailoring questions to gain insight into those that do not speak naturally about a certain topic (e.g., analytical details).

The three main methods employed in this study, namely IBM Watson, correspondence analysis and LIWC, are summarized in Table 6 below. In the table, for the convenience of the reader, each tool or method is briefly described, as well as its function, what is required to use it, what the input and output are, what the questions are that it can answer, and what users can learn from the tool.

Marketers are always searching for new ways of gaining insight into how their customers think and behave, in order to best design marketing strategies that will effectively target specific market segments. Psychographic segmentation has been around for more than forty years (Wells, 1975), and has traditionally relied on large scale surveys to identify the activities that consumers engage in, what they are interested in, and what their opinions are on a range of issues. The rationale behind the approach was that while two consumers might be identical demographically (same gender, same age, same income, same education etc.), they might be very different with regard to how they spent their time, what they were interested in and what they thought about different issues. Stated even more simply, their personalities might differ. Gathering the data that this type of segmentation has required has always been expensive and time consuming, and has typically either involved large scale surveys using long questionnaires, or subjecting consumers within a population to personality measures such as the "Big Five", and then subjecting this data to further analysis, typically using Q-Factor sorts.

The approach described in this paper suggests alternative ways of gathering and analyzing data that can provide insights into consumer behavior that can assist in market segmentation and targeting. There is a host of information available in text, much of it online and usually free to access. This text can be used in place of surveys and interviews to assess a variety of constructs such as personality, values and more specific dimensions of behavior such as the LIWC variables referred to. While the study reported here used the text obtained in a series of depth interviews, it should be remembered that similar data can often be obtained online in the form of reviews and blogs.

Using personality assessment tools such as those on the Watson platform is relatively easy, and automated text analysis tools such as LIWC are inexpensive and also easy to use, not only by marketing academics but by practitioners too. While the scores produced by these tools are frequently in the form of percentiles, the doubling technique suggested in this paper for use in correspondence analysis overcomes this limitation. Correspondence analysis in turn provides an effective, and especially visual way of comprehending multivariate data in a way that managers can not only understand and distinguish among groupings or segments but can also use to plan future marketing strategies in order to best reach those segments. When coupled with tools such as LIWC, the identified segments can be understood even more effectively.

Limitations and future research avenues

Like all studies, ours is not without its limitations. The research is limited by a relatively small sample, which, although very acceptable for a qualitative in-depth study, may limit the generalizability of the results in a quantitative sense. Further research could address this with larger samples. Additionally, study respondents were talking about a specific topic, namely the collecting of art, which might impact how the natural language processing software assesses individuals' personalities in a general sense, although, at the same time, this raises an opportunity for additional research. Future studies could investigate whether, and to what extent the personality traits derived from analyzing an art collectors' recount of their preferences and behavior differ from traits derived from a personality trait scale. The further application of the LIWC dimensions in this study, and that the fact that the identified segments were also significantly different on three out of four of these does provide some face validity for the identification of the segments by personality dimensions; however, it would be interesting and worthwhile to subject individuals to both a computerized personality assessment of their writing and compare this to an actual test of their personality on the Big Five dimensions. For example, using the short measure of the Big Five model developed by Gosling, Rentfrow and Swann (2003), the scores on the five dimensions could be compared between text-based measures and those measured on a scale.

Also, the relationship between personality traits and art consumption behavior could be a fruitful avenue for further inquiries. While our study focused on fine arts collectors in general, future studies could explore the relationship between personality traits and genres of art individuals collect, such as representational, abstract or non-objective art.

Concluding Thoughts

This paper uses the data gathered from in-depth interviews with consumers (in this case art collectors) as input to an artificial intelligence program that assesses their personalities based on the words they use and how they use them. While marketing researchers have long used depth interviews to gain qualitative consumer insights, the approach employed here adds another dimension to this type of research by enabling quantification. Numerical data can then be used as inputs to multivariate statistical techniques such as correspondence analysis and clustering and in this way shed more light on the homogenous groupings that might exist within a heterogeneous set of respondents. The tools available to researchers today in many ways bridge the traditional divide between qualitative and quantitative approaches to research.

Marketers will always seek greater insights into consumers in order to target offerings to specific groups in more effective ways. In the past, the search for these insights has always focused on asking consumers questions, whether by way of structured survey questionnaires or by qualitative means such as focus groups and depth interviews. The advent of the internet has meant that consumers also generate insight into themselves, by reviewing or blogging or engaging in social media. This has meant an explosion in the amount of data that is available to marketers, and it has also necessitated the development of new tools that enable the gathering, processing and interpretation of this data. The research in this paper has focused on one specific group of consumers, namely art collectors, and shows the use of two tools to make more sense of what they are saying about themselves. It then shows how this data can be further analyzed using well known statistical tools. In this sense, the paper is specific in its focus. However, we would contend that similar approaches could be used in any number of different market situations and in this way uncover phenomena that would previously not have been apparent. Consumers who collect things are especially enthusiastic about these pursuits, and share their insights and experiences on websites and on blogs. The text generated and available on these platforms can be analyzed in the same way that has been described in this study, and provide insight into both individual consumer behavior and at a more macro-level in the form of potential market segments. Moving beyond the activity of collection, text data generated by individuals provides a rich source of information for marketing decision makers.

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APPENDIX: SEMI-STRUCTURED INTERVIEW GUIDE

Section A: Rapport-Building Questions

1) How long have you been collecting art for?
2) Is there a particular area of fine art that you invest in?
3) How did you begin investing in art?
4) What is your favourite piece that you currently own?

Section B: Decision-Making Questions

1) What is your most valuable piece of art that you currently own? What makes it valuable?
2) In general, how do you decide on art purchases you make?
3) How much does your emotion play a role in your decision-making?
4) How much does what you know about the artist play a role in your decision-making?
5) Has anyone guided you as you began to buy/invest in artwork?
6) Taking you back to the first painting you purchased, tell me about the piece? How did you decide to ultimately purchase?
7) How did it feel purchasing the painting? Where is it now? If you still own the painting, how much would you sell it for?
8) Do you see your collection as a financial investment? Why or why not? Have you ever sold a painting you invested in?
9) Why do you invest in art as opposed to other goods?

Section C: Deeper Psychological Questions

1) Do you display the art work you own? If so, where?
2) Have you ever purchased a painting to commemorate a certain event?
3) Have you ever bought a painting you think is ugly or offensive? If so, what motivated you to purchase the painting?
4) Are there any paintings you chose not to buy that you now regret passing up? Or paintings you bought that you wish you hadn't?
5) Have you ever gotten a painting as a gift? If so, how much would you sell the painting for?
6) Have you ever given a painting as a gift? Do you know what the receiver did with the gift you gave?
7) If money wasn't an issue and there were no logistical restrictions, what painting would you buy for resale? To keep forever? Why?

Section D: Conclusion Question

1) Is there anything else that I should have asked you that I didn't?