Segmentation Of The Off-Peak Wine Tourist In Canada's Niagara Region

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ABSTRACT

This paper segments the off-peak wine tourist in Canada's Niagara region. Three factors, Wine Knowledge (cognition), Winery Enjoyment (affect), and Winery Behaviour (behavioural intention), grounded in attitude theory, were discovered.

INTRODUCTION

The nascent wine tourism industry in Canada's Niagara region faces dramatic seasonal climatic variations not found in many other wine producing regions of the world. The difficult Canadian winters provide the world's best ice-wine, but simultaneously provide significant challenges for the wine tourism industry. Most Niagara wineries remain open year-round, to the amazement of many tourists, and not a few locals. Canadians do not run from winter; we embrace and celebrate it. We admit to being a bit strange, but how does one explain the tourists who make pilgrimages to Niagara wineries when there is snow on the ground? Who are these people, and why are they here?

This paper posits that these winter wine tourists have very different levels of involvement with wine and with adventurous tourism than do the local off-peak wine customers. Understanding these differences in involvement, if in fact they exist, is critical for the development of effective advertising and promotional campaigns. Strategies for changing attitudes through advertising are predicated upon a clear understanding of the involvement levels of the person to whom the advertising is directed (Maheswaran and Meyers-Levy, 1990), and it would seem likely that Canadians trying to promote winter wine tourism may need to change a few attitudes.

Involvement is the degree of personal relevance of an object, product, or service to a customer (Sheth and Mittal, 2004). Involvement has been explored as an explanatory construct in the purchase of wine, and as a basis for wine consumer segmentation (Berti, 2003; Lockshin, 2001; Zaichkowsky, 1985). Many studies have treated involvement as a unidimensional construct, whereas more recent involvement research has demonstrated that involvement consists of more than one dimension (Cullen and Edgett, 1991). One study (Edgett and Cullen, 1993) demonstrated that the degree (high vs. low) and the type of involvement (cognitive vs. affective) influences the type of information utilized by consumers in making purchases.

THE STUDY

Study Design and Data Collection

A two-page questionnaire was distributed to customers by winery staff at the tasting bars of four Niagara wineries in December 2003 and January 2004. The wineries participating in the study tended to be among the larger winery operations in the region. There was no prescreening of respondents, and no quota. Every customer approaching the tasting bar in the winery was to have been offered a free taste of wine for a completed questionnaire. Informal mystery shopping by confederates of the researchers, however, suggests that many potential respondents were not approached. No data were collected on the numbers who refused to participate. Ultimately, 164 usable questionnaires resulted from the three-week data collection period. The instrument used for data collection included items from the involvement scale utilized by Berti (2003), items adapted from Cullen's (1990) Shopping Involvement scale, and items generated through interviews with Niagara wineries, twenty items in total, listed in Table 1.

Table 1: Items And Some Descriptive Statistics

Item	N	Mean	Skeweness	Std. Err.	Kurtosis	Std. Err.
v1_Drinking wine gives me pleasure	164	6.08	-1.821	.190	4.221	.377
v2_I feel competent about the subject of wine	163	4.52	-.227	.190	.004	.378
v3_I have a strong interest in wine	164	5.33	-.542	.190	-.215	.377
v4_I don't know much about wine compared to other people	162	3.67	.345	.191	-.430	.379
v5_I like to take my time when I purchase a bottle of wine	164	4.84	-.652	.190	.803	.377
v6_I am perceived as somewhat of a wine expert among my friends	162	3.68	-.028	.191	-.879	.379
v7_I don't understand very much about wine	164	3.15	.619	.190	-.127	.377
v8_Wine is something important for me	162	4.92	-.534	.191	.566	.379
v9_Shopping for wine is fun	163	5.61	-.876	.190	.777	.378
v10_Where I buy wine is irrelevant to me	163	3.79	.118	.190	-.768	.378
v11_Wineries are a great vacation destination	164	5.42	-.872	.190	.692	.377
v12_The appear. of a winery is a good indic. of the quality of wine	163	4.56	-.428	.190	-.612	.378
v13_I prefer to buy wine dir. from wineries than from other source	164	4.88	-.259	.190	-.118	.377
v14_The décor of a winery is of no concern to me	161	3.39	.424	.191	-.379	.380
v15_I often plan my vacations around wine and wineries	163	3.43	.157	.190	-.578	.378
v16_Wineries are a great place to take guests or visitors	164	5.85	-1.029	.190	1.511	.377
v17_I seldom go to wineries	164	3.14	.515	.190	-.608	.377
v18_Visiting wineries is less about the wine than the experience	164	3.79	.097	.190	-.190	.377
v19_Wine is an excellent gift to give and receive	164	6.26	-2.077	.190	5.352	.377
v20_Wineries should stay open all year	164	6.29	-2.165	.190	5.094	.377

DATA ANALYSIS

Detection Of Outliers

The data were examined for the presence of outliers both from a univariate and multivariate perspective. These two approaches complement each other. An observation can be an outlier in the joint distribution of the variables without being an outlier in any of the univariate analysis (e.g., Tufte, 1983, p. 14).

Univariate descriptive statistics of each variable were calculated. Some of them are presented in Table 1. The variables were also standardized and cases with standard scores exceeding 3.0 recorded. Three questionnaires were subsequently re-examined. One respondent was found to be exceptionally and unusually negative about wine and wineries. All his responses were either "7 = Strongly agree" for negative Likert statements or "1 = Strongly disagree" for positive statements. On the other hand, this respondent indicated fairly frequent wine consumption (once per week), and wine publications as a source of info that brought him into the winery. He also pointed to "Visit wineries" as a purpose of the visit to Niagara. Based on these discrepancies, it was decided that this case be removed from the data. Similar discrepancies were found in the other two questionnaires.

The data were also examined from a multivariate perspective, with the principal components method. The resulting objects' scores in several multidimensional spaces (2 to 6) were hierarchically clustered with the Ward's method. One observation was a very distinct outlier and therefore it was discarded as well.

Factor Analysis

Assumptions

The correlation matrix was constructed from the twenty-item involvement scale then factor analyzed in order to condense the information contained in the twenty variables into a smaller set of new dimensions with a minimum loss of information. The typical for other techniques (e.g., regression analysis) assumptions of normality, homoscedasticity, and linearity, are not very important in factor analysis, unless one wants to apply statistical tests (rarely used) of the significance of the factors. In our case, the assumption of normality is particularly violated, because the data come from 7-point Likert scales measuring attitudes towards wine and wineries among the visitors to the wineries. Such data, by definition, are often skewed toward one end of the scale and, therefore, are not normally distributed (e.g., variables v1, v16, v19, and v20 in Table 1). Despite this lack of normality in some of the variables, the principal factor analysis can still be a useful tool for understanding the correlation structure (Iacobucci, 2001).

For the factor analysis to be appropriate, the variables must be correlated, because the objective is to identify interrelated sets of variables. Visual inspection revealed a substantial number of correlations greater than 0.30 or less than -0.30 (64 out of 190, i.e., 33.7%). Encouraged by this preliminary result, we tested the presence of correlations among the variables with the Bartlett's test of sphericity. The null hypothesis that the population correlation matrix is an identity matrix was rejected (χ^2 = 1053.3; df = 190; sig = 0.00). We also used another measure to quantify the degree of intercorrelations among the variables, the Kaiser-Meyer-Olkin measure of sampling adequacy. Its value was very large (MSA = 0.823) thus again indicating that these data were suitable for factor analysis. The Bartlett's test and the K-M-O measure examine the entire correlation matrix. A researcher should examine the adequacy for factor analysis not only on an overall basis but also for each variable separately. To this end, the main diagonal elements of the anti-image correlation matrix (matrix of the partial correlations among variables after factor analysis) can be visually inspected. These diagonal elements are the individual variables' measures of sampling adequacy (MSA) and should be at least 0.50. The variable with the lowest MSA below 0.50 should be removed, and the factor analysis repeated, etc., until all the MSA are greater than 0.50. Following this procedure, we removed two variables from the data set: v12, with MSA = 0.458, and v14, with MSA = 0.453.

Factors

The VARIMAX rotation of the factors summarizing the remaining 18 variables resulted in four (based on the scree test and the cumulative variance) interpretable factors. Except for two items, v1 and v3, all items loaded on a single factor. These two items were therefore removed from the data set, and the factor analysis repeated. Factor scores for each factor were calculated using the regression approach and saved for further analysis. The full scales, factor loadings, and the final reliabilities are provided in Table 2.

The first factor, labeled Wine Knowledge, accounted for 29.9% of the variance. Cronbach's alpha for its five items was 0.784. This factor appears to represent the self-proclaimed wine knowledge of the respondents. The second factor, labeled Winery Affect, accounted for 13.2% of the variance. Its four items, with a Cronbach's alpha of 0.760, seem to reflect the participants' level of enjoyment with respect to visiting and shopping for wine at wineries. The third factor, Winery Behaviour, accounted for 8.2% of the variance. Cronbach's alpha for its five items was 0.694. This factor gives the impression to be related to behavioral intention with respect to wineries. These three factors appear to tap into the dimensions of the classic Tri-partite Theory of Attitudes: Cognition – Affect – Behaviour (Solomon et al., 2002). The fourth factor has a low Cronbach's alpha (0.324), but seems to be related to those consumers who are indifferent to the way they buy wine.

Table 2: Rotated Component Matrix

Item\Component	1	2	3	4
V2_I feel competent about the subject of wine	.754			
V4_I don't know much about wine compared to other people	-.750			
V6_I am perceived as somewhat of a wine expert among my friends	.716			
V7_I don't understand very much about wine	-.686			
V8_Wine is something important for me	.597			
V19_Wine is an excellent gift to give and receive		.858		
V20_Wineries should stay open all year		.797		
V16_Wineries are a great place to take guests or visitors		.618		
V9_Shopping for wine is fun		.579		
V15_I often plan my vacations around wine and wineries			.788	
V11_Wineries are a great vacation destination			.629	
V13_I prefer to buy wine directly from wineries than from other sources			.627	
V5_I like to take my time when I purchase a bottle of wine			.549	
V17_I seldom go to wineries			-.486	
V10_Where I buy wine is irrelevant to me				.781
V18_Visiting wineries is less about the wine than the experience				.640
Eigenvalue	4.787	2.120	1.302	1.211
Percentage of variation	29.9%	13.2%	8.2%	7.6%
Coefficient alpha	.784	.760	.694	.324

Extraction Method: Principal Component Analysis. Rotation Method: VARIMAX with Kaiser Normalization.
Loadings less than .400 have been suppressed.

Cluster Analysis

Outliers

Cluster analysis was used to develop consumer segments. The factor scores estimated from the solution to the four involvement scales were used as the input to hierarchical cluster analysis with Ward's method. We used factor scores rather than the raw data, because raw data contain interdependencies that are likely to bias the cluster solution (Singh, 1990). In its search for structure, cluster analysis is very sensitive to outliers which can greatly distort the final solution. For this reason, a preliminary screening for outliers is always necessary. As we have already mentioned, before conducting factor analysis we tested our data set for the presence of outliers from univariate and multivariate (principal components method) perspectives. For the purpose of cluster analysis we also checked its input (the factor scores) for the presence of outliers. There were two factor scores exceeding 3.0 or -3.0 and hence they were removed from the data set.

The Number Of Clusters

The first step was to select the optimal number of clusters for analysis. To get an idea of the number of clusters, we followed the procedures recommended by Punj and Stewart (1983).

The initial Ward's hierarchical cluster analysis suggested between three and six clusters, based on the agglomeration coefficients and the dendograms. Then, the sample was randomly divided into two parts (app. 50% each) – the analysis sample and the holdout sample.

Ward's hierarchical cluster analysis was carried on the analysis sample, and cluster centroid vectors were obtained for the number of clusters ranging from three to six. K-means cluster analysis was then performed twice for each number of clusters, the first time using the centroids from the analysis sample (a constrained approach), and the second time using the centroids obtained from the holdout sample with Ward's procedure (an unconstrained approach). The degree of agreement between the assignments of objects to clusters based on the constrained and unconstrained approach is an indication of the stability of the solution (Punj and Stewart, 1983). A coefficient of agreement, kappa, may be used as an objective measure of stability. The three, four, five, and six cluster solutions produced kappa of 0.216, 0.644, 0.500, and 0.543, respectively. Since the decision criterion is to maximize kappa, the four cluster solution was chosen. It's presented in Table 3 along with the cluster sizes.

Description Of The Clusters

We label and describe these clusters as follows:

- *Cluster 1 (22%):* Wine Neophytes who appreciate wineries, but do not relish them. This cluster represents consumers who absolutely do not consider themselves wine experts (Cognition = -1.10386). Although they have positive attitude toward wine and wineries (Affect = .30786), these consumers will not make any planned effort in order to visit a winery and/or buy wine there (Behaviour = -.64568).
- *Cluster 2 (21%):* Wine Connoisseurs who appreciate wineries, but do not really care where they buy their wine. Describes consumers who consider themselves wine experts (Cognition = .38084) and think very highly of wine and wineries (Affect = .42576). This knowledge and love for wine does not, however, translate to behaviour that would make wineries happy. These wine lovers are only average on visits /plans involving wineries (Behaviour = .03724). They really do not care from where they get their wine. (Indifference = 1.35597).
- *Cluster 3 (39%):* Wine Connoisseurs who exhibit an affinity for both wine and wineries (39%). Depicts consumers about whom wineries dream. They are highly knowledgeable wine/wineries aficionados (Cognition = .39298, Affect = .33099) who tend to organize their leisure time around wine and wineries (Behaviour = .28657) and absolutely positively care where they buy their wine (Indifference = -.73576).
- Cluster 4 (18%): Hangers on. That's who they seem to be. They are low on wine knowledge (Cognition = -.13144) and extremely detached from wine or wineries (Affect = -1.46946; Indifference = .20093). Despite all this they do visit wineries (Behaviour = .28923), probably accompanying Cluster 3 members.

Table 3: Final Cluster Centers*

Factors	Cluster			
	1 (n=33)	2 (n=31)	3 (n=58)	4 (n=28)
Cognition	-1.10386	.38084	.39298	-.13144
Affect	.30786	.42576	.33099	-1.46946
Behaviour	-.64568	.03724	.28657	.28923
Shopping Indifference	-.14761	1.35597	-.73576	.20093

* Note: the cluster descriptors are based on factor scores that have a mean of zero and standard deviation of one.

External Validity Check: Factor Differences Across Clusters

Multiple discriminant analysis was used to test the differences among the four factors across the four clusters. The factors scores were treated as independent (metric) variables and the K-means vector of cluster assignments as the dependent (categorical) variable.

Assumptions of discriminant analysis. The assumptions of discriminant analysis were tested. They involve the formation (normality, linearity, and multicollinearity) and estimation (equal covariance matrices) of the discriminant function. The normality was tested with the K-S test. The results of the test (Table 4) provide strong evidence that none of the null hypotheses as to the normality of the factors can be rejected at the .05 significance level.

Table 4: One-Sample Kolmogorov-Smirnov Test

	Cognition	Affect	Behaviour	Shopping Indifference
Kolmogorov-Smirnov Z	.541	1.174	.480	.772
Asymp. Sig. (2-tailed)	.932	.127	.975	.590

Since the factors were obtained through the orthogonal rotation, they cannot be multicollinear. In order to test the assumption of equal covariance matrices, the Box's M test was used. The following statistics were obtained: Box's M = 40.949; approx. F = 1.291; df1 = 30, df2 = 38,062; p = .132. Since p>.05, the null hypothesis cannot be rejected at the .05 significance level.

Estimation of the discriminant functions and assessing overall fit. Discriminant functions were estimated with the direct method. We used this method because we wanted the discrimination to be based on all the four predictors. The hypotheses of equality of group means across the clusters can be decisively rejected for each factor at the significance levels well under .05 (Table 5). This indicates that when the factors are considered individually, each of them is significant in differentiating between the four clusters.

Table 5: Tests Of Equality Of Group Means

Factors	Wilks' Lambda	F	df1	df2	Sig.
Cognition	.629	28.716	3	146	.000
Affect	.451	59.230	3	146	.000
Behaviour	.836	9.526	3	146	.000
Shopping Indifference	.416	68.326	3	146	.000

Three discriminant functions were extracted (Table 6). Each eigenvalue accounts for a substantial amount of the explained variance, which makes each of the three functions important in discriminating among the four clusters. This is confirmed also by Wilks' lambdas associated with different combinations of the functions (Table 7). Each combination significantly discriminates among the four clusters. Overall, the discrimination model is significant with Wilks' lambda = .089, chi-square = 351.5 (df = 12), and p = .000.

Table 6: Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.568	41.6	41.6	.781
2	1.189	31.6	73.2	.737
3	1.008	26.8	100.0	.708

Table 7: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 3	.089	351.453	12	.000
2 through 3	.227	214.689	6	.000
3	.498	101.071	2	.000

Assessing group membership prediction accuracy. The final step of assessing overall model fit is to determine the predictive accuracy level of the discriminant functions. To accomplish this, we calculated a classification matrix obtained with the "leave-one-out" cross-validation procedure (Table 8). Instead of randomly dividing the total sample into analysis and holdout samples once, this procedure is repeated (n -1) times, each time eliminating one observation from the original sample.

Table 8: Classification Results (b,c)

		Cluster	Predicted Group Membership				Total
			1	2	3	4	
Original	Count	1	30	0	3	0	33
		2	0	28	3	0	31
		3	0	0	58	0	58
		4	0	0	1	27	28
	%	1	90.9	.0	9.1	.0	100.0
		2	.0	90.3	9.7	.0	100.0
		3	.0	.0	100.0	.0	100.0
		4	.0	.0	3.6	96.4	100.0
Cross-validated(a)	Count	1	29	0	4	0	33
		2	0	27	3	1	31
		3	0	0	58	0	58
		4	0	0	1	27	28
	%	1	87.9	.0	12.1	.0	100.0
		2	.0	87.1	9.7	3.2	100.0
		3	.0	.0	100.0	.0	100.0
		4	.0	.0	3.6	96.4	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
b 95.3% of original grouped cases correctly classified.
c 94.0% of cross-validated grouped cases correctly classified.

The hit ratio for the analysis sample is 95.3%, whereas that for the holdout sample is 94.0%. Although both hit ratios are extremely high, they must be compared with chance criteria in order to assess their "true" effectiveness. There are several such criteria available, for example, chance ratio, maximum chance criterion, proportional chance criterion, or Press's Q statistic. Because the cluster sizes were different, we calculated the proportional chance criterion (PCC) and obtained PCC = $.22^2 + .21^2 + .39^2 + .18^2 = .277$. However, because the maximum chance criterion MCC = .39 is greater than PCC, we used the MCC as the final criterion. The rule of thumb suggests multiplying the final criterion by 1.25 and comparing the result with the hit ratios. Obviously, in this case, both the overall hit ratios and individual hit ratios calculated for each group separately are much higher than 49% (=1.25*MCC). This result indicates that the discriminant analysis predicts cluster membership much better than chance.

Interpretation of the multiple discriminant analysis results. The Structure Matrix (Table 9) indicates that Function 1 is positively associated with Indifference (.791) and negatively with Affect (-.536), Function 2 is positively associated both with Indifference (.591) and Affect (.787), and Function 3 is positively associated with Cognition (.764) and Behaviour (.377).

These comments can subsequently be interpreted based on Table 10 of functions evaluated at group centroids. It can be seen that Clusters 2 and 4 have the highest values (1.672 and 1.337, respectively) on Function 1, and Clusters 3 and 1 the lowest (-1.216 and -.537, respectively). Because Function 1 is primarily positively associated with Indifference (.791 in Table 9), one would expect the four clusters to be ordered on this variable. Those with high Indifference are likely to belong to Clusters 2 and 4, whereas those with low Indifference to Clusters 3 and 1. This finding corresponds amazingly well with the description of the clusters provided in Table 3.

Table 9: Structure Matrix

Factors	Function		
	1	2	3
Shopping Indifference	.791(*)	.591	.089
Affect	-.536	.787(*)	.174
Cognition	.008	-.039	.764(*)
Behaviour	.032	-.206	.377(*)

Pooled within-group' correlations between discriminating variables and standardized canonical discriminant functions. Variables ordered by absolute size of correlation within function.

(*) Largest absolute correlation between each variable and any discriminant function.

Table 10: Functions At Group Centroids

Clusters	Function		
	1	2	3
1	-.537	.599	-1.729
2	1.337	1.554	.756
3	-1.216	-.357	.705
4	1.672	-1.686	-.261

Unstandardized canonical discriminant functions evaluated at group means

In Table 10 it can also be seen that Clusters 2 and 1 have the highest values on Function 2 (1.554 and .599, respectively), and Cluster 4 the lowest (-1.686). Function 2 is primarily positively correlated with Affect (.787 in Table 9), so Clusters 2 and 1 should contain consumers with high Affect, and Cluster 4 with low Affect, which they do (Table 3).

Finally, Clusters 2 and 3 have the highest values on Function 3 (.756 and .705, respectively), and Cluster 1 the lowest (-1.729). Function 3 is primarily associated with Cognition (.764 in Table 9) and Behaviour (.377), so Clusters 2 and 3 should be high on Cognition and Behaviour, and they are (Table 3). On the other hand, Cluster 1 is, indeed, low on Cognition and Behaviour (Table 3).

The consistent similarities between the discriminant and cluster solutions give us confidence that the four factors do significantly discriminate across the four clusters.

External Validity Check: Wine Consumer Differences Across Clusters

Another means of testing the differences across clusters is to compare the proportions for each of the clusters using the other measures collected, such as demographics, wine consumption frequency, etc. Results from Pearson's goodness-of-fit tests across the clusters are provided in Table 11. The null hypothesis of independence or homogeneity of proportions across the clusters is rejected for large values of the test statistic. It can be seen that variation across the four clusters is significant ($p<.05$) for demographics (gender, age categories 18_24, 35_44 and 45_54, postgraduate education, medium income), wine consumption (consumption of wine 3 times per week, white wine), city of residence (tourists from the Niagara Region, from the USA), purpose of visit to Niagara (visit wineries, other unspecified reasons), source of info about the winery (other unspecified sources).

The results suggest that at least one or two categories from each group of variables vary significantly across the four clusters thus providing additional external validity check for the four-cluster solution.

Assigning Consumer Measures To The Clusters

Based on these findings, we offer the following additional sketches of the four cluster groupings:

- *Cluster 1 (22%):* Wine Neophytes who appreciate wineries, but do not cherish them. This cluster primarily represents females (72%), and consumers with medium or upper medium income (63%) and the lowest proportion among all the clusters of high-income earners (27%). This group has the second largest proportion (18%) of young (18-24 years of age) people. A substantial majority of the group (69%) drinks wine rarely (once a week or twice a month). They appear to be indifferent to the colour of wine (mostly red – 41%, mostly white – 35%). However, this proportion of white wine drinkers is the largest for a single cluster among all the clusters. In other words, if any group is biased in any way towards the white wine, this is Cluster 1. These consumers are also the least undecided as to the colour of wine – only 24% of them declare drinking both red and white. These consumers are not locals (only 10% of the cluster). They arrive mainly from the USA (34%) and the Greater Toronto Area (31%) with the purpose other than visit wineries (they represent only 15% of those in the total sample who declared wineries as their destination choice). They also represent the largest percentage (38%) of the total sample who found the winery by chance, thanks to the road signs, and the lowest (6%) of those who learned about the winery from a website. They appear to be accidental tourists who had other unspecified reasons (31%) for visiting the Niagara Region.
- *Cluster 2 (21%):* Wine Connoisseurs who appreciate wineries, but do not really care where they buy their wine. This group includes mainly males (69%) with the largest proportion of people above 45 years (45%) old and high-income earners (41%). It has also the lowest proportion (10%) of low-income consumers. This cluster has the largest proportion among all the clusters of those who drink wine every day (33%). Only 13% of the group drinks mostly white wine (the worst result for white wine across all the clusters). They arrive mainly from Ontario (37%) and the Greater Toronto Area (30%). The percentage structure of the purpose of their visit to the Niagara Region is very similar to that of Clusters 3 and 4, i.e., they emphasize sightseeing the wineries (35%). The source of information about the winery is, however, different from the other clusters. This group is proportionally the highest (23%) on the use of the Internet in the search for their winery, although almost every fifth of them (19%) got to the winery by following the road signs.
- *Cluster 3 (39%):* Wine Connoisseurs who demonstrate their affinity for wine and wineries. This is the largest among the four clusters, which should be good news to wineries. Males (55%) and females (45%) are almost evenly distributed in it, with the largest proportion (19%) of very young people (18-24 years) – another bit of good news. They are even larger wine drinkers than Cluster 2. An amazing 76% of the group drinks wine at least three times per week (19% every day). They are more into red (39%) than white wine (25%) and come rather evenly distributed from the four regions, although this cluster includes the largest proportion of locals (27%). They (similarly to Cluster 4) show the largest proportion of other than the web, road signs, friends, or wine publications, sources of information about the winery.
- *Cluster 4 (18%):* Hangers on. They are mostly males (69%) with the largest proportion of those in their younger-middle age (77% between 25 and 44 year old). They drink red (39%) rather than white wine (18%). A majority of them arrived from the Greater Toronto Area (44%) and the USA (36%) – the largest percentages among the four clusters. They learned about the winery from their friends (48%) – the largest percentage across the four clusters.

DISCUSSION

There are four types of off-peak winery tourist in Canada's Niagara region: the Neophytes, the Connoisseurs who cherish wineries, the Connoisseurs who do not cherish wineries, and the Hangers On. These four segments differ along managerially relevant dimensions such as demographics, wine consumption, purpose of trip, and information source utilized for selection of winery destination. The underlying basis for this segmentation was the classic ABC model of attitude formation. These segments can now be used for prioritizing winery communication strategy and expenditures. It is clear that signage, for example, is critical for generating winery patronage behaviour. Some signage is the responsibility of the individual wineries, but it is also imperative that government agencies responsible for the tourist industry pay careful attention to the need for clear and comprehensive signage in the Niagara region of Canada.

There are some limitations to this study, and several directions for additional research. Foremost among the limitations is that the data were collected during one season, and from only four wineries. Research is currently planned to collect data in each of the three remaining seasons, and from more wineries, to examine whether the segments will change.

Table 11: Pearson's Goodness-of-Fit Test

Count (% within) (% across)	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Chi-square (p-value)
Male	9 (28%) (12%)	20 (69%) (27%)	26 (45%) (36%)	18 (69%) (25%)	8.151 (.043)
Female	23 (72%) (32%)	9 (31%) (13%)	32 (55%) (44%)	8 (31%) (11%)	22.333 (.0)
Age18_24	6 (18%) (27%)	3 (10%) (14%)	11 (19%) (50%)	2 (8%) (9%)	8.909 (.031)
Age25_34	10 (30%) (22%)	8 (28%) (17%)	15 (25%) (33%)	13 (50%) (28%)	2.522 (.471)
Age35_44	9 (27%) (24%)	5 (17%) (13%)	17 (29%) (45%)	7 (27%) (18%)	8.737 (.033)
Age45_54	5 (15%) (16%)	11 (38%) (35%)	13 (22%) (42%)	2 (8%) (6%)	10.161 (.017)
Age55up	3 (9%) (30%)	2 (7%) (20%)	3 (5%) (30%)	2 (8%) (20%)	0.4 (.527)
High school diploma	3 (9%) (18%)	5 (17%) (29%)	7 (13%) (41%)	2 (7%) (12%)	3.471 (.325)
University degree	22 (67%) (23%)	20 (69%) (21%)	32 (59%) (34%)	21 (72%) (22%)	3.905 (.272)
Postgraduate degree	8 (24%) (24%)	4 (14%) (12%)	15 (28%) (45%)	6 (21%) (18%)	8.333 (.04)
Income_Low	3 (10%) (11%)	7 (24%) (26%)	9 (16%) (33%)	8 (28%) (30%)	3.074 (.38)
Income_Medium	9 (30%) (26%)	4 (14%) (11%)	16 (29%) (46%)	6 (21%) (17%)	9.457 (.024)
Income_Upper Medium	10 (33%) (31%)	6 (21%) (19%)	12 (21%) (38%)	4 (14%) (13%)	5 (.172)
Income_High	8 (27%) (16%)	12 (41%) (24%)	19 (34%) (38%)	11 (38%) (22%)	5.2 (.158)
Consumption_1xday	4 (12%) (13%)	10 (33%) (31%)	11 (19%) (34%)	7 (25%) (22%)	3.75 (.29)
Consumption_3xwk	6 (18%) (11%)	9 (30%) (16%)	33 (57%) (59%)	8 (29%) (14%)	34.714 (.0)
Consumption_1xwk	11 (33%) (38%)	5 (17%) (17%)	9 (16%) (31%)	4 (14%) (14%)	4.517 (.211)
Consumption_2xmonth	12 (36%) (38%)	6 (20%) (19%)	5 (9%) (16%)	9 (32%) (28%)	3.75 (.29)
Mostly white wine	12 (35%) (33%)	4 (13%) (11%)	15 (25%) (42%)	5 (18%) (14%)	9.556 (.023)
Mostly red wine	14 (41%) (23%)	13 (42%) (21%)	23 (39%) (38%)	11 (39%) (18%)	5.567 (.135)
Both white and red wine	8 (24%) (15%)	14 (45%) (25%)	21 (36%) (38%)	12 (43%) (22%)	6.455 (.091)
From the Niagara Region	3 (10%) (12%)	5 (19%) (19%)	16 (27%) (62%)	2 (8%) (8%)	19.231 (.0)
From Greater Toronto Area	9 (31%) (21%)	8 (30%) (19%)	14 (24%) (33%)	11 (44%) (26%)	2 (.572)
From the Ontario Province	7 (24%) (22%)	10 (37%) (31%)	12 (20%) (38%)	3 (12%) (9%)	5.75 (.124)
From the USA	10 (34%) (25%)	4 (15%) (10%)	17 (29%) (43%)	9 (36%) (23%)	8.6 (.035)
To visit Falls	6 (19%) (21%)	4 (13%) (14%)	12 (20%) (41%)	7 (24%) (24%)	4.793 (.188)
To visit wineries	7 (22%) (15%)	11 (35%) (23%)	20 (33%) (42%)	10 (34%) (21%)	7.833 (.05)
To attend a special event	4 (13%) (25%)	3 (10%) (19%)	4 (7%) (25%)	5 (17%) (31%)	2.375 (.305)
To visit a historic city	5 (16%) (23%)	4 (13%) (18%)	9 (15%) (41%)	4 (14%) (18%)	1.182 (.554)
Other reason	10 (31%) (27%)	9 (29%) (24%)	15 (25%) (41%)	3 (10%) (8%)	7.865 (.049)
Info from a website	1 (3%) (6%)	7 (23%) (41%)	8 (14%) (47%)	1 (3%) (6%)	3.647 (.161)
Info from road signs	10 (32%) (38%)	6 (19%) (23%)	7 (12%) (27%)	3 (10%) (12%)	3.846 (.279)
Info from friends	13 (42%) (24%)	10 (32%) (18%)	18 (31%) (33%)	14 (48%) (25%)	2.382 (.497)
Info from wine publications	3 (10%) (18%)	3 (10%) (18%)	9 (15%) (53%)	2 (7%) (12%)	4.353 (.113)
Info from other sources	4 (13%) (11%)	5 (16%) (14%)	17 (29%) (49%)	9 (31%) (26%)	11.971 (.007)

It is clear that there are segments of off-peak winery tourists. We have identified that differences among these four segments exist. We do not know, however, *why* these differences exist. It seems apparent that additional consumer behaviour research, perhaps through laddering, into the underlying values of winery tourists would be beneficial. This would also serve as a check on the implicit value-laden advertising campaigns currently employed in attempts to attract Canadian wine drinkers to the Niagara region.

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