

Are There Underlying Subpopulations of College Attachment?

An Application of Mixture Modeling.

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## Abstract

Prior research in the domain of attachment has implied that there may be qualitatively distinct latent classes of attachment. These latent classes were hypothesized to be characterized by asymmetries in the levels of group and member attachment. The current study provided a preliminary investigation into the meaningfulness of the latent classes that emerged when studying student responses to the University Attachment Scale. Three ordered classes emerged that also differed in form. Class 1 embodied the attachment profile of common-identity groups defined in prior research: students were higher on group than member attachment. Class 3 embodied the attachment profile of common-bond groups; students were approximately equal on group and member attachment. Class 2 fell between Class 1 and 3 with respect to both magnitude and form. In order to better inform class membership and gather construct validity evidence for the classes, two covariates were used to predict latent class membership. We found that feelings of morale toward the university differed across classes in expected ways (e.g., higher morale for Class 1 than Class 2 or 3) and the odds of being in Class 1 versus Class 2 or 3 were significantly lower if a student transferred to the university. Given that interpretation of the classes from a single study is premature and possibly misleading, the importance of a programmatic study of these classes was noted.

**KEYWORDS:** university attachment, group attachment, member attachment, mixture modeling, latent profile analysis

Peter, Megan, Carol, and Pamela are students enrolled at James Madison University (JMU). However, they each have different levels of attachment to the university itself versus to the members of the university. For example, Peter has strong attachment to JMU. When describing himself, he always mentions that he is a JMU student and does what he can to promote the university (e.g., wears JMU t-shirts, donates money to the university). In addition, Peter has many close friends at JMU, for which he has developed strong attachments. Megan also identifies strongly with JMU; it was her first choice out of all the colleges to which she applied, and she is proud to be a JMU student. However, Megan has weak attachment to the members of JMU because she has not made many friends or developed strong interpersonal relationships. Carol, on the other hand, has many very close friends who attend JMU. However, Carol has very weak attachment to the university itself. JMU was not her first choice and she does not identify herself as a JMU student. She would much rather be a Virginia Tech student. Finally, Pamela has weak attachment to the university itself and to the members of the university. She is looking into transferring to a different school.

As highlighted in this example, people's attachment to the *members of a group* (members of JMU) and attachment to the *group itself* (JMU) may be similar or different. The current study investigated if particular types of attachment profiles existed within a college student population. That is, instead of profiling levels of group and member attachment for the entire population of university students (i.e., reporting an average group attachment score and an average member attachment score for the entire population), it may be more accurate to profile attachment scores for subpopulations of students. Unlike common analyses such as ANOVA or MANOVA which could be used to compare levels of group and member attachment across *known* populations

(e.g., gender, ethnicity, members of various organizations), mixture modeling allows the comparison across underlying, *unobserved* (latent) subpopulations (Gagné, 2006).

Before investigating the existence of distinct subpopulations of university attachment, we briefly introduce the theoretical conceptualization of attachment in general and then highlight the importance of assessing *university* attachment. We also introduce mixture modeling and explain how this technique can answer important questions surrounding the existence of university attachment subpopulations, which are represented by distinct attachment profiles.

### *Group and Member Attachment as Distinct Constructs*

The importance of studying and profiling both group and member attachment has become an area of interest in social psychology over the last decade. Unfortunately, for many years the two leading theories in the domain (social cohesion and social identity) focused on either attachment to the members of the group or attachment to the group itself, but not both (Prentice et al., 1994). Briefly, social cohesion theorists believed group formation was entirely a function of individual member relationships; as members were attracted to one another, they were consequently attracted to the group as an entity (Allport, 1962; Hogg & Abrams, 1988; Hogg & Turner, 1985; Turner, 1982). However, social identity theorists uncovered the phenomenon of “minimal groups”, which challenged the social cohesion model (Turner, 1982). In minimal groups, people form group attachment based on trivial criteria (e.g., preference for a painting), without having any contact or even knowing the other members in their group (Billig & Tajfel, 1973; Tajfel, 1981).

The merger of the social cohesion model (focused on member attachment) and social identity theory (which allowed for the possibility of group attachment without member attachment) led researchers to consider the importance of assessing levels of *both* member and

group attachment (Hogg & Abrams, 1988; Karasawa, 1991; Prentice et al., 1994; Sassenberg, 2002; Utz, 2003; Utz & Sassenberg, 2002). The distinction between member and group attachment has been empirically studied using various construct labels (i.e., attachment, cohesion, attraction, identity/identification, relationships), and these studies have been conducted in various domains such as sports teams (e.g., Carron & Chelladurai, 1981; Hogg & Hardie, 1991), social clubs (e.g., Prentice et al., 1994), and Internet communities (e.g., Utz, 2003; Utz & Sassenberg, 2002). For example, Hogg and Hardie (1991) found personal attraction (similar to member attachment) and social attraction (similar to group attachment) to be empirically distinct. Moreover, when studying attachment in a vocational school context, Karasawa (1991) found support for the distinction between member and group attachment for Japanese students. Similarly, Prentice et al. (1994) supported the distinction between member and group attachment in the context of social organizations within an American university. In sum, results of empirical studies have suggested that feelings toward the members of a group can be different from feelings for the group itself.

#### *Why is it Important to Study Group and Member Attachment?*

*Correlates of Group and Member Attachment.* Researchers have theorized that attachment might be related to adherence to group norms (Sassenberg, 2002), group welfare (Utz & Sassenberg, 2002), group evaluation (Karasawa, 1991; Utz, 2003), and duration of membership (Utz, 2003). For example, norms of a group (expectations of attitudes, beliefs, and behavior) dictate how members of a particular group should behave (Hogg & Abrams, 1988). Groups populated with members having high group attachment should be more likely to adhere to group norms than groups populated with members having lower group attachment. This

hypothesis was supported using on-line communities that differed in their group and member attachment profiles (Sassenberg, 2002).

Group welfare also differed depending on level of group and member attachment. Specifically, it was hypothesized that a group dominated by individuals with low member attachment and high group attachment would display pro-group behavior, whereas a group dominated by individuals with high member attachment and low group attachment would make choices biased in an egocentric direction because individual goals, not group goals, would be dictating behavior (Utz & Sassenberg, 2002). To study this phenomenon, participants were assigned to one of two experimental conditions: “high member” condition (assumed to elicit high member attachment) vs. “high group” condition (assumed to elicit high group attachment). The results indicated that individuals in the “high member” condition tended to be more egocentric in their decisions, whereas individuals in the “high group” condition acted more for the welfare of the group.

Several studies have also found that group cohesion/attachment is positively related to the evaluation of the group (see Brewer, 1979, for a review). The more group members identify with the group (i.e., the higher group attachment), the more positive they described their group compared to an outside group (Utz, 2003). In fact, strong group attachment has been found to buffer the effect of group inferiority on evaluation of the group (Karasawa, 1991).

Attachment has also been correlated with duration of membership. More specifically, member attachment was positively correlated with duration of group membership, whereas group attachment was not (Utz, 2003). The longer a person is part of a group, the more opportunity to develop interpersonal relationships. For example, an individual may initially join a group due to the characteristics or purpose of the group (e.g., student government) and have immediate high

group attachment; however, member attachment will likely increase over time due to interactions with group members. Obviously, this pattern may not be salient for all individuals. For example, students may join a Greek organization because their close friends join that same organization; yet, they may feel little attachment to the actual organization, its cause, or ideals. However, group attachment may still develop over time as the student is further exposed to the values and mission of the group. Again, empirically, the relationship between duration of membership and member attachment was positive, whereas the relationship with group attachment was found to be nil.

*Why Study Attachment in a University Context?* Given the previous research identifying the various correlates of group and member attachment, it would seem that knowing students' level of university attachment would have utility in informing our understanding of college student behavior and attitudes. Specifically, do students with different attachment profiles differ on important academic-related variables? In related lines of research, identification or connection to a university (similar to group attachment) and relationships with peers (similar to member attachment) have been theorized, and in some studies found, to relate to a number of affective and behavioral variables in post-secondary education (Astin, 1985; Chickering, 1974; Kuh, Schuh, & Whitt, 1991; Light, 2001; Pascarella, 1985; Pascarella, Duby, Terenzini, & Iverson, 1983; Tinto, 1987). For example, students with high group attachment should be more likely to follow the social norms of the university (e.g., respect the facilities, follow the rules). Conversely, students with low group attachment may be more likely to rebel against these norms (e.g., vandalize university property, disrespect the university staff). This phenomenon, known as Tinto's theory of student departure (Pascarella & Terenzini, 2005), has received empirical support in a middle-school context: sense of school connectedness (analogous to group

attachment) was inversely related to delinquent behavior and drug use (Battistich & Hom, 1997; Resnick et al., 1997). Moreover, given the positive relationship found between group attachment and pro-group behavior, one may posit that students who are attached to their university may become involved. This involvement may subsequently benefit their school through their participation in altruistic university-sponsored organizations such as student government and resident advising

Furthermore, the role of attachment in the post-secondary context is important because students with high university attachment are likely to evaluate their university more positively and report enjoyment and satisfaction of the collegiate experience (Astin, 1993; Light, 2001). Consequently, students who report positive evaluation of the university may demonstrate higher motivation for involvement in group activities (Bollen & Hoyle, 1990; Chin, Salisbury, Pearson, & Stollak, 1999).

Attachment may not only be influenced by the length of time one belongs to a group; attachment may also *influence* the duration of one's membership. Specifically, attachment to an institution (group attachment) has been theorized to be associated with persistence in college (Tinto, 1987) and secondary schools (Finn, 1989). This connection between attachment and persistence is a critical for post-secondary educators as students who are attached to a university may tend to persist and graduate rather than drop-out.

Finally, university attachment may also be related to important academic outcomes. The relationship between academic outcomes and social relationships/school belonging has mostly been studied in primary and secondary schools (see Osterman, 2000 for a review of this literature). For example, in primary and secondary schools, it was found that school belonging (group attachment) was related to achievement (e.g., GPA) and academic valuation (Anderman

& Anderman, 1999; Goodenow, 1993a, 1993b; Goodenow & Grady, 1993). Additionally, relatedness to peers and teachers (member attachment) has been associated with engagement in middle school (Furrer & Skinner, 2003). Finally, university belonging has been investigated in relation to achievement motivation for college students at the classroom level (Freeman, Anderman, & Jenson, 2007). Classroom belonging was positively related to academic self-efficacy, intrinsic motivation, and value of academic tasks.

### *Profiling Attachment Using Known Groups*

Clearly, studying university attachment may shed light on students' attitudes and behaviors. Given the recent emphasis on the importance and distinctiveness of group and member attachment, assessing both attachment to the university and to the university members should have the most utility. In fact, when examining the attachment literature, there appears to be a not so subtle message that there may be attachment "types" that are qualitatively distinct. More specifically, Prentice et al (1994) hypothesized that "People's feelings toward a group (mankind) may be distinct from their feelings toward the members of the group (men). In addition, this observation suggests the hypothesis that individuals with a stronger attachment to their group than to its members can be meaningfully and qualitatively distinguished from individuals with stronger attachments to the members of their group than to the group itself" (p. 484). In order to test this hypothesis, Prentice and colleagues sought out groups that they believed "exemplify the distinction" between group and member attachment. Specifically, within a college setting, they selected known groups (e.g., eating clubs, dorms, sports teams) that they thought would demonstrate different profiles of member and group attachment. Groups they thought would be characterized by higher group attachment than member attachment they labeled common-identity groups, and groups thought to have similar group and member

attachment or higher member than group attachment they labeled common-bond groups. They collected group and member attachment scores from both types of groups and did indeed find that common-identity groups had higher group than member attachment and that common-bond groups had approximately equal group and member attachment. Using these results, they stated that there can be asymmetries in group and member attachment, and that this is moderated by the type of group one is examining (common-identity vs. common-bond).

Moreover, when reviewing the basic research that examined the correlates of group and member attachment, known groups with different attachment profiles were often sought out or were experimentally manipulated (e.g., higher group, lower member; higher member, lower group). Using these groups with diverse attachment profiles, differences on the variables of interest (e.g., group norms, group welfare) would be examined in order to highlight the distinctiveness of people having different attachment profiles.

*Profiling Attachment Without Known Groups: Are there Underlying, Unobserved Subpopulations of Attachment?*

As noted above, researchers have sought out known student groups or populations to try to better understand asymmetries in feelings of group and member attachment. Although these types of analyses are powerful, they necessitate the identification of the grouping or population classification variable a priori (e.g., member of sports team vs. member of fraternity). What if one believes that that the individuals sampled are from different populations with different attachment profiles but population membership is not known? Or what about the possibility of different attachment profiles characterizing members *within* a particular known group (i.e., sports team)? Prentice and colleagues profiled member and group attachment for each known group by reporting mean levels of attachment; this assumes that the average group and member attachment

represents all members of the group well. There is no evidence to support this assumption. In fact, Prentice and colleagues made a point of noting that individuals have individual representations of the group and its members. Therefore, just because one person perceives a group as being a common-identity group (higher group than member attachment), doesn't mean that all the individual members within the group perceive the group in the same way. Within a particular sample, there may be different subpopulations that represent individuals that are homogenous with respect to their pattern of group and member attachment (e.g., high group, high member; high group, low member; low group, high member; low group, low member). A person-centered approach, such as mixture modeling, can be used to identify if unobserved subpopulations of attachment exist, the size of each subpopulation, the form these subpopulations take, and if membership in the subpopulations is related to external variables.

More specifically, mixture modeling can be used to uncover latent (unobserved) classes or subpopulations using the observed responses patterns. Said another way, a latent categorical variable is assumed to underlie the response patterns. The different levels or classes of the categorical latent variable represent different response patterns within the sample under study. These different response patterns are assumed to represent different subpopulations of individuals that were mixed together to form the sample under study. The response patterns within a class are similar but differ across classes. The response patterns that characterize the classes may differ in magnitude, form, or both. Classes that differ only in magnitude have the same form but the level of endorsement of the observed variables differs across classes. For example, if we measured university group and member attachment using a one to five scale, we may find a high university attachment class that has approximately equal group and member attachment (4.2, 4.0) and a low university attachment class that has the same pattern but just

lower endorsement (3.0, 2.8). Classes that differ in form may have a different rank order of the observed variables with respect to endorsement or have differences between the observed variables that are more or less extreme. For example, using Prentice's findings of common-identity and common-bond groups, we may find a class with higher group than member attachment (4.5, 3.5) and another class with approximately equal group and member attachment (4.5, 4.5). Of course, classes that differ in form may also differ in magnitude. For example, the second class mentioned above may have equal group and member attachment but much lower levels than the first class (~2.5 for both types of attachment). Mixture modeling can help us to understand how the university attachment classes differ: in magnitude, form, or both.

#### *Purpose of the Current Study*

The purpose of the current study was to study group and member attachment for a sample of university students. Specifically, we were interested in studying the students' level of attachment to the university they were attending and level of attachment to the members of the university. Given the differing experiences of students, we believed that there may be underlying subpopulations of students that have differing attachment profiles. That is, reporting the average member and group attachment scores may not represent the attachment profiles of all students well. Instead of trying to identify known groups that may (or may not) distinguish between these possible subpopulations, we took a person-centered approach to explore the possible existence of university attachment classes. More specifically, mixture modeling was employed to uncover empirically derived attachment classes.

If interpretable subpopulations/classes emerged, predictors (often called covariates) of class membership will be added to the mixture model in order to better understand the type of student within each class. The inclusion of covariates provides more information to inform class

membership, in addition to providing validity evidence for the classes (Bauer & Curran, 2004; Muthén, 2004). Transfer status (transfer student vs. nontransfer student) and feelings of morale toward the university were selected as covariates given the empirical evidence supporting the relationship between these variables and attachment. Specifically, transfer status was selected given the relationship found between length of group membership and member attachment; the longer one is a member of a group the more opportunity to develop stronger member attachment (Utz, 2003). Feelings of morale toward the university was chosen given the positive relationship between positive evaluations of the group and group attachment (Brewer, 1979; Karasawa, 1991; Utz, 2003). As group attachment increases, positive evaluation of the group should increase. We purposefully selected covariates that were related to the different dimensions of attachment as we believed this would best facilitate our understanding of the differences between the attachment classes that emerged. Specifically, we suspected that transfer students would have lower member attachment than non-transfer students because they haven't been members of the university as long, and typically missed out on important member-bonding experiences (e.g., orientation, living in dorms). Therefore, we expected transfer status to distinguish between groups that differed most in member attachment. Feelings of morale, on the other hand, should discriminate those groups that differ most on group attachment. However, both covariates will be used in the model together in order to provide the most information about class type; therefore, these relationships may not be this simple. Given the lack of previous research investigating the existence of university attachment classes and, consequently, the exploratory nature of the study, we didn't hypothesize the type of classes that would emerge and, in turn, it was impossible to predict relationships with the covariates in any more detail than this. The mixture solution with

and without the covariates will be compared to evaluate the utility of including theoretically-related covariates.

## Methods

### *Participants and Procedures*

Data from 683 university students were analyzed in the current study. Instruments representing university attachment and feelings of morale were administered to students, along with a battery of cognitive and developmental tests, as part of a required assessment day at JMU. All students had completed between 45 and 70 credit hours, 64.7 % were female, 85.2% were Caucasian, and the average age was 20.2. Students' transfer/non-transfer status was gathered from university records. A total of 79 students were transfer to JMU, whereas 604 started as freshman at the university.

### *Instruments*

*University Attachment Scale (UAS)*. We created the nine-item attachment measure by adapting items from Prentice et al.'s (1994) measure. Specifically, we changed the item wording in order for the items to apply to an entire university rather than a club or group within a university. For example, "How often do you acknowledge the fact that you are a member of your club?" (Prentice et al., 1994), a group attachment item, was changed to "How often do you acknowledge the fact that you are a member of JMU?". Six of the items were written to represent group attachment and three of the items were written to represent member attachment. We created a response scale of 1 to 5 for each item (see Appendix A for all items and instructions).

Preliminary study of the measure revealed adequate psychometric properties (France, Finney & Swerdzewski, 2007). A two-factor model fit the data well and was championed over an ill-fitting one-factor model. Internal consistency was adequate (Group  $\alpha = .87$ , Member  $\alpha = .72$ )

and external validity evidence was gathered via empirically supported a priori specified hypotheses regarding relationships with theoretically-related constructs.

*Perceived Cohesion (PCS; Bollen & Hoyle, 1990).* The Perceived Cohesion Scale was designed to measure the *perceived* cohesion aspect of overall cohesion, which is defined as a group member's personal assessment of his or her membership in a group. It has been found empirically that the PCS represents two dimensions of perceived cohesion: feelings of morale and sense of belonging (Bollen & Hoyle, 1994; Chin et al., 1999). The current study used feelings of morale as a predictor of latent class membership. Feelings of morale is defined as individual's emotional response to belonging to the group. Feelings of morale are thought to arise from a global, overall emotional response to one's relationship to or participation in the group. It is believed that feelings of morale have implications for motivation (i.e., excitement of belonging to the group may motivate participation in group activities). The students completed the items scale using a 1 (*strongly disagree*) to 9 (*strongly agree*) scale. Cronbach's coefficient alpha for the current study was .91 for feelings of morale.

## Results

### *Descriptive Statistics*

The means, variances, and relationship between group and member attachment are reported in Table 1. In addition, the relationships between the covariates and attachment are reported for the full sample. If there is evidence that multiple classes do not exist or are not meaningful, the values in Table 1 can be used to describe attachment for this sample and the relationships with transfer status and feelings of morale.

As predicted, feelings of morale was more strongly related to group attachment than member attachment. Also, as predicted, transfer students had significantly lower member

attachment than non-transfer students, but the two types of students did not differ significantly with respect to group attachment. Moreover, feelings of morale and transfer status were not significantly correlated. Again, by selecting covariates that related differentially to the two attachment dimensions and were not multicollinear, we hoped to garner the most useful auxiliary information that would help inform our understanding the mixture modeling solution.

### *Mixture Modeling without Covariates*

Given the lack of research in the domain of university attachment, the analyses were exploratory in nature. We tested a number of different of classes with different parameterizations. Specifically, we tested models with one to four classes using four different parameterizations (Model A through Model D). Model A's parameterization specified the two attachment means (group and member) to be freely estimated across classes, fixed the variances to be equal across classes (e.g., member variance in class 1 equals member variance in class 2), and fixed the covariance between group and member attachment within each class to be zero (fixing the covariance to zero forces local independence of the two attachment scores). Model B's parameterization specified the two attachment means for each class to be freely estimated and fixed the covariance between member and group attachment to be zero, but unlike Model A, the two variances were freely estimated across classes. Model C's parameterization specified freely estimated means and variances, but unlike Model B, the covariance between member and group attachment was estimated but fixed to be equal across classes. Model D's parameterization freely estimated means, variances, and the covariance of member and group attachment across classes.

In addition to estimating unique model parameters for each class,  $k - 1$  mixing proportions are estimated, where  $k =$  the number of classes. The mixing proportions indicate the

proportion of the sample that can be described using each class's parameters. If two classes were uncovered and the mixing proportion for Class 1 was .80, then 80% of the sample is characterized by the parameters associated with Class 1 and 20% of the sample is characterized by the parameters associated with Class 2. These proportions give us insight into how common the particular patterns of scores are in the sample; it may be that one class is extremely small whereas another is extremely large.

Model fit was assessed using several fit indices. All of these fit indices assess relative fit, not absolute fit; that is, fit of competing models are compared, not absolute fit of the model to the data. The Akaike Information Criterion (AIC; Akaike, 1987), Bayesian Information Criterion (BIC; Schwartz, 1978), the Sample Size Adjusted BIC (SSABIC; Sclove, 1987), and the Lo-Mendell-Rubin likelihood ratio test (LMR; Lo, Mendell, & Rubin, 2001) were all employed to help identify the best fitting model. The AIC, BIC, and SSABIC can be used to compare solutions that differ in the number of classes and differ in parameterization. For all three of these indices, lower values indicate better relative fit. The LMR test can be used to compare models that differ in the number of classes but share the same parameterization (e.g., comparing 3 Class Model C to 2 Class Model C). Statistical non-significance indicates that the additional class is not necessary to better describe the data. All four fit indices will be examined to inform decisions regarding model fit; however, the SSABIC will be given the most weight given its superior ability to identify the correct number of classes (Henson, Reise & Kim, 2007; Tofighi & Enders, in press)

Table 2 includes the fit indices for the estimated models. The SSABIC was the lowest for 3 Class Model C (3MC). Just a slightly higher SSABIC value was associated with 3 Class Model D; however, the LRM test indicated that when Model D's parameterization was employed, three

classes were not needed over two classes. The BIC was lowest for 2 Class Model C (2MC) and the SSABIC was only slightly higher for this model compared to 3MC; however, the LMR test suggested the need for three classes over two classes.

Both the 2 and 3 Class Model C means are plotted in Figure 1 in order to observe the differences across classes (see top half of Table 3 for estimated parameters for the two models). Interestingly, 2MC depicts two classes that are very similar to the description of Prentice and colleague's (1994) common-identity (Class 1) and common-bond (Class 2) groups. Specifically, Class 1 (64.7%) had higher group attachment (attachment to the university itself) than member attachment, whereas Class 2 (35.7%) had similar levels of both group and member attachment. Interestingly, Class 1 had less variability around the group and member means than Class 2. Given the differences in variability across the classes, the correlation between member and group differed even though the covariance was fixed to be equivalent. The positive relationship between member and group attachment was stronger for Class 1 (.57) than Class 2 (.28).

When modeling three classes (3MC), we found two classes with similar form to those of 2MC; however, the means of both group and member attachment were more extreme for the three class model. Class 1 continued to have higher attachment to the university itself than to the members but both means from the 3MC solution were higher for Class 1 than they were from the 2MC solution. Also, notice that this more extreme Class 1 became smaller in size (15.1%), had less variability in member and group scores, and had a stronger relationship between member and group attachment than Class 1 from the 2MC solution. Class 3 in 3MC had the same form as Class 2 of 2MC, but the means were lower for 3MC and the class was smaller in size (26.5%). Again, Class 1 and Class 3 appeared to be representing "common-identity" and "common-bond" profiles. Finally, Class 2 of 3MC fell between Class 1 and Class 3 with respect to magnitude,

variability, and form. Overall, the three classes differed in respect to magnitude and form. The rank order of both group and member attachment across classes was the same, therefore, the classes could be labeled “ordered” in nature (i.e., Class 1 is higher than Class 2, Class 2 is higher than Class 3). However, the classes also differed in form, especially Class 1 and Class 3. Class 1 had much higher endorsement of group attachment than member attachment (over half of a point on a five-point scale), whereas group and member attachment were endorsed approximately equally for Class 3.

#### *Mixture Modeling with Covariates*

In order to better understand both the 2MC and 3MC solutions, we included covariates into the model. Table 4 presents the fit indices associated with the various mixture models when transfer status and feelings of morale served as predictors of the categorical latent variable. Again, 3MC had the lowest SSABIC and the LRM test indicated that three classes were needed over two classes. Three things are of note when examining the results with and without covariates. First, notice in Table 4 that the SSABIC values associated with the 3MC and 2MC models are much more distinct when modeling the data with covariates. Also, notice that the entropy statistic, which represents classification accuracy, increased across all models when using covariates. Including covariates provided more information that could be used to inform classification, therefore, the differences in fit between solutions was more distinct, the classification of students into classes was more accurate (higher entropy), and the size of the classes changed when using the covariates (see Muthén, 2004 for a discussion on the importance of including covariates into the model).

Although 3MC clearly fit better than 2MC, it was interesting to examine the effects of the covariates on the 2MC model (see the bottom half of Table 3 and Figure 3). Notice that the class

parameters changed only slightly: the classes became more even in size and member and group attachment increased just slightly for both classes. Feelings of morale was a significant predictor of class membership, after controlling for transfer status. Compared to Class 2, Class 1 students felt significantly higher feelings of morale toward the university (logit = .93,  $p < .05$ ). Said another way, the odds of being in Class 1 versus Class 2 (odds ratio = 2.53) increased significantly with increasing levels of feelings of morale toward the university. Interestingly, transfer status was not related to class membership (logit = 3.34,  $p > .05$ ), after controlling for feelings of morale.

When comparing the 3MC results to the 3MC solution with covariates, one can see that the classes from the latter solution were shifted down on the attachment continuum. Although the form of the classes remained fairly stable, the average group and member attachment were lower. Class 1 still reflected a pattern similar to the common-identity profile: higher group than member attachment; whereas, Class 3 still reflected a pattern similar to the common-bond profile: similar group and member attachment. Notice, however, that with this shift came a change in class size. Class 1 became larger and Class 3 became smaller than the class size reflected in the 3MC solution without covariates. Given that Class 1 was not as extreme along the attachment continuum, whereas Class 3 became more extreme, this change in class size is understandable. This change in class size was coupled with a change in the variability of the group and member scores within classes. Notice that the smaller Class 3 had less variability of scores around the member and group means than the same model without the covariates. On the other hand, Class 1 had more variability around the mean scores. It is important to point out, however, that the rank order of variability across 3MC with and without covariate remained the same, with Class 1 having the least variability in scores. Finally, notice that the covariance between group and

member attachment was weaker when covariates were added to the model. This decrease in covariance coupled with the increase in variability for Class 1 and 2 resulted in lower group and member correlations when modeling the covariates with the latent class variable.

With respect to the covariates, both transfer status and feelings of morale were significantly related to class membership from the 3MC solution, after partialling out the effects of each other. Compared to Class 3, Class 1 (logit = 1.67,  $p < .05$ ) and Class 2 (logit = .46,  $p < .05$ ) students felt significantly higher feelings of morale toward the university. In addition, compared to Class 2 students, Class 1 students felt significantly higher feelings of morale (logit = 1.21,  $p < .05$ ). After controlling for feelings of morale, the odds of being a member of Class 1 versus Class 2 increased by a factor of over 39, if a student had non-transfer status (logit = 3.67,  $p < .05$ ). The odds of being a member of Class 1 versus Class 3 increased by a factor over 57, if a student has non-transfer status (logit = 4.06,  $p < .05$ ). The odds of being in Class 2 versus Class 3 increased by a factor of 1.47, if a student had non-transfer status; this was not statistically significant (logit = .383,  $p > .05$ ).

### Discussion

The purpose of the study was to investigate if subpopulations of university attachment existed in a sample of undergraduate college students. Prior research examining group and member attachment focused on asymmetries in attachment levels across known groups. These known groups were selected in order to highlight the distinction between group and member attachment. However, researchers assumed that all members within a particular group (e.g., eating club, dorm) were drawn from the same underlying population and, therefore, the average group and member attachment represented all students' attachment levels well (e.g., Prentice et

al., 1994). Mixture modeling relaxes the assumption that a single population underlies the scores and allows multiple unobserved subpopulations that differ in their parameters.

Using mixture modeling, we found three subpopulations or classes that differed in magnitude and form of attachment. Class 1 had higher group and member attachment than Class 2 and 3, and endorsed group attachment more than member attachment. This class aligned with the profile of common-identity groups found in previous studies (Prentice et al, 1994). Class 3 had lower group and member attachment than Class 1 and 2, and endorsed group and member attachment approximately equally. This class aligned with the profile of common-bond groups found in previous studies. This class was smaller than Class 1 or Class 2, but it is one that could be a concern with respect to retention given the low attachment levels. Finally, Class 2 was not as extreme as Class 1 or Class 3 with respect to attachment endorsement; Class 2 fell between Class 1 and Class on the attachment continuum. Also, group attachment was higher than member attachment for Class 2 but not to the extent found for Class 1.

In addition, we found that feelings of morale had a clear relationship with these classes; as attachment in general decreased (move from Class 1 to Class 2 to Class 3), feelings of morale decreased. This may be driven primarily by the large differences in group attachment across the three classes; however, this is impossible to evaluate because member attachment had the same rank order as group attachment across the classes. Also, the odds of being a transfer compared to a non-transfer student was significantly lower for Class 1 than Classes 2 or 3. There was no difference between Class 2 and 3 with respect to transfer status. Given the high level of member attachment for Class 1 it is not surprising that the odds of being a transfer student is significantly lower than the other two groups. Transfer students have had less time on campus to develop

interpersonal relationship (member attachment) therefore, they are less likely to feel strong interpersonal bonds.

*Are There Underlying Subpopulations of Attachment?*

One may question if these three classes of attachment are “real”. What is the answer to the question posed in the title: Are there underlying subpopulations of college attachment? Maybe. Continued study is needed before conclusions stronger than that can be made. The distribution of attachment scores may have come from one population and, therefore, the three latent classes would not be meaningful. We can not simply assume that the latent classes are substantively meaningful simply because they were “found”. As Muthén (2004) so clearly notes, “The issue of alternative explanations is classic in finite mixture statistics. Mixtures have two separate uses. One is to simply fit a nonnormal distribution without a particular interest in the mixture components. The other is to capture substantively meaningful subgroups” (p. 355).

So, what can we do to better understand the nature of data? First, replication of findings is crucial to assess the stability of the mixture results; if the results don’t replicate there most likely aren’t substantively meaningful classes. In addition, validity evidence for the classes is necessary in order to assign meaning. Much like validity evidence via relationships with theoretically-related variables is necessary to understand factors that emerge via factor analysis, construct validity evidence is just as necessary to understand the validity of classes (Bauer & Curran, 2004; Muthén, 2003). We attempted to begin the validity gathering process by including covariates in the latent model. We are well aware that collecting information on two covariates isn’t sufficient to label the classes and conclude that they “truly” exist. In fact, multiple empirical studies with different covariates are needed to best understand the attachment construct and still then we will never know if the classes “truly” exist. Finally, as

noted by methodologists (e.g., Bauer & Curran, 2004; Muthén, 2003; 2004), the utility of the classes that emerge via mixture modeling has to be informed by substantive theory and practical use, in addition to empirical evidence of classes and their relationships with external variables. Given the past theory suggesting different attachment profiles and the existence of differing profiles for known groups, we believe that two of the classes that emerged align with the theory in the domain. Whether the additional class (Class 2) will replicate (or any of the classes for that matter) has yet to be studied.

### *Conclusion*

In sum, by using mixture modeling we were able to find classes of students who were homogeneous with respect to their attachment profile. One may question the utility of mixture modeling when ordered classes emerge, as found in the current study. The ordered classes may suggest that one population underlies the scores and, therefore, a latent categorical variable should not be used to model the data; a variable-centered approach should instead be undertaken. It is important to note that other models that don't uncover mixtures can represent this same data equally well (Bauer & Curran, 2004; Muthén, 2001; 2003). We believe that the results of modeling the data in this manner should be used to compliment results from other modeling procedures such as factor analysis; this provides the most information about the structure of the data. As Muthén (2004) notes when discussing the fact that different models can represent data equally well (i.e., factor models and latent class models), "This should not be seen as a problem but merely as two ways of looking at the same reality" (p. 355).

## Appendix A

## University Attachment Scale

In this section, the response options are different for every item, so please read each item and their accompanying options carefully before responding to each item. **As with the previous items, there are no right or wrong answers; everyone behaves and feels differently. Just answer as honestly as possible.**  
PLEASE BUBBLE IN ONLY ONE ANSWER FOR EACH STATEMENT.

1. How often do you acknowledge the fact that you are a member of JMU?

1	2	3	4	5
Never	Rarely	About Half the Time	Most of the Time	Always

2. How accurate would it be to describe you as a typical JMU student?

1	2	3	4	5
Not at all Accurate	Slightly	Moderately	Very	Extremely Accurate

3. How important is belonging to JMU to you?

1	2	3	4	5
Not at all Important	Slightly	Moderately	Very	Extremely Important

4. How good would you feel if you were described as a typical JMU student?

1	2	3	4	5
Not at all Good	Slightly	Moderately	Very	Extremely Good

5. When you first meet people, how likely are you to mention JMU?

1	2	3	4	5
Not at all Likely	Slightly	Moderately	Very	Extremely Likely

6. How attached do you feel to JMU?

1	2	3	4	5
Not at all	Slightly	Moderately	Very	Extremely

7. How close do you feel to other members of the JMU community?

1	2	3	4	5
Not at all Close	Slightly	Moderately	Very	Extremely Close

8. To what extent have members of JMU influenced your thoughts and behaviors?

1	2	3	4	5
Not at all	Slightly	Moderately	Very	Extremely

9. How many of your close friends come from JMU?

1	2	3	4	5
None	Few	About Half	Most	All

## References

- Akaike, H. (1987). Factor analysis and AIC. *Psychometrika*, 52, 317 – 332.
- Allport, F. H. (1962). A structural-conceptual conception of behavior: Individual and collective. *Journal of Abnormal and Social Psychology*, 64, 3-30.
- Anderman, L. H. & Anderman, E. M. (1999). Social predictors of changes in students' achievement goal orientations. *Contemporary Educational Psychology*, 25, 21-37.
- Astin, A. W. (1993). *What matters in college? Four critical years revisited*. San Francisco, CA: Jossey-Bass.
- Astin, A. W. (1985). *Achieving academic excellence*. San Francisco, CA: Jossey-Bass.
- Battistich, V., & Hom, A. (1997). The relationship between students' sense of their school as a community and their involvement in problem behaviors. *American Journal of Public Health*, 87, 1997-2001.
- Bauer, D.J., & Curran, P.J. (2004). The integration of continuous and discrete latent variable models: Potential problems and promising opportunities. *Psychological Methods*, 9, 3-29.
- Billig, M. & Tajfel, H. (1973). Social categorization and similarity in intergroup behavior. *European Journal of Social Psychology*, 3, 27-52.
- Bollen, K. A. & Hoyle, R. H. (1990). Perceived cohesion: A conceptual and empirical examination. *Social Forces*, 69(2), 479-504.
- Brewer, M. B. (1979). In-group bias in the minimal intergroup situation: A cognitive – motivational analysis. *Psychological Bulletin*, 86, 307-324.
- Carron, A. V., & Chelladurai, P. (1981). The dynamics of group cohesion in sport. *Journal of Sport Psychology*, 3, 123-139.
- Chickering, A. W. (1974). *Commuting versus resident students: Overcoming educational inequities of living off campus*. San Francisco: Jossey-Bass.
- Chin, W., Salisbury, W., Pearson, A., & Stollak, M. (1999). Perceived cohesion in small groups: Adapting and testing the Perceived Cohesion Scale in a small-group setting. *Small Group Research*, 30, 751-766.
- Finn, J. D. (1989). Withdrawing from school. *Review of Educational Research*, 59, 117-142.
- Freeman, T. M., Anderman, L. H., & Jensen, J. M. (2007). Sense of belonging in college freshmen at the classroom and campus levels. *The Journal of Experimental Education*, 75, 203-220.
- France, M., Finney, S. J., & Swerdzewski, P. (2007, October). *Are University and Student Attachment Distinct Constructs: An Examination of Factor Structure and External Validity*. Paper presented at the annual meeting of the Northeastern Education Research Association, Rocky Hill, CT.
- Furrer, C. & Skinner, E. (2003). Sense of relatedness as a factor in children's academic engagement and performance. *Journal of Educational Psychology*, 95, 148-162.
- Gagné, P. (2006). Mean and covariance structure mixture models. In G.R. Hancock & R.O. Mueller (Eds.), *Structural equation modeling: A second course* (pp.197-224). Greenwich, CT: Information Age Publishing.
- Goodenow, C. (1993a). Classroom belonging among early adolescent students: Relationships to motivation and achievement. *Journal of Early Adolescents*, 13, 21-43.
- Goodenow, C. (1993b). The psychological sense of school membership among

- adolescents: Scale development and educational correlates. *Psychology in the Schools*, 30, 79-90.
- Goodenow, C. & Grady, K. E. (1993). The relationship of school belonging and friends' values to academic motivation among urban adolescent students. *Journal of Experimental Education*, 62, 60-71.
- Henson, J.M., Reise, S. P., & Kim, K. H. (2007). Detecting mixtures from structural model differences using latent variable mixture modeling: A comparison of relative model fit statistics. *Structural Equation Modeling*, 14, 202 – 226.
- Hipp, J. R., Bauer, D. J. (2006). Local solutions in the estimation of growth mixture modeling. *Psychological Methods*, 11, p. 36 – 53.
- Hogg, M., & Abrams, D. (1988). *Social identifications: A social psychology of intergroup relations and group processes*. London, UK: Routledge.
- Hogg, M. A., & Hardie, E. A. (1991). Social attraction, personal attraction, and self-categorization: A field study. *Personality and Social Psychology Bulletin*, 17, 175-180.
- Hogg, M. A., & Turner, J. C. (1985). Interpersonal attraction, social identification and psychological group formation. *European Journal of Social Psychology*, 15, 51-66.
- Karasawa, M. (1991). Toward an assessment of social identity: The structure of group identification and its effects on in-group evaluations. *British Journal of Social Psychology*, 30, 293-307.
- Kuh, G. D., Schuh, J.H., Whitt, E.J., et al. (1991). *Involving colleges: Successful approaches to fostering student learning and development outside the classroom*. San Francisco: Jossey-Bass.
- Light, R. J. (2001). *Making the most of college*. Cambridge, MA: Harvard University Press.
- Lo, Y., Mendell, N. R., & Rubin, D. B. (2001). Testing the number of components in a normal mixture. *Biometrika*, 88, 767-778.
- Muthén, B. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In *Handbook of Quantitative Methodology for the Social Sciences*, (pp.345-368). Newbury Park, CA: Sage Publication.
- Muthén, B. (2003). Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran (2003). *Psychological Methods*, 8, 369 – 377.
- Muthén, B. (2001). Latent variable mixture modeling. In G.A. Marcoulides & R.E. Schumacker (eds.), *New Developments and Techniques in Structural Equation Modeling* (pp.1-33). Mahwah, NJ: Lawrence Erlbaum Associates.
- Osterman, K. F. (2000). Students' need for belonging in the school community. *Review of Educational Research*, 70, 323-368.
- Pascarella, E. T. & Terenzini, P. (2005). *How college affects students, volume 2: A third decade of research*. San Francisco: Jossey-Bass.
- Pascarella, E. T., Duby, P., Terenzini, P., and Iverson, B.A. (1983). Student-faculty relationships and freshman year intellectual and personal growth in a non-residential setting. *Journal of College Student Personnel*, 24, 395-402.
- Pascarella, E. T., Duby, P., Terenzini, P., and Iverson, B.A. (1983). Student-faculty relationships and freshman year intellectual and personal growth in a non-residential setting. *Journal of College Student Personnel*, 24, 395-402.
- Prentice, D. A., Miller, D. T., & Lightdale, J. R. (1994). Asymmetries in attachments to groups and to their members: Distinguishing between common-identity and common-

- bond groups. *Personality and Social Psychology Bulletin*, 20, 484-493.
- Sassenberg, K. (2002). Common bond and common identity groups on the internet: Attachment and normative behavior in on-topic and off-topic chats. *Group Dynamics: Theory, Research, and Practice*, 6, 27-27.
- Schwartz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, 6, 461-464.
- Sclove, L.S. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika*, 52, 333 – 343.
- Tajfel, H. (1981). *Human groups and social categories*. Cambridge, UK: Cambridge University Press.
- Tinto, V. (1987). *Leaving college: Rethinking the causes and cures of student attrition*. Chicago: The University of Chicago Press.
- Tofghi, D. & Ender, C.K. (in press). Identifying the correct number of classes in growth mixture modeling. In G. R. Hancock (Ed.), *Mixture Models in Latent Variable Research*. Information Age: Greenwich, CT.
- Turner, J. C. (1982). Towards a cognitive redefinition of the social group. In H. Tajfel (Ed.), *Social identity and intergroup relations* (pp. 15-40). Cambridge, UK: Cambridge University Press.
- Utz, S. (2003). Social identification and interpersonal attraction in MUDs. *Swiss Journal of Psychology*, 62, 91-101.
- Utz, S., & Sassenberg, K. (2002). Distributive justice in common-bond and common-identity groups. *Group Processes & Intergroup Relations*, 5, 151-162.

Table 1

*Descriptive statistics and correlations among variables for entire sample under study*

	Group Attachment	Member Attachment	Feelings of Morale	Transfer <sup>1</sup> Status
Group Attachment	1.0			
Member Attachment	.640*	1.0		
Feelings of Morale	.737*	.535*	1.0	
Transfer Status	.048	.207*	.016	1.0
Mean	22.25 (3.72) <sup>2</sup>	10.24 (3.41) <sup>2</sup>	20.89	0.88
Standard Deviation	04.87	02.22	05.72	0.32
Skewness	-0.68	-0.49	-1.11	-2.41
Kurtosis	0.08	0.05	0.66	3.81

*Note.* <sup>1</sup> Transfer = 0, Non-Transfer = 1. <sup>2</sup> Means in parentheses are computed to range from 1 to

5. *N* = 683. \* *p* < .05

Table 2

*Fit for mixture models using group and member attachment as observed indicators*

	AIC	BIC	SSABIC	LMR	Entropy	LL	Number of free parameters
1 Class							
Model B	7130.795	7148.901	7136.200	NA	NA	-3561.397	4
Model C	6773.072	6795.704	6779.829	NA	NA	-3381.536	5
2 Class							
Model A	6813.061	6844.746	6822.520	$p < .001$	0.769	-3399.530	7
Model B	6781.126	6821.865	6793.288	$p < .001$	0.688	-3381.563	9
Model C	6672.629	6717.894	6686.143	$p < .001$	0.538	-3326.315	10
Model D	6670.053	6719.845	6684.918	$p < .001$	0.460	-3324.027	11
3 Class							
Model A	6741.974	6787.239	6755.487	$p < .001$	.746	-3360.987	10
Model B	6685.984	6749.355	6704.903	$p < .001$	.703	-3328.992	14
Model C	6661.422	6729.319	6681.692	$p < .010$	.521	-3315.711	15
Model D	6659.701	6736.651	6682.674	$p = .066$	.642	-3312.850	17
4 Class							
Model A	6715.088	6773.932	6732.655	$p = .002$	.687	-3344.544	13
Model B	6660.648	6746.652	6686.324	$p < .004$	.739	-3311.324	19
Model C	6657.795	6748.325	6684.822	$p = .132$	.692	-3308.898	20
Model D	6653.992	6758.101	6685.073	$p = .161$	.726	-3303.996	23

$N = 683$

Table 3

*Parameter estimates for 2 Class Model C and 3 Class Model C with and without covariates*

Model and Class	$\pi$	“Group” Mean <sup>1</sup>	“Member” Mean <sup>1</sup>	“Group” Variance	“Member” Variance	Cov.	Corr.
2MC							
Class 1	.647	24.85 (4.14)	11.22 (3.74)	08.65	02.57	2.69	.57
Class 2	.353	18.17 (3.03)	08.70 (2.90)	19.53	04.61	2.69	.28
3MC							
Class 1	.151	27.05 (4.51)	11.84 (3.95)	03.87	01.77	2.09	.80
Class 2	.584	23.58 (3.93)	10.85 (3.62)	09.03	02.81	2.09	.42
Class 3	.265	17.30 (2.88)	08.30 (2.77)	18.95	04.37	2.09	.23
2MC with covariates							
Class 1	.539	25.33 (4.22)	11.31 (3.77)	07.55	02.69	2.45	.54
Class 2	.461	18.65 (3.11)	9.00 (3.00)	17.30	04.42	2.45	.28
3MC with covariates							
Class 1	.434	25.87 (4.31)	11.47 (3.82)	05.75	02.39	1.79	.48
Class 2	.433	21.00 (3.50)	09.81 (3.27)	10.51	03.76	1.79	.28
Class 3	.123	13.94 (2.32)	07.43 (2.48)	12.43	03.91	1.79	.26

*Note.*<sup>1</sup> Mean in parentheses was computed to range from 1 to 5.  $\pi$  = proportion of students within each class. Cov. = covariance between member and group attachment. Corr.= correlation between member and group attachment.

Table 4

*Fit for mixture models with transfer status and feelings of morale as covariates in model*

	AIC	BIC	SSABIC	LMR	Entropy	LL	Number of free parameters
<b>2 Class</b>							
Model A	6492.254	6532.992	6504.416	$p < .001$	.828	-3237.127	9
Model B	6450.697	6500.488	6465.562	$p < .001$	.790	-3215.348	11
Model C	6338.700	6393.018	6354.916	$p < .001$	.792	-3157.350	12
Model D	6320.333	6379.177	6337.901	$p < .001$	.808	-3147.166	13
<b>3 Class</b>							
Model A	6312.077	6375.448	6330.996	$p < .030$	.817	-3142.038	14
Model B	6273.536	6355.013	6297.861	$p = .198$	.756	-3118.768	18
Model C	6201.225	6287.228	6226.901	$p = .004$	.800	-3081.612	19
Model D	6204.674	6299.730	6233.053	$p = .045$	.806	-3081.337	21
<b>4 Class<sup>1</sup></b>							
Model A	6390.904	6458.801	6411.174	$p = .006$	.789	-3180.452	15

*Note.* <sup>1</sup> Models B, C, D with four classes did not produce stable solutions (see Hipp & Bauer, 2006 for details regarding local solutions) and, therefore, are not presented.

$N = 683$ .

### Figure Caption

Figure 1: Two-Class Model C solution and Three-Class Model C solution

Figure 2: Comparison of Two-Class Model C solution with and without covariates

Figure 3: Comparison of Three-Class Model C solution with and without covariates





