AUTHOR
TITLE

PUB DATE NOTE

PUB TYPE

EDRS PRICE DESCRIPTORS

IDENTIFIERS

## ABSTRACT

A market segmentation analysis was conducted on students at a large midwestern urban university using two forms of hierarchical cluster analysis on student characteristics: an agglomerative procedure using a matching-type association measure and a divisive chi-square based automatic interaction detection (CHAID) procedure. Data were extracted from institutional records and a survey of 872 students concerning satisfaction with 48 different campus aspects and importance of 18 goals for college study. Eight clusters resulted from a matching-type measure/Ward's method clustering analysis, while the CHAID procedure resulted in a six cluster solution. Comparative analysis revealed that both procedures produced differences across only $\cdots$, of six satisfaction scales. The matching-type measure clusters resulted in significant differences on 11 of 18 college study priority items compared to only 6 of 18 for the CHAD clusters. The study concludes that the matching-type measures/Ward's method procedure produced more easily interpretable clusters with more corresponding differences in student priorities for attending college. The CHAID procedure serves better when there is a single outcome of high interest for distinguishing among students, in this case general academic satisfaction. The usefulness of market segmentation strategies for planning, evaluating, and improving academic and student support programs is discussed. (Contains 20 references.) (Author/JDD)


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# Segmenting Student Markets 

## With a Student Satisfaction and Priorities Survey

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Paper Presented at the 34th Annual Forum of the Association for Institutional Research (AIR)

New Orleans, May 29-June 1, 1994

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This paper was presented at the Thirty-Fourth Annual Forum of the Association for Institutional Research held at The New Orleans Marriott, New Orleans, Louisiana, May 29, 1994 - June 1, 1994. This paper was reviewed by the AIR Forum Publications Committee and was judged to be of high quality and of interest to others concerned with the research of higher education. It has therefore been selected to be included in the ERIC Collection of Forum Papers.

Jean Endo<br>Editor<br>Forum Publications

# Segmenting Student Markets With a Student Satisfaction and Priorities Survey 

Victor M. H. Borden<br>Indiana University-Purdue University Indianapolis (IUPUI)


#### Abstract

A market segmentation analysis was conducted on students at a large midwestern urban university using two forms of hierarchical cluster analysis on student characteristics: an agglomerative procedure using a matching-type association measure and a divisive chi-square based automatic interaction detection (CHAID). The resulting segments were compared for their ability to distinguish among students according to six satisfaction scales and measures of students' priorities for college study derived from a general satisfaction survey. As expected, the CHAID clusters discriminated better among students according to their levels of satisfaction, although both procedures produced differences across only two of six satisfaction scales. The matchingtype measure clusters resulted in significant differences on 11 of 18 college study priority items compared to only 6 of 18 for the CHAID clusters. Final discussion describes the usefulness of market segmentation strategies for planning, evaluating, and improving academic and student support programs.


## Introduction

The student population at many universities is becoming increasingly diverse. Recent estimates indicate that over one-half of all current college students are older than 25 years and over one-half now attend college part-time (Jacoby, 1990). The increasing diversity of students, both in tenns of backgrounds and lifestyle, has led to a call for identifying meaningful subgroups of students when designing support programs (Borden \& Gentemann, 1993).

Market segmentation strategies provide methods for identifying important subgroups of students for needis assessment and program development (Wakstein, 1987). This paper describes a study that compares two hierarchical clustering procedures for deriving market segments: one
employing matching-type measures and an agglomerative clustering algorithm and another using the chi-square based automatic interaction detection (CHAID), a divisive algorithm using binary splits on categorical variables. The analyses use as input demographic characteristics of a sample of students at a large public midwestern urban university. The validity of the resulting market segments is explored using student responses to a general satisfaction survey.

## Market Segmentation in Higher Education

Bonoma and Shapiro (1983) define market segmentation as a "process of separating a market into groups of customers...such that the members of each resulting group are more like the members of that group than like members of other segments" (p. 1). They argue that this activity provides a better understanding of buying behaviors, the ability to choose market segments that a company can best serve, and support for the development of plans to profit from meeting the needs of targeted market segments.

The predominant use of market segmentation strategies in higher education has been in the development of college marketing and recruitment programs (Goldgehn, 1989; Grabowski, 1981; Merante, 1982). These methods have also been used for other areas of program development such as public relations (Grunig, 1990) and career planning and placement (Cowles \& Franzak, 1991). More generally, market segmentation has been suggested as a strategy for understanding college choice (Rickman \& Green, 1993; Muffo, 1987; Zemsky \& Oedel, 1983).

## Cluster Analysis as a Method for Segmenting the Student Market

Cluster analysis refers to any of a wide variety of numerical procedures that can be used to create a classification scherne. Clustering methods have long been recognized for their potential usefulness and recent versions of standard statistical packages (e.g., SAS, SPSS, BMDP) include a variety of ciustering procedures. Conceptually, cluster analysis is easy to understand and well suited to market segmentation. However, unlike other multivariate procedures, it is not supported by extensive statistical reasoning and its use of various heuristic strategies provides for inconsistent results (Aldenderfer \& Blashfield, 1984). Despite these limitations, cluster analysis
has been used successfully to define market segments as exemplified by Beder's (1986) study of adult basic education students.

Selecting Variables. The most popular forms of cluster analysis are based on measures of "similarity" among objects according to some combination of attributes. In the context of identifying student market segments, the objects are students and the attribuies can be virtually any student characteristics including personal or family demographics, levels of academic preparation, attitudes and interests, expectations and goals, program of study, college performance, etc. Because of the inherent inconsistency among various clustering procedures, Aldenderfer and Blashfieid (1984) argue that the choice of variables is one of the most critical steps in the analysis process and that it should be guided by an explicit theory.

The selection of variables for a student market segmentation analysis can be guided by both theory and practicality. Theories of student involvement in college, like those of Tinto (1975) and Astin (1987), propose that success in college is directly related to a student's ability to become involved, psychologically and behaviorally, in the college environment. Students' ability to become involved has, in turn, been positively associated with being a full-time student, living on campus, working on campus, and other time spent outside class on campus, while lack of involvement has been associated with number and strength of off-campus commitments, such as work and family.

On the practical side, higher education researchers typically have ready access to certain types of student characteristics from college and university operational information systems. These include such attributes as prior academic experience along with some measures of performance, personal and family demographics, and level of progress and performance in college. These are often supplemented by surveys to assess student satisfaction in college, reasons for attending college, as well as other aspects of students' lives, such as employment and living situation. From among these sources of information, one can select student characteristics that have been associated with levels of student involvement in the academic and social milieus of the
campus environment. These can include academic background, work and family commitments, living situation, and level of progress within college. The specific variables chosen for this study are presented in the method section below.

Choosing a Similarity Measure and Clustering Algorithm. After selecting variables, cluster analysis requires the selection of a similarity measure and a clustering algorithm. ${ }^{1}$ Similarity measures can be either measures of distance (geometric distance between points in a multi-dimensional space) or similarity (association or correlation coefficients). The type of variables chosen for analysis constrains the choice of similarity measure. When using nominal variables such as sex, marital status, and race, one must either use measures based on association coefficients ("matching-type" measures) or use a technique called chi-square based automatic interaction detection (CHADD).

The use of matching-type measures requires choosing a clustering algorithm. Clustering algorithms are generally based on hierarchical or partitioning techniques. Hierarchical algorithms can either start with each object occupying its own cluster and then fuse together clusters (agglomerative method) or start with one large group and divide the objects into smaller subgroups (divisive method). Partitioning techniques require the prior statement of number of clusters and then use a predefined criterion for optimizing distances between clusters. The choice of clustering algorithm is complex involving questions of expected geometric shapes of the resulting clusters, number of clusters present, overlap of clusters, and presence of outliers (Aldenderfer \& Blashfield, 1984). Hierarchical agglomerative methods, such as the average linkage method and Ward's (1963) error sum of squares method, have been most popular in the

[^0]social sciences. Ward's method, which is biased toward tight hyperspherical clusters, is utilized in this study to represent a popular hierarchical agglomerative clustering algorithm.
. Automatic interaction detection (AID) is a method of clustering developed by Sonquist and $\operatorname{vr}:-$ (1964) that has become increasingly popular for market segmentation analysis. Unlike other forms of cluster analysis, AID uses a criterion variable in addition to classification variables, so as to optimize cluster differences. AID is a hierarchical divisive method that uses binary splits to divide the sample into successive subgroups based on selecting a predictor variable that maximizes reduction in the unexplained variation of the criterion variable. Chi-square based automatic interaction detection (CHAD) can be used when at least some of the classification variables are measured on a nominal scale. The growing popularity of the CHADD procedure has been fostered by its availability in the popular software package SPSS. Lay and Maguire (1983) demonstrated the usefuiness of the CHAID procedure for estimating qualified inquiries from among a market of prospective applicants.

This study compariza the clusters derived from student characteristic data using Ward's method with a matching-type similarity measure to the clusters derived from the CHAID procedure. The results of the clustering procedures will be evaluated by their ability to distinguish among students according to their levels of satisfaction with various aspects of their college experience and their personal priorities for college study.

## Method

The data for this study were extracted from institutional records and a survey of undergraduate students enrolled in degree programs at a large midwestern urban university. The survey instrument included ratings of satisfaction with 48 different aspects of the campus, including acidenics, academic supports, and student support services. Students also related the importance of 18 goals for college study including ones relating to academic progress, career preparation, career improvement, social and cultural participation, and personal enrichment.

Finally, students provided information abcut their lives outside college, including employment and living circumstances.

Surveys were mailed to a sample of 1700 undergraduate degree-seeking students in the spring 1993 semester and responses were received from 872 students ( $51.3 \%$ ). The respondents were found to represent the student population in terms of ethnicity, major, class level, course load status. The sample over-represented women ( $67 \%$ in sample; $60 \%$ in population) and older students ( $57 \%$ aged 25 or older in sample; $45 \%$ in population).

Clustering Characteristics. A matching-type measure of similarity requires that the classification variables be converted into binary (0-1) variables. To do this, each characteristic (e.g., sex) has to be converted in a series of variables, one for each value ${ }^{2}$ (e.g, male-0,1; and female-0,1). For the CHADD procedure, as supported by the SPSS software, the classification variables can have as many as 31 distinct values. The CHAID procedure will create subsets of the categories on each variable that maximize between group variation and minimize within group variation. Table, 1 shows the student characteristics that were used in the clustering procedures with the corresponding variables employed for the matching-type measure analysis and the corresponiding values for the CHAID analysis.

[^1]Paper presented at the 34th Annual AIR Forum, New Orieans, May 29-June 1, 1994

Table 1. Student Characteristics Used in Cluster Procedures.

| Student Charactoristic | Clustering Procedure |  |
| :---: | :---: | :---: |
|  | Matching-type Measure (N) | CHAID |
| Academic Unit | 6 Variables | 17 values including 14 academic schools, undeclared majors, continuing studies and a sattelite campus |
|  | Undeclared (222) |  |
|  | Arts and Sciences (170) |  |
|  | Nursing (93) |  |
|  | Engineering \& Tech (94) |  |
|  | Satellite Campus (51) |  |
|  | All Other (224) |  |
| Maritai Status | 3 Variables | 3 values-single, married, separated/widowed/divorced |
|  | Single (462) |  |
|  | Married (307) |  |
|  | SeparMidow/Divorce (93) |  |
| Children at home | 2 Variables | 2 values-yes, no |
|  | Yes (276) |  |
|  | - No (586) |  |
| Work hours | 4 Variables | 15 values (Cuns then groups based on increments of five hours-1-5, 6-10...66-70) ORDERED |
|  | Not working (178) |  |
|  | 1-19 hourstwk (117) |  |
|  | 20-35 hours/wk (235) |  |
|  | $36+$ hours/wk (343) |  |
| Course Load | 3 Variables |  |
|  | 1-6 hours (309) |  |
|  | $7-11$ hours (160) |  |
|  | 12+ hours (404) |  |
| Clase Lever | 4 Variables | 4 Values (froshman, sophomore, junior, senior) |
|  | Freshman (198) |  |
|  | Sophomore (264) |  |
|  | Junior (154) |  |
|  | Senior (247) |  |
| First Generation Status | 2 Variables | 2 Values (yes, 0 - |
|  | Yes (512) |  |
|  | No (349) |  |
| Age | 4 Variables | $\overline{2} \overline{2}$ values ( 18 or less, then single year increments through 27,2 year increments through 52, and $53+$ ) ORDERED |
|  | 15-21 (234) |  |
|  | 22-25 (210) |  |
|  | 26-34 (235) |  |
|  |  |  |
| Sex | 2 Variables | 2 Values (Male, F--- ${ }^{\text {Female }}$ ) |
|  | Female (573) |  |
|  | Male (286) |  |
| Minority Status | 2 Variables | 7 values (standard EEO catagoriea) |
|  | Minority (129) |  |
|  | Not Minority (726) |  |

## Criterion and Validity Variables.

A principal components factor analysis with vari-max rotation was conducted on the 48 student satisfaction items. Six different satisfaction subscales were identified. Variables with factor loadings greater than 0.50 were included in each of the six sc es but the actual scales were constructed using unit weights, rather than factor loadings. Table 2 displays the resulting scales along with their reliability coefficients (Cronbach's alpha). The first scale represents a more general rating of students' satisfaction with academics and subsequent scales related to more specific support areas, such as financial aid and computer availability. These scales were employed to compare the results of the two clustering procedures.

Students indicated their personal priorities for college study by rating each of 18 items as being of low, medium, or high importance. Table 3 lists the 18 items that students rated organized into the general areas of academic, career-preparation, career-improvement, social and cultural participation, and personal enrichment.

## Clustering Procedures

All clustering procedures were performed using SPSS ${ }^{\circledR}$ for Windows ${ }^{\text {TM }}$ Version 6.0 software. Matching-type measures using binary data are based on counts of the number of attributes that are present or absent among cases. That is, for each possible pairing of subjects, a two-by-two matrix is formed with counts of the number of attributes that both subjects have in common (both have or both do not have), and the two ways in which one subject has the attribute and the other does not. Different distance measures can be calculated depending on which cells are included in calculating the association coefficient. For the current analysis, the Jaccard measure was used, which excludes the counts for when both subjects do not have the attribute. This was chosen to exclude missing values that were coded as zero on all attribute variables for a given characteristic (e.g., if sex is :nissing then male $=0$ and female $=0$ ). The resulting coefficient is the number of attributes both subjects have in common over the total number of attributes considered.
Victor M. H. Borden-Segmenting Siudent Markets...
Täble 2. Satisfaction Scales Derived from a Student Satisfaction Survey.

| General Academic Satisfaction (alpham.85) | Academic Facilities (alphax.73) | Student Support Climate (alpha=.69) |
| :---: | :---: | :---: |
| Overall Quality of Instruction <br> Relevance of Classes to Work <br> Relevance of Classes to Life <br> Academic Advising in a School <br> Information about course requirements <br> Discussion with Faculty <br> Information about major requirements <br> Getting through to staff on the telephone <br> General helpfulness of faculty <br> General helpfulness of staff <br> General helpfulness of administrators <br> Getting courses in needed sequence | Spaces for group study <br> Spaces for individual study <br> Library hours <br> Library holdings <br> Uses of technology for learning <br> Finding an available computer <br> Getting help with computers <br> Quality of laboratories <br> Classroom environ (iighting, heating, ..) <br> Getting books for classes | Opportunities for cultural events <br> Diversity of students <br> Diversity of facully <br> Opportunities to live near campus <br> Opportunities for student employment <br> Opportunities for extra-curricular activities <br> Getting food on campus <br> Counseling for personal probiems <br> Tutoring services <br> Availability of child care |
| Financial Aid (alpha $=.74$ ) | Admissions and Orientation (alpha $=.75$ ) | Availability of Classes (alpha $=.74$ ) |
| The process of applying for financial ald Getting information about financial aid Obtaining financial aid checks The amount of financial aid available The process of paying for classes | Process of applying for admissions Information received prior to applying Orientation services | Availability of evening classes Availability of weekend classes Availability of classes at off-campus sites |

## Table 3. Personal Priorities for College Study: Survey Items. <br> Academic Goals

To increase my knowledge and understanding in an academic field
To obtain a certificate or degree
To complete courses necessary to transfer to another college/university
To increase my grade-point average

## Career-Preparation Goals

To discover career interests
To formulats, long-term career plans and/or goals
To prepare for a new career
Job or Career-improvement Goals
To improve iny knowledge, skills, and competencies for my job or career
To increase my chances for a raise and promotion
To get a better job
Social- and Culturai-Participation Goals
To become actively involved in student life and campus activities
To increase my participation in cultural and social events
To meet people
Personal-Development and Enrichment Goals
To increase my self-confidence
To improve my leadership skills
To improve my ability to get along with others
To learn skills that will enrich my daily life
To develop my ability to be independent, self-reliant, and adaptable

The general academic satisfaction scale was chosen as the criterion variable for the CHAID procedure and an ordinal analysis was performed to match the scale of this criterion. For the CHAID procedure, clustering is performed using one predictor variable at a time. Typically, objects are first clustered according to the predictor that accounts for the largest differences on the criterion variable. Subsequent clusters are identified by taking the next most significant predictor and breaking up the first set of groups according to the values of the second predictor. Different predictors may be selected for each cluster formed by the preceding predictor. The user can create different solutions by choosing different combinations of predictors during different passes. Automatic mode was chosen to let the CHAD procedure build the cluster tree starting with the most significant predictor and continuing until no further significant predictors were found.

## Results

## Cluster Solutions

Table 4 shows the eight clusters that resulted from the matching-type measure/Ward's method clustering analysis. Each cluster is identified by the profile of student demographics and is described according to the distinguishing features of that profile. For example, Cluster M1 is characterized by younger students ( $83 \% 18-21$ years old compared to $27 \%$ of full sampie), who are first generation college students in their families ( $91 \%$ compared to $60 \%$ of sample), single ( $97 \%$ compared to $54 \%$ of sample), and attend college full-time ( $92 \%$ compared to $46 \%$ of sample). An empty cell within a cluster signifies that the group does not differ significantly from the population profile on that characteristic.
Victor M. H. Borden-Segmenting Student Markets...
Table 4. Eight Cluster Solution Using Matching-Type Measure/Ward's Method Analysis

|  | $N$ | $\begin{aligned} & \text { Meritol } \\ & \text { Statese } \\ & \text { (pat.single) } \end{aligned}$ | Children at Home (pot. Yes) | Work Status | Course load (\% full-lime) | Class Leval | Firat Genneration (pat. yes) | Age | Sex (pct. fomale) | Mincrixy Straus (pat. minority) | Description |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Full Sample | 87\% | 54\% | 32\% | 20\% Not; 40\% FT | 46\% | even | 60\% | 27\% 18-2; 40\% 35+ | 67\% | 15\% |  |
| M1 | 85 | 97\% | 0\% |  | 92\% |  | 91\% | $\begin{gathered} 83 \% 18-21 ; \\ 1 \% 35+ \end{gathered}$ |  |  | Young, 1st generation, single, full-time students |
| NR | 119 | 93\% | 0\% |  | 85\% |  | 14\% | $\begin{gathered} 52 \% \text { 18-21; } \\ 1 \% 35+ \end{gathered}$ | 88\% |  | Fultime, not ist gen., single women students |
| M3 | 79 | 88\% | 1\% |  | 86\% | 67\% Senior |  | 10\% 35+ |  | 2\% | Single, non-minority, fulltlme seniors |
| M4 | 55 | 86\% | 4\% | 47\% Not; 2\% FT | 74\% |  | 25\% | $\begin{gathered} 63 \% \text { 18-21; } \\ 2 \% 35+ \end{gathered}$ |  | 88\% | Minority full-time sludents |
| MS | 198 | 68\% | 5\% | 4\% Not; 69\% FT | 7\% |  |  |  |  |  | Part-time student, fulltime worker, no children |
| M6 | 194 | 10\% | 81\% | 73\% FT | 6\% |  | 75\% | $\begin{aligned} & 4 \% 18-21 ; \\ & 70 \% 35+ \end{aligned}$ | 97\% |  | Older, fü-time working. part-time student whamily |
| M7 | 82 | 4\% | 80\% | $\begin{gathered} 53 \% \mathrm{Na}: \\ 3 \% \mathrm{FT} \end{gathered}$ |  |  | 85\% |  |  |  | Non-working Adult student with family |
| M8 | 61 | 3\% | 54\% |  | 70\% |  | 9\% | $\begin{gathered} 6 \% ~ 18-21 ; \\ 4 \% 35+ \end{gathered}$ | 15\% |  | Heavy work, school, and family obligations |



## Paper presented at the 34th Annual AIR Forum, New Orieans, May 29-June 1, 1894 <br> 16

The first four clusters generally represent full-time students who are relatively young, single, and have no children. Cluster M1 is distinguished among this group as having the youngest students who are first-generation college goers. Cluster M2 includes the non-firstgeneration female students. Cluster M3 has many senior-level students and few minorities. Finaily, within this group of more "traditional" college students, Cluster M4 contains the majority of the sample's minority students who tend to have lower course and work load levels compared to the other three clusters.

The last three clusters contain relatively older students who are married and have children. Cluster M6 includes the oldest group of students, almost exclusively females, who work full-time and take only one or two courses. Cluster M7 includes many adult learners who are either out of work completely or work part-time while maintaining as much as a full-time course load. Cluster M8 contains adult students who maintain significant work, family, and school obligations.

Cluster M5 represents a middle-ground between the first four and last three clusters. Like the first four clusters and unlike the last three, this group is not likely to have significant family obligations. Unlike the first four clusters, they tend to maintain a part-time course-load while working full-time. This group is typical of the full sample, that is, diverse, in terms of class level, first generation status, age, sex, and minority status.

Figure 1 shows the cluster tree that resulted from the CHAID analysis using the general academic satisfaction as the criterion variable. Although the criterion is treated as an ordinal categorical variable in the procedure, Figure 1 displays the normalized group average for the satisfaction scale. Therefore, for the full-sample, the base value is zero and the values for clusters represent stuidard deviation units from the overall mean.
Victor M. H. Borden--Segmenting Student Markets...
Figure 1. CHAID Cluster Tree Using General Academic Satisfaction as the Criterion.


The single best predictor of differences students' general academic satisfaction was the academic unit in which the student was enrolled. Three clusters of academic units emerged as indicated in Figure 1, with the first cluster having the highest average satisfaction ratings and the third group the lowest. The second pass of the analysis split the first cluster into two additional groups, the first containing freshinan, sophomore and juniors, and the second containing all seniors. A different predictor was identified for the second academic unit cluster. Here the group was subdivided according to sex. A third pass found age to be a further significant predictor within the male cluster, separating students under 25 years old from those who were 25 or older. There were no further predictors of satisfaction among the third academic unit group.

When all significant predictors had been found, the CHAID procedure resulted in a six cluster solution. Clusters C 1 and C 2 represent the non-seniors and seniors, respectively, from the first set of academic units. Clusters C 3 and C 4 represent the younger and older males, respectively from within the second academic unit group, and Cluster C5 represents the female students from the second academic unit group. Finally, Cluster C 6 represents all students in the third academic unit group.

## Cluster Validity

To compare cluster solutions, differences among clusters were examined according to the overall student satisfaction ${ }^{3}$, and the six satisfaction scales and 18 goal items described earlier. Tables 5 show the results of these comparisons for the matching-type measure/Ward's method and CHAID analyses, respectively. The table includes only those items for which significant differences were found for either set of clusters at the $p=.05$ level ${ }^{4}$.

[^2]Table 5. Differences in Student Satisfaction and Priorities by Cluster Set.

|  | Matching Type Clusters |  |  |  |  |  |  |  |  | CHAID Clusters |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | p-level | C1 | C2 | C3 | C4 | C5 | C6 | p-level |
| Overall Satisfaction |  |  |  | -- |  |  |  |  | * | ++ | + |  |  |  | -- | *** |
| Satisfaction Scales |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| General Academic | -- | - | + |  |  |  |  |  | * |  | ++ |  | ++ |  | -- | *** |
| Financial Aid |  |  |  |  |  |  |  |  |  |  | + | -- | + |  |  | ** |
| Availability of Courses |  | $+$ | ++ |  |  | - |  |  | ** |  |  |  |  |  |  |  |
| Goals |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Cbtain degree |  |  |  |  |  |  |  |  |  |  | - |  | -- |  |  | *** |
| Transfer courses | + |  |  | ++ |  |  | -- |  | *** |  |  |  |  |  |  |  |
| Improve GPA | ++ | ++ | - | ++ |  | - | -- |  | *** |  | -- | + | -- |  |  | *** |
| Find Career interests | + | , |  |  |  | - |  |  | * |  | - |  |  | + |  | ** |
| Set career goals | ++ |  |  |  |  | -- |  | + | *** |  | - |  | - |  |  | * |
| Find new career |  |  |  |  |  | - | ++ | + | ** |  |  |  |  |  |  |  |
| Get a raise |  | -- | - |  |  |  |  |  | ** |  |  |  |  |  |  |  |
| Be involved on campus | + | + | + | ++ |  | -- | -- |  | *** |  |  | ++ |  |  |  | * |
| Attend camp. events |  |  | + | + |  |  |  |  | ** |  |  |  |  |  |  |  |
| Meet new people | ++ | ++ |  | ++ |  | -- |  |  | *** |  |  | ++ | - |  |  | * |
| Get along w/others |  | + |  |  |  |  |  |  | * |  |  |  |  |  |  |  |
| Gain independence | + |  |  |  |  | - |  |  | * |  |  |  |  |  |  |  |

$* p<.05 ; * p<.01 ; * * p<.001$
$++(-)$ more than (less than ) 0.25 standard deviation units above mean.
$+(-)$ between 0.20 and 0.25 standard deviation units above (below) mean

The two different cluster solutions are associated with a number of significant differences in student satisfaction and priorities. The CHAID clusters yield larger differences in student satisfaction. This is to be expected since the CHAID procedure used the general academic satisfaction group as the criterion variable. On the other hand, the matching-type clusters also yielded some significant differences in student satisfaction and yielded generally larger differences in student priorities, neither of which were used to form the clusters. Each set of cluster solutions produced differences in only two of the six satisfaction scales (general academic for both, financial aid for CHAID, and course availability for Matching-Type). The Matching-Type procedure yielded significant differences on 11 of the 18 pricrity items, while the CHAID analysis yielded differences on only 6 of them.

For the Matching-Type clusters, the difference in student priorities corresponds in expected ways with the Cluster composition. For example, Cluster M5, which represented the "middle-ground" group is also found in the middle ground with respect to satisfaction and priorities. Clusters M1 through M4, which represent the more traditional students, have higher priorities for involvement on campus and personal enrichment, while the older student clusters show generally lower priorities in these areas. Cluster M7, which includes many out-of-work adults, shows a high interest in finding a new career. As a final example, the older working students, who are attending school part-time (Cluster M6) do not appear to be as driven by ihese college study goals. One would expect that these students are less involved in college than others who are looking for more specific social, academic, and career gains from their college experience.

The results of the CHAID clustering are not as easily interpreted. The groups with the highest level of general academic satisfaction (the criterion variable) tend to rate some critical college study priorities relatively low. Specifically, Clusters C2 and C4 are the most satisfied, but appear to care less than the others about obtaining a degree or improving their GPA.

Furthermore, the least satisfied group, Cluster C6, shows average levels of priorities across all
items. The young male students in Cluster C3 do appear more interested in the campus social climate compared to members of the other clusters.

## Implications

Market segmentation strategies hold great promise for program planning and evaluation, especially at large institutions that serve diverse student populations. It is becoming increasingly clear that programs cannot be designed for a typical student when students differ so greatly, nor are resources available to make individualized approaches to program development feasible.

Cluster analytic procedures are useful for identifying market segment for programmatic planning, design, and evaluation, but these procedures impose some complex challenges for the researcher. There are many choices for measuring similarity between cases and for choosing a clustering algorithm. The literature for evaluating cluster methods and solutions is geared more toward conceptual issues such as geometric shape and density and less toward conditions of applied research.

The present study set out to compare two specific types of clustering solutions that can be used for higher education market segmentation based on common measures of student characteristics. Of the two procedures compared in this study, the matching-type measures/Ward's method procedure produced more easily interpretable clusters with more corresponding differences in student priorities for attending college. The ability to target students based on known or knowable demographic characteristics can be very useful to support service development or targeted market penetration.

The CHAID procedure serves better when one has a single outcome of high interest for distinguishing among students. In the present study, the CHADD results were more directly related to differences in general academic satisfaction. These results were included in an internal report on the satisfaction results and led those academic units at the low end of the satisfaction scale to ask for further analyses to better understand and work to improve the sources of student dissatisfaction.

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[^0]:    ${ }^{1}$ For a brief treatment of the topic of cluster analysis, see Dillon and Goldstein (1984) and Aldenderfer and Blashfield (1984). A more complete treatment of clustering algorithms is available in Hartigan (1975). Sokal and Sneath's (1963) book Principles of Numerical Taxonomy is often cited as the seminal work in this field.

[^1]:    ${ }^{2}$ It is possible to use a variable for all but one of the values and have the last value represented by zero values for all other variables. For the present study, all values were represented by a variable and the all zero value condition was reserved for missing values.

[^2]:    ${ }^{3}$ The overall student satisfaction was measured by a single item that asked students "Overall, how satisfied are you with your experiences at this university." Responses were allowed in one of four categories: 'very satisfed', 'satisfied', 'dissatisfied', and 'very dissatisfied'.
    The reader can refer back to Tables 2 and 3 for the complete set of items.

