2012-07-27

A Comparison of Attitudes Towards Time Management, Usage of Time, and Self-Expression by High-Performing and Low-Perfoming Students at Brigham Young University

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A dissertation submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

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December 2012

ABSTRACT

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Time log data (time-spent and adjective evaluations), a six question survey about time management attitudes, and the Adult Self Expression Scale (behavioral and situational subscales), were examined regarding how well each predict GPA. This paper contains two studies. The first study uses canonical correlations to examine the natural relationships between GPA and the five sets of predictor variables. The second study is hypothesis testing with regard to four groups: males and females on academic probation, and males and females with high GPAs. The effects of academic probation and gender on the same four sets of variables are examined: time spent on selected activities, adjective evaluations of activities, a six question survey, and the behavioral and situational dimensions of the ASES. The six question survey shows the strongest connection with GPA. The time log data, while not very compelling, shows promise for future research. Of all of the variable sets, the ASES is the weakest predictor of GPA.

Keywords: time management, Brigham Young University, academic probation

ACKNOWLEDGMENTS

I would like to thank my husband, Jeremy, for believing in me, putting up with lots of long nights (and early mornings), and helping me face my uncertainties with courage and confidence. I would also like to thank my mom and dad, without whom none of this would have been possible. The love and guidance they have given me over the years has made me who I am today. And, of course, this dissertation would not be what it is today if it weren't for Dr. Brown. He continually pushed me towards excellence, and never let me settle for 'good enough'. I am unbelievably grateful for all of his (and Sister Brown's) sacrifices.

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A Comparison of the Attitudes Towards Time Management, Usage of Time, and Self-Expression by High Performing and Low Perfoming Students at Brigham Young University

Predicting the academic success of college students has been studied extensively for many years by psychological and educational researchers alike. A large number of predictive factors have been identified, and the literature has become large, complicated and often contradictory. In 2004, the situation improved dramatically when Robbins, Lauver, Le, Davis, Langley, and Carlstrom published a meta-analysis of over one-hundred studies. They examined and systematized the relationship between college outcomes and a variety of psychosocial and study skill factors (PSFs). This study brought a sense of order out of chaos, and with the resultant increase in sample size, it provided a solid foundation for further research in this area.

Robbins et al. (2004) surveyed 109 studies. They group the PSFs of their meta-analysis into nine broad constructs: achievement motivation, academic goals, institutional commitment, perceived social support, social involvement, academic self-efficacy, general self-concept, academic-related skills and contextual influences. The researchers predicted, based on previous findings, that four predictors (academic self-efficacy, academic goals, achievement motivation, and academic-related skills) would all have strong effects on academic performance (GPA).[1]

Academic self-efficacy is indeed found to be a strong predictor of GPA, with an "estimated operational validity[2] of .378 and true-score correlation[3] of .496" (p. 271). Academic self-efficacy is defined as a "self-evaluation of one's ability and/or chances for success in the academic environment." The remaining three constructs, contrary to predictions, are not found to

[1] It should be noted that Robbins et al. were interested not only in predicting GPA from these factors, but also retention. However, for the scope of this paper I will not include retention as a dependent variable.
[2] The authors define the "mean operational validity" as the average correlation between measures of the predictor and academic performance, that is, the correlation corrected for measurement error in the predictors but not in the criterion.
[3] The estimated "true score correlation" is defined as the next step beyond "mean operational validity," not only corrected for measurement error in the predictors, but also fully corrected for measurement error in the criterion.

have a strong effect on GPA. It is particularly surprising that academic-related skills, which included measures related to time management skills, study skills and habits, leadership skills, and communication skills, have the smallest effects out of the remaining three, with an estimated operational validity of .129 and true-score correlation of .159 (Table 5 and p. 271). The authors state that they are not surprised that academic-related skills do not emerge as strong predictors of academic success in the meta-analysis, as the literature surrounding this construct has typically not indicated a uniformly strong relationship between the two.

It is true that the previous research on time management, the largest representative measure in the academic-related skills construct, has not produced consistent findings as to whether time management is requisite to academic success. Some researchers report that time management skills are more important than SAT scores in predicting college GPA (Britton & Tesser, 1991). However, other researchers indicate that time management skills and practices have little, if anything, to do with success in academics, business, or other aspects of life (Pychyl, Morin, and Salmon, 2000). Clearly the connection between time management and academic performance merits closer scrutiny.

With indications of confusion and contradiction within the time management literature itself, one questions how Robbins et al. (2004) were able to combine them. Their results are further obscured by combining time management skills with other measures under the general construct of academic related skills, which includes: time-management skills, study skills and habits, leadership skills, problem-solving and coping strategies, and communication skills. Attempting to represent all of these skill sets with a single predictive correlation coefficient is probably not justified.

Although Robbins et al. (2004) report the estimated combined effect sizes, they do not report the chi square tests of heterogeneity of the effect sizes entering into the combining process (the Q statistic in the meta-analysis procedure). This makes it impossible to determine whether there were high levels of heterogeneity among the surveyed studies, something usually taken to be a red flag in combining statistics. Their failure to address the issue of effect size agreement leads the reader to question whether their process treats all studies fairly, or perhaps silences dissenting results. It may be that they achieve order by ignoring large effect size discrepancies within their studies. Perhaps a more defensible procedure would be to separate the studies into groups that are homogeneous with respect to effect size, and look for factors accounting for the differences among these subgroups.

Finally, there may be some confusion because of semantic issues in the studies. The term "time management skills", for example, is used very loosely in many of the studies. Perhaps one way to differentiate between the many aspects of time management is to separate them into two subcategories: *internal conceptions* and *external manifestations*. *Internal conceptions* of time management would include items like knowledge about time management, an understanding of time management principles, time management skills, attitudes towards time management, and perceptions of time.[4] *External manifestations* of time management would refer to actual time usage, that is, behavior and practices. A survey of actual time usage and time management behavior might show a substantially higher predictive relationship to GPA than internal knowledge of time management.

[4] In many of the studies, what is referred to as time management "skill" is defined as a knowledge or understanding of the principles. In Polanyi's terms (from chapter 4 "Skills" of his classic 1962 book *Personal Knowledge*) the two are actually quite different, with skills being a kind of tacit knowledge, a practiced action, in contrast to knowledge that can be "spelled out" explicitly. But I would maintain that both of these aspects, the knowledge of time management principles, and also acquired skill in using them, is of little value to academic performance if the person does not actually put the knowledge and skill into practice.

There are several possible ways to investigate and correct the oversights and problems in the Robbins et al. (2004) review. The first possible approach would be to call their entire meta-analysis into question and replicate it with a much more aggressive method of assessing and dealing with heterogeneity, expanding the review in the process, by adding the additional evidence from studies published since 2004. Presumably this would create a much more detailed account of the effects of each of the PSFs on GPA (and perhaps retention) in that many that have been combined with one another would now be broken out according to moderating factors.

A second possibility, however, would be to adopt a more focused approach. One could, for example, do this same kind of heterogeneity-based meta-analysis but restrict the focus to time management variables. Even though time management is only one aspect out of five from within only one PSF out eight, it can also be further broken down into a number of aspects, such as knowledge of the principles, skill in using them, attitudes toward managing one's time, actual time usage, and effectiveness of that time usage.

Perhaps the aspect of time management that would best predict GPA would not be skills, or attitudes, or even verbal reports of practices, but actual time spent studying, the kind of thing that would show up in a behavioral investigation of time logs. This suggests a third possible way of correcting the Robbins et al. (2004) review – a new empirical study using a time logs approach. It may be one of the most important things that could be done to clarify the relationship between time management and academic performance.

The focus of this dissertation is time management, and so the large scale heterogeneity-attuned meta-analysis of the full Robbins et al. (2004) review will be left to future research. The other two suggested corrective approaches are taken. First, the literature review for this dissertation is structured around a heterogeneity-based reanalysis of the 32[5] academic-related skills studies from Robbins et al. as they relate to GPA. It is intended that this heterogeneity analysis will clarify the reasons for the weak predictive relationship. This reanalysis sets the stage for the actual empirical studies of the dissertation which directly test the strength of time logs data in predicting academic performance in the context of several other measures.

Heterogeneity-Based Reanalysis of Academic-Related Skills Studies

The meta-analysis statistics include a combined effect size (represented by theta), a U statistic (which is a chi square test for the significance of that effect size), and a Q statistic (a chi square test for heterogeneity). My re-calculation of the meta-analysis of the 32 studies belonging to the academic-related skills PSF in the Robbins et al. (2004) article includes 72 correlation coefficients between academic skills and academic performance. They range from -.19 (Long, Gaynor, Erwin & Williams, 1994) to .52 (Gadzella & Williamson, 1984).

In running the meta-analysis combining procedure on the 72 correlation coefficients, I find the effect size for the entire academic-related skills PSF to be $\theta = .238$. This can be converted to a "combined r" value of .118, which is reasonably close to Robbins et al's (2004) "mean observed correlation" of .129 in their Table 5 (p. 270)[6]. My obtained Q statistic for heterogeneity among these 72 correlation coefficients is 432.763, which, with 71 degrees of

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[5] Robbins et al. (2004) had 33 studies in their "academic-related skills PSF. The Nonis, Hudson, Logan, and Ford (1998) study was dropped from my analysis because the reported correlation coefficient could not be verified.
[6] My re-calculated "combined r" value is about ten percent lower than the Robbins et al. (2004) "mean observed correlation" value reported in Table 5 (p. 270). This should be explained. They indicate in the table that their value is the mean of 33 correlation coefficients, whereas ours is the "combined r" value from 72 correlation coefficients. Their process is apparently to use meta-analysis methods to combine multiple reported correlation coefficients within each study into one "combined r" value, and then to simply average these 33 values to obtain the reported "mean observed correlation" value of .129 for all academic-related skills. Sometimes these "combined r" values summarize correlations from more than one academic-related skill variable. Since my purpose is to deal with these variables separately, we entered all 72 of the correlation coefficients individually into a single meta-analysis operation to examine heterogeneity. There is a contrast between calculating mean correlations as compared to combining them through the use of meta-analysis. Meta-analysis combining of r values, or of effect sizes, weights them according to sample size rather than just averaging them.

freedom, is highly significant (p < .0000), supporting my concerns regarding the presence of heterogeneity in their omnibus analysis of the five types of academic-related skills.

The next step is to break the 32 studies into the five individual areas in order to conduct a separate meta-analysis for each: *time management skills*, *study skills and habits*, *leadership skills*, *problem solving and coping strategies*, and *communication skills*. One of the problems in the Robbins et al. (2004) meta-analysis is that there is more than one academic-related skill variable examined in each study, and the authors often combine all of them into a single correlation coefficient. Whereas they obtained a single correlation for each of their 33 studies, I deal with each of the 72 reported correlation coefficients separately.

I will now report my meta-analysis results for each of the five "representative measures" subcategories of academic-related skills, but first will indicate how the 72 correlation coefficients and the 21 studies are allocated to each of the five subcategories. The *time management skills* category consists of 18 correlation coefficients from 11 studies that were included in the Robbins et al. meta-analysis (Britton & Tesser, 1991; Dreher & Singer, 1985; Gadzella, Ginther & Williamson, 1987; Gadzella & Williamson, 1984; Garavalia & Gredler, 2002; Kern, Fagley & Miller, 1998; Long et al., 1994; Macan, Shahani, Dipboye & Phillips, 1990; Rugsaken, Robertson & Jones, 1998; Stoynoff, 1997; Trockel, Barnes & Egget, 2000). In addition, it contains three correlation coefficients from two studies (Nonis & Hudson, 2006, and Trueman & Hartley, 1996) that were not included in the Robbins et al. meta-analysis. The *study skills and habits* category contains 27 correlation coefficients from 16 studies (Allen, 1992; Baker & Siryk, 1984b; Bender, 2001; Dreher & Singer 1985; Gadzella, et al., 1987; Gadzella & Williamson, 1984; Garavalia & Gredler, 2002; Gold, Burrell, Haynes & Nardecchia, 1990; Haines, Norris & Kashy, 1996; Kern et al., 1998; Larose, Robertson, Roy & Legault, 1998; Long et al., 1994; Rugsaken et al., 1998; Scott & Robbins, 1985; Simons & Van Rheenen, 2000; Stoynoff, 1997). The *leadership skills* category contains 11 correlation coefficients from six studies (Ancis & Sedlacek, 1997; Eiche, Sedlacek & Adams-Gaston, 1997; Fuertes & Sedlacek, 1995; Sedlacek & Adams-Gaston, 1992; Ting & Robinson, 1998; Young & Sowa, 1992). The *problem solving and coping strategies* category contains 13 correlation coefficients from nine studies (Ancis & Sedlacek, 1997; Eiche et al., 1997; Fuertes & Sedlacek, 1995; Fuertes, Sedlacek & Liu, 1994; Hackett, Betz, Casas & Rocha Singh, 1992; Scott & Robbins, 1985; Sedlacek & Adams-Gaston, 1992; Ting & Robinson, 1998; Young & Sowa, 1992). And finally, the *communication skills* category contains five correlation coefficients from three studies (Hawken, Duran & Kelly, 1991; Rubin, Graham & Mignerey, 1990; Ting & Robinson, 1998).

The effect sizes for the five categories are: *time management skills*, $\theta = .320$ (with a corresponding r value of $r = .158$); *study skills and habits*, $\theta = .310$ ($r = .153$); *leadership skills*, $\theta = .175$ ($r = .087$); *problem solving and coping strategies*, $\theta = .117$ ($r = .058$); and *communication skills*, $\theta = .116$ ($r = .058$). The effect sizes range from a high of .320, for *time management skills*, to a low of .116, for *communication skills*. The U statistics indicate that all of these effect sizes are highly significant, with communication skills being the least significant at $p < .000097$.

The Q statistic test of heterogeneity is <u>not</u> significant for *leadership skills* ($Q(10) = 8.138$, $p = .615$) or for *communication skills* ($Q(4) = 8.829$, $p = .066$), showing relatively good homogeneity among the studies in these two areas. However, for the other three categories, *time management skills* ($Q(21) = 36.015$, $p = .015$), *study skills and habits* ($Q(26) = 233.475$, $p = .000$), and *problem-solving and coping strategies* ($Q(12) = 38.637$, $p = .000$), the Q statistics <u>are</u> significant. These results indicate a need to look at the included studies in these three areas and perhaps break down the categories even further. This will now be done for time management, the specific focus of this dissertation.

The effect sizes for the prediction of academic performance from "time management skills", as measured by the *g* statistic (Hedges & Olkin, 1985), vary greatly among the studies, ranging from -0.200 (Long, 1994) to 0.720 (Kern, 1998). One major problem becomes apparent when looking closely at the included studies – they use a variety of measures and scales that approach time management in diverse ways. A second problem is that almost all of the scales of measurement for time management are highly heterogeneous within themselves, combining knowledge aspects, evaluations of how well students perform various time management practices, and occasionally reports of actual time management behaviors.[7]

The 21 correlation coefficients used in the meta-analysis came from eleven diverse studies. And in those 11 studies, nine different measures or scales were administered. The questions that are posed range from inquiries about "what students know about effective study skills" (Gadzella, 1987, p. 171) to questions regarding how participants <u>feel</u> about their use of time. One study had participants keep a journal of their activities, allowing for a more concrete exploration of the participants' time usage (Nonis & Hudson, 2006). This was particularly interesting because most studies merely have subjects <u>evaluate</u> their time management behavior, occasionally giving *verbal generalizations* concerning their time management behavior, but almost never ask for a direct report of relative allocations of time. One of the major contributions

[7] In examining the 21 studies carefully, it is surprising that there is as much homogeneity of results as there is. Even when studies use the same measures of time management "skill" they often do so in such a way that the measure cannot be interpreted in the same way. A case in point is the Trueman and Hartley (1996) follow-up to the Britton and Tesser (1991) study where they use the Britton and Tesser time management questionnaire, but they group the items quite differently (through their factor analysis). Neither study reports the full correlation matrices among the 18 items, nor do they give the correlations of the outcome measure of academic performance with the individual items (which would provide comparability). Both papers only give correlation coefficients of academic performance with the factor scores. One is left with the impossible task of trying to interpret the predictive correlations entirely from the titles the authors have chosen to give their factors. Britton and Tesser at least give the factor loadings of the items with their three factors, but Trueman and Hartley do not (for their two factors).

of the empirical part of this dissertation is to obtain logs of time actually spent in a variety of activity categories and then have respondents evaluate the time spent with regard to such things as productive versus unproductive. These more fundamental behavioral measures are expected to predict academic performance substantially better than attitudinal measures.

Following up on the question of semantics mentioned earlier, and in an attempt to achieve some level of homogeneity among studies, the studies in the time management category are divided into two sub-categories. The first includes the studies that examine the *internal conceptions* (IC) of time management – knowledge, skills, attitudes and perceptions. And the second includes studies that examine the *external manifestations* (EM) of time management – behaviors or practices. The studies in the EM subcategory rely heavily on self-reports of time utilization behavior.

The meta-analysis on the IC subcategory reveals an effect size of $\theta = .260$. This can be converted to a "combined r" value of .129. The Q statistic for heterogeneity is 15.56, which with three degrees of freedom is significant ($p = .001$). The meta-analysis on the EM subcategory produces an effect size of $\theta = .343$. This can converted to a "combined r" value of .169. The Q statistic for heterogeneity in the EM subcategory is 35.162, which with 17 degrees of freedom is also significant ($p = .004$). Figure 1 shows the effect size correlation coefficients from the four main meta-analyses we have performed up to now: all 72 correlation coefficients from the academic-related skills PSF; the 21 correlation coefficients from studies relating specifically to time management; the four correlation coefficients from the IC subcategory, and the 17 correlation coefficients from the EM subcategory – all in comparison to the original results from Robbins et al. (2004). In sum, I have found up to now that time management performs somewhat better as a predictor of academic performance than Robbins et al.'s conglomerated category of academic-related skills. I also have some indication that the *external manifestations* (EM) subcategory is a better predictor than the *internal conceptions* (IC) subcategory. Finally, I find that even when breaking the studies into these two groupings, they are still too heterogeneous. I now move on to a more detailed consideration of each of the four studies in the IC subcategory and each of the 18 studies in the EM subcategory.

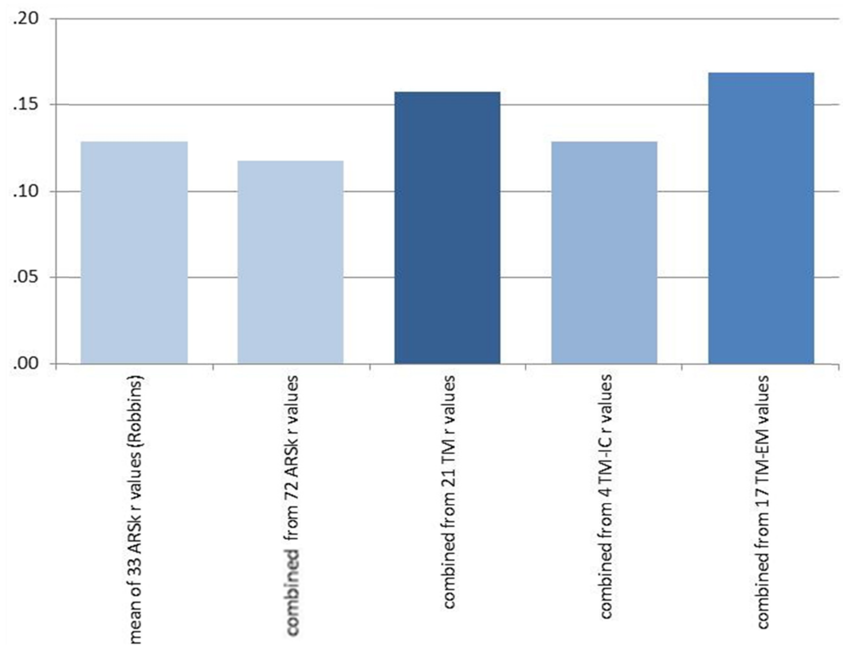


Figure 1. The effect-size correlation coefficients for predicting academic performance from psychosocial and study skill factors (PSFs). A comparison of the four meta-analyses results with one another and with the Robbins et al. results: 72 academic-related skills correlations, 21 time management correlations, four time-management internal conceptions correlations, 17 time-management external manifestations correlations.

Internal Conceptions (IC) Subcategory

The IC subcategory was comprised of only four correlation coefficients from four studies, which included the use of three different scales of measurement. The Computer-Assisted Instruction Study Skills Test (CAISST) was used in two of the studies. The CAISST is a self report measure that "indicates what students know about effective study skills" (Gadzella et al., 1987, p. 171). The test questions are designed to measure 10 areas: *managing time, memory* *improvement, textbook reading, examination taking, note taking, report writing, oral reporting, scholastic motivation, interpersonal relations,* and *concentration improvement*. The *managing time* correlation coefficient was the only one used in the Robbins et al. meta-analysis.

Gadzella et al. (1987) examine the correlations between the *managing time* scores on the CAISST, academic achievement (GPA), and a third very interesting measure, the *deep processing scale* of the Inventory of Learning Processes (DPS). The DPS assesses "the extent to which students evaluate, analyze, organize, compare and contrast information" (Gadzella et al., 1987, p. 169). Time management knowledge correlates significantly with both the DPS ($r = .22$, $p <.05$) and with GPA ($r=.23$, $p < .05$). The final effect size for the correlation of CAISST time management knowledge with GPA is .471, which is moderate. These results suggest that students who understand the management of time well may be more likely to be deep processors, and do better in school.

Gadzella & Williamson (1984) also use the CAISST in their study. This time the test is used in conjunction with GPA and the Tennessee Self-concept Scale, Clinical and Research Form (TSS). The TSS consists of 100 statements from eight subscales which "assess an internal frame of self-reference (*Identity*, *Self-Satisfaction*, *Behavior*) and an external frame of reference (*Physical*, *Moral-Ethical*, *Personal*, *Family*, *Social*) for self-concept" (Gadzella & Williamson, 1984, p. 925). The *managing time* subscale of the CAISST correlates significantly with GPA ($r = .27$, $p < .05$), once again. It also correlates significantly with eight of the nine subscales of the TSS (the exception was the *physical self* subscale). These results indicate, once again, that students who understand the management of time may well be more likely to do better in school. They also suggest that with the exception of how participants feel about their physical selves, students who understand time management may also have better internal and external frames of references for their general self-concepts.

The second scale of measurement that appears in the IC subcategory is the Lifestyle Approaches Inventory (LSA).

> [The LSA] assesses self-management effectiveness in four areas: *performance focus and efficiency* (knowing what is important to do at any given time and then concentrating on that task until it is completed); *goal-directedness* (basing personal actions on clearly defined priorities and goals); *timeliness of task accomplishment* (initiating work on high priority tasks and moving through those tasks in a timely fashion); and *organization of physical space* (keeping one's work and living space orderly and attractive) (Long, 1994, p. 24).

The only subscale of the LSA applicable to the IC subcategory is *performance focus and efficiency* (PFE). This subscale could have also been categorized under the *external manifestations* subcategory, because it does include questions that refer to behaviors. However, the majority of the questions were based on a sense of knowledge.

Long et al. (1994) use the LSA in addition to selected items from three other measures. They use three subscales from Entwistle and Ramsden's (1983) Approaches to Studying Inventory (internal motivation, external motivation and disorganized study methods). They also use nine items from Nixon and Frost's (1990) Study Habits and Attitudes Inventory (SHAI). The selected items "were primarily those that focused on timeliness and organization in studying," (Long, 1994, p. 25). Six items from the Perceived Quality of Academic Life Scale (PQAL) were also included. The items deal with the students' feeling towards education, classes, course material, and instructors, and their progress and success in school.

Long et al. (1994, p. 29) find that the PFE subscale of the LSA correlates significantly with internal motivation ($r = .28$, $p < .01$), disorganized study methods ($r = -.54$, $p < .01$), the PQAL ($r = -.24$, $p < .01$), and the SHAI ($r = .38$, $p < .01$). None of the LSA subscales, including PFE, correlate significantly with GPA; in fact, the correlation coefficient for PFE was only .02, which, when converted to Hedges & Olkin's 'g' in my meta-analysis, is an effect size of -.200. These results suggest that knowing how to prioritize time may not help one to achieve better grades in school.

The last of the four IC time management scales is found in Macan et al. (2000). They use the Time Management Behavior Scale (TMB), a 46 item questionnaire they created for this study with four factors that "[account] for 72% of the common variance" (Macan et al., 1990, p. 761). The four factors are: *setting goals and priorities; mechanics-planning* (such as making lists) *and scheduling*; *perceived control of time*; and *preference for disorganization*. The Macan et al. (2000) study is one of the stronger papers reviewed by Robbins et al. (2004). It is strong for several reasons. First, it is focused on actual time management behavior, or at least verbal reports of actual time use behavior, rather than merely attitudes toward or knowledge of time management methods. As such, it would be expected to be more predictive of academic performance. Secondly, the authors have the good sense to focus on <u>only</u> behavior, a clear, unidimensional, single aspect of time management, rather than mixing responses on time management attitudes, knowledge, skills, perceptions, behavior, and practices, as many of the questionnaire-based studies have done. Since the focus is behavior, Macan et al.'s TMB study is reported in depth in the next section, the *external manifestations* subcategory, but it is mentioned here because one of the four factors of the TMB scale, *perceived control of time,* represents participants' beliefs that they have control over how they use their time, and is less behavioral than the other three factors.

The primary outcome measure of interest for my review is grade point average, which Macan et al. (2000) found to have a correlation of $r = .22$ ($p < .01$) with factor three, *perceived control of time*. They also report the correlation of factor three with seven additional outcome measures,[8] all seven of which correlate significantly with this third factor. Factor three is negatively correlated with four of the seven additional outcome measures: role ambiguity ($r = -.27$, $p <.05$), role overload ($r = -.35$, $p < .01$), job-induced tension ($r = -.36$, $p < .01$), and somatic tension ($r = -.45$, $p < .01$). It is positively correlated with the remaining three outcome measures: job satisfaction ($r = .32$, $p < .01$), life satisfaction ($r = .31$, $p < .01$) and the participants' personal evaluations of their academic performance ($r = .37$, $p < .01$).

While this study uses self-reports for outcome measures, and is thus limited in some ways, these findings indicate that students who perceive they have greater control of their time report greater satisfaction with their schoolwork and in their lives as a whole. These students also appear to do better in school, experience less stress and feel better about their performance.

The External Manifestations (EM) Subcategory

The EM subcategory is comprised of 17 correlation coefficients from 11 studies, which include the use of eight scales of measurement. The other three factors from Macan et al. (2000)—*setting goals and priorities, mechanics-planning* (such as making lists) *and scheduling*; and *preference for disorganization*—fit well in this subcategory. In fact, when a test of heterogeneity is done on these three factors alone, we find no evidence of heterogeneity ($Q = 0.915$, $p = .633$). As mentioned earlier, factor three, *perceived control of time,* also contains

[8] Two of the outcome measures, consist of a single response: GPA a single self-reported value, and academic performance self-rating on a seven point scale. The remaining six outcomes were combined scales consisting of two to seven items.

behavioral items, and when added to the heterogeneity test with the other three factors, the Q statistic increases, but only slightly ($Q = 1.451$, $p = .694$). This shows the value of utilizing a well formulated scale of measurement that assesses a single aspect of time management.

Two of the three behavior/practices factors from Macan et al. correlate significantly with GPA. *Mechanics-planning and scheduling* has a correlation coefficient of .20, with a significance level of $p < .05$. And, although this may be surprising, *preference for disorganization* is also positively correlated with GPA ($r = .17$, $p < .05$). The only factor with a non-significant correlation is *setting goals and priorities* ($r = .10$).

These findings are in agreement with Britton & Tesser (1991), who maintain that time management practices are a more accurate indication of college GPA than standardized test scores (SAT/ACT). In their study, freshmen students are given a time management questionnaire that includes items based on three factors: *short-range planning*, *time attitudes* and *long-range planning*. After four years, the participants' cumulative college GPA information is gathered. Britton and Tesser (1991) find that two of the three factors, *short-range planning* and *time attitudes,* significantly correlate with college GPA ($r = .25$, $p < .05$ and $r = .39$, $p < .05$, respectively). The researchers conclude that students with short-range planning skills and positive attitudes towards time management perform better in school.

In their study four years later, Trueman and Hartley (1996) base their Time Management scale on the questionnaire developed by Britton and Tesser (1991). They eliminated several questions, and extract only two factors, instead of three. Their two factors are *daily planning* and *confidence in long-term planning*. Unlike Britton and Tesser (1991), Trueman and Hartley (1996) find that *confidence in long-term planning* correlates significantly with academic performance ($r = .21$, $p < .001$), but *daily planning* does not ($r = .04$). Their results suggest that while some students may believe they organize their time better on a daily basis, this does not necessarily translate into better academic performance. Trueman and Hartley (1996) also note that women report better time-management skills than men, and that older students (25 or older) report better time-management skills than younger students (younger than 25).

A Gabriel biplot clearly illuminates these findings as shown in Figure 2. The biplot shows the vectors for factor one (daily planning), factor two (long term planning), and total time management superimposed on the means for men and women students at three ages (young, borderline mature, and older mature). Note that for both men and women, the older students have higher scores than the two younger groups, particularly on factor two, but also somewhat on factor one.

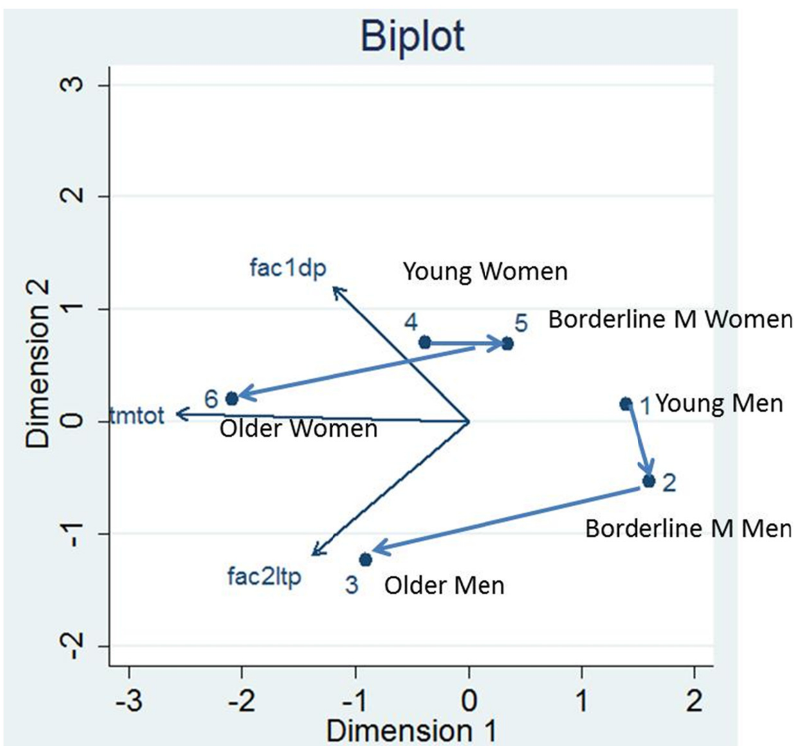


Figure 2. Gabriel (1971) biplot showing the vectors for Trueman and Hartley's (1996) factor 1, daily planning, Factor 2, long-term planning, and total time management, with the bivariate location of six respondent groups superimposed.

The next study to be considered is the Long et al. (1994) study that uses the Lifestyle Approach Inventory (LSA). In addition to the *performance focus and efficiency* subscale that was discussed earlier in the IC subcategory, the LSA contains the *timeliness of task accomplishment* (TTA) subscale that fits well in the EM subcategory. Long et al. (1994) found that the TTA subscale correlates significantly with internal motivation ($r = .39$, $p < .01$), disorganized study methods ($r = -.47$, $p < .01$), the PQAL ($r = -.20$, $p < .01$), and the SHAI ($r = .41$, p < .0

1). As noted above, none of the LSA subscales correlate significantly with GPA, although the TTA subscale does have the highest correlation of all four ($r = .10$). Unfortunately, that correlation coefficient only has an effect size of .040. These results suggest that accomplishing your tasks quickly (or at least reporting that you do) may not help you to achieve better grades in school. This could be because you give up a level of quality when you try to move too rapidly through your tasks, or it could be a reflection of the illusory nature of self-report measures.

Dreher & Singer (1985) utilize the California Study Methods (CSMS) survey in their study. The CSMS is a self-report questionnaire that yields separate scores on three subscales: *attitudes toward school, mechanics of study, and planning and systems*. The authors report the following correlation coefficients between the subscales and GPA: .32, .18, and .23, respectively. Because the *attitudes toward school* subscale has the highest correlation coefficient, and is the only one with significance, the authors essentially ignored the other two subscales in their discussion. The *planning and systems* subscale, which indicates how students allocate their study time, is the only one of the three CSMS subscales related to time management. Its effect size is .47, which is the fifth highest among the correlation coefficients included in my meta-analysis of the *external manifestations* subcategory. These results suggest that how students organize their study time could have an impact on their academic performance, and may be more important than the actual study techniques used (the *mechanics of study* subscale).

The Learning and Study Strategies Inventory (LASSI) is used in three of the EM subcategory studies (Kern et al., 1998; Rugsaken et al., 1998; Stoynoff et al., 1997). The LASSI is a self-report measure that assesses thoughts and behaviors related to successful learning. The inventory items form 10 subscales: *attitude*, *motivation*, *time management*, *anxiety*, *concentration*, *information processing*, *selecting main ideas*, *study aids*, *self-testing* and *test strategies*.

Kern et al. (1998) use the LASSI in addition to a measure of testwiseness, or how "students' use secondary cues in multiple-choice test items" (p. 28). They also use an abbreviated form of the Intellectual Achievement Responsibility Questionnaire (IARQ), a measure of "student's beliefs about their control and responsibility for academic success and failure" (p. 28). Correlations are given between the aforementioned variables, GPA and attrition. Both of the IARQ subscales (*success* and *failure*) correlate negatively, albeit minimally, with GPA ($r = -.05$ and $r = -.07$, respectively). The measure of testwiseness correlates positively, but not significantly with GPA ($r = .19$). Four of the ten subscales of the LASSI correlate significantly with GPA, including *time management* ($r = .34$, $p < .001$). The *time management* subscale of the LASSI examines the participants' use of time management principles for academic tasks. The effect size from my meta-analysis for this variable is .720, the largest of all the effect sizes. This seems to indicate that students who utilize time management principles in their academic endeavors perform better in school.

The results from Kern et al. (1998) were not, however, replicated in other studies. Both Rugsaken et al. (1998) and Stoynoff (1997) correlate scores from the LASSI *time management* subscale with GPA, and neither of them find significance; in fact their correlation coefficients are quite small ($r = .17$ and $r = .07$, respectively). The effect sizes for those two correlations were .345 and .139. If there is such diversity in the results of studies that utilize the same measurement tool, it is no wonder there is so much heterogeneity among the variety of measurement tools employed across time management studies.

Garavalia & Gredler (2002) use the Self-efficacy for Self-regulated Learning (SESRL) test. The evaluation is "designed to measure student-initiated activities and cognitions related to learning" (p. 224). The SESRL is composed of five components: *general organizing/planning strategies*, *task preparation strategies*, *environmental restructuring*, *recall ability* and *typical strategies*. The *general organizing/planning strategies* component is included in the EM subcategory. This component asks the participants questions in the form of "How well can you…" (Gredler & Schwartz, 1997), with some item examples being, "finish assignments by deadlines, prepare for courses when there are other interesting things to do" (Garavalia & Gredler, 2002, p. 225). The correlation coefficient between the *general organization/planning* component and GPA is .34, with a calculated effect size of .718, the second largest effect size in the EM subcategory.

Trockel et al. (2000) developed a questionnaire primarily comprised of items that relate to health-behavior variables that are potential predictors of academic performance. One of those questions is "How often do you use a planner or action list to manage time and meet responsibilities?" (Table 1, p. 127). While this appears to be one of the most basic time management practices, it was one of only seven variables that correlates significantly with GPA ($r = .224$, $p < .01$). These results indicate that although use of a planner, or similar tool, may be basic, it could affect academic performance.

A Social/Personality Dimension - The Adult Self-Expression Scale (ASES)

In addition to the aforementioned internal conceptions and external manifestations of time management, I believe that time management is also affected by a social/personality dimension. In observing over several years the struggles of students on academic probation, one of the most common similarities is a difficulty to communicate with, or express themselves to, peers and teachers. In addition to observation, prior research suggests that success with time management, and academics as a whole, may be affected by people's ability to express and assert themselves.

In 2001, Huang & Zhang, developed the "Time Management Disposition Scale" (TMDS). The scale is designed to measure the time management disposition of adolescents. The TMDS has three subscales: *sense of time value*, *ability of time control*, and *sense of time efficacy*. In administering the TMDS and the Scale of A-type Personality to 526 college students, Gong (2000) reports a statistically significant positive correlation ($p < .01$) between students with Type-A personalities, and time management disposition. Gong concludes that Type-A personality college students have better time management dispositions than Type-B personality college students. People with Type-A personalities are described as ambitious, aggressive and time-conscious (Friedman, 1996). Typically these people are comfortable expressing themselves freely, without apprehension.

Communication apprehension (CA) is defined as "an individual's level of fear or anxiety associated with either real or anticipated communicative interaction with another person or persons during a social gathering" (Wrench, Brogan, McCrosky & Jowi, 2008, p.411). CA is generally observed, and studied, in four contexts (group, meeting/classroom, interpersonal and public). Some studies have shown that high CA students have lower GPAs and higher dropout rates, than low CA students. High CA students avoid situations that require communication, including meeting with teachers or peers to discuss class material (McCroskey &Sheahan, 1978). High CA students are also less effective at understanding and remembering class content (Booth-Butterfield, 1988).

A four year longitudinal study by McCroskey, Booth-Butterfield & Payne (1989), indicates that the impact of CA on college students is considerable. Results show that high CA college students are significantly more likely to achieve lower GPAs and drop out, than low CA students. They find these connections to be especially strong during the first two years of college.

Clearly, a student's propensity to act, be assertive, and engage within the social system of school is extremely important to academic success. The Adult Self-Expression Scale (ASES), a measure of assertiveness, assesses the aforementioned variables by producing scores on many kinds of social behavior (expressing opinions, refusing unreasonable requests, etc.) in a variety of interpersonal situations (with parents, with friends, with authority figures, etc.).

The ASES, a forty-eight question inventory, was developed in 1975 by Gay, Hollandsworth and Galassi. At the time "existing instruments designed to measure assertiveness [were] either unstandardized or standardized on relatively homogenous college populations" (Gay et al., 1975, p. 340). There are two dimensions present in the ASES. One dimension relates to "interpersonal situations", and the other relates to "assertive behaviors." The "interpersonal situations" dimension examines the following six specific situations: "interactions with parents, the public, authority figures, friends, intimate relations" (Gay et al., 1975, p. 341) and global situations. The "assertive behaviors" dimension examines the following seven specific behaviors: "expressing personal opinions, refusing unreasonable requests, taking the initiative in conversations and in dealing with others, expressing positive feelings, standing up for legitimate rights, expressing negative feelings, and asking favors of others" (Gay et al., 1975, p. 341).

Gay et al. (1975) find that subjects who score high on the ASES view themselves as more self-confident. They state that "high scorers are more achievement-oriented, more often seek leadership roles in groups or influence and controlling roles in individual relationships,… are more attention seeking, [and] are more independent" (p. 343). We expect the ASES to have strong predictive usefulness in accounting for academic performance, particularly when combined with the behavioral and attitudinal predictors from the first two studies.

The Big Picture and Problem

The confusion of the results obtained through both meta-analyses (Robbins' et al. and my own) calls the effectiveness of time management evaluations into question. Looking at each of the individual studies from the meta-analysis up close, a number of clues begin to explain the unclear and contradictory nature of the findings with respect to the prediction of academic success from time management. Nearly all of the measures are based upon loose, abstract, self-report Likert scale items, that are combined into double-barreled (or triple-barreled or worse) scales that combine diverse aspects of time management (knowledge of principles, skills, time management strategies, attitudes about time management, actual usage of one's time, etc.) into single scales. The whole literature is based upon correlative networks among ambiguous scales that result in the production of very little information of substance. The resulting problem is undoubtedly related more to the studies themselves than the meta-analysis procedures used to combine them in the Robbins et al. (2004) paper.

The Proposed Solution

The approach to be taken in this dissertation is to separate time management into three aspects: time actually allocated, evaluation of the use of that time, and more general attitudes toward the practice of time management. In addition a fourth predictive domain is added, a multi-dimensional measure of assertiveness. The strategy is to keep each of these four measurement domains separate from one another, so that each domain can be compared to the others in its contribution to the prediction of academic performance. Each domain, including academic performance, will also be considered multivariately. That is, rather than summarizing each domain with a single total score, each of the items within each domain will be analyzed individually, as well as holistically with multivariate analyses, such as principal component analysis and associated principal component plots.[9] This gives a holistic picture of the structural relationships among the variables while not losing the comparative information from each of the individual variables.

We will also take a holistic approach to prediction, using canonical correlation between each of the predictor sets and the academic performance criterion set. Just as a multiple correlation will always be at least as large as any of the bivariate correlations implicit within it, so also canonical correlation between two sets of variables, an X set and a Y set, will always be at least as large as any of the multiple correlations within it. As such, it becomes a filter for identifying the largest possible multiple R-squared in the set of multiple regressions that are

[9] One of the great errors in previous studies that have used multivariate methods, such as factor analysis, is that they often report only factor scores without sufficient information to compare across studies. For example, Trueman and Hartley (1996) use the same scale as Britton and Tesser's earlier study (1991), and yet the two studies cannot be compared, since Trueman and Hartley obtain different factors than Britton and Tesser and only report factor scores. This renders meta-analysis difficult or impossible. To guard against this error we will report results for each individual item but in their multivariate context using principal component plots.

possible in predicting each of the Y variables from the combined set of X variables. Canonical correlation will be used in that way in this dissertation.

The time log measurement tool is the centerpiece of this dissertation. It is my belief that this approach will show that measures that assess actual time usage will correlate strongly with GPA. Findings from Scott's (2011) time log study support this hypothesis. Results showed that students on academic probation (those whose grades drop below 2.0 two semesters in a row) do not spend as much time on academic-based activities as students who are high academic achievers. High performing students report studying two hours or more for every hour they are in class, as recommended by Brigham Young University (BYU) policy. Students on academic probation, however, studied less than one hour outside of class for every hour in class. High performing students obviously take this policy more seriously than students on academic probation.

I believe that the six question time management attitude survey will also correlate with GPA. The survey is based on self-descriptor questions from Scott's 2011 study. These questions were the only part of the survey significantly related to GPA. Although I do think the six question survey will do an adequate job of predicting GPA, I do not think that the results will be as strong as time log data.

Although the ASES will correlate with GPA, I do not think the relationship will be as strong as the time log data or the six question survey. The ASES is essentially an ancillary measurement that will simply add another dimension to the time management literature.

In addition to the aforementioned solutions, I intend to take a more holistic approach to understanding time management than previously completed studies. Each one of the variable sets in this dissertation includes more than one variable when predicting GPA. Many of the other studies rely on a single scale score to encompass the results from multi-dimensional evaluative tools. Having more than one predictor variable within each variable set, allows for more accurate and stable prediction.

The Dissertation

This dissertation consists of two studies. The first study uses canonical correlations to examine the natural relationships between GPA and five sets of predictor variables: time spent on selected activities, adjective evaluations of time spent on activities, the combination of time spent and time evaluations, a six question survey, and the behavioral and situational dimensions of the ASES.

The second study is hypothesis testing with regard to four groups: males and females on academic probation, and males and females with high GPAs. The effects of academic probation and gender on the same four sets of variables are examined: time spent on selected activities, adjective evaluations of activities, a six question survey, and the behavioral and situational dimensions of the ASES.

Methods

Participants

After receiving approval from the BYU Institutional Review Board, undergraduate psychology majors (ages 18 to 30 years) are recruited based on gender and GPA, and participation in a Psychology 430R capstone course. The participant numbers vary depending on study and variable set.

Eighteen participants are recruited specifically for the hypothesis testing in Study 2 (completing time logs, a six question survey and the ASES). One group consisted of female and male students with a GPA above 3.6 (six male and five female students); the second group contained female and male students whose GPA was less than 2.0 for more than two semesters in a row, placing them on academic probation (four males and three females). Students meeting the GPA criteria are identified using data from BYU's Student Academic & Advisement Services and the Registrar's office. Complying with FERPA requirements, the identifying data are kept in a locked cabinet. To keep the study blind and follow the qualifications of FERPA, only Dr. Bruce Brown, my dissertation chair, knows which students fall into which GPA groups.

The other 27 participants are a convenience sample. They are students who participated in a capstone course that studied time management. They completed only the time logs. Of the total 45 participants, only 30 of them produced complete, balanced time logs (both time spent and adjective ratings were given for the selected days of Monday, Tuesday and Saturday). No GPA data could be found on two of the 30 participants, due to lack of BYU academic records, bringing the total to 28 participants. Because not all of the subjects completed all of the tasks, the number of participants varies by study and analysis section of the study. In Study 1, three of the predictive analysis datasets (time spent, time evaluation, and the combination of these two) have 28 participants, and the other two datasets (six question survey and ASES) have 18 participants. In Study 2, two of the datasets (time spent and time evaluation) have 12 participants, and the other two (six question survey and ASES) have 18 participants. Specific participant numbers are also reported in the respective results sections.

Time Log Materials and Procedure

An electronic time log tool is created in Microsoft Access by a contracted computer programmer. In an effort to get a sampling of participants' typical week, they are asked to record their activities for three days, a Monday, a Tuesday and a Saturday. Because most classes at BYU run on either a Monday/Wednesday/Friday schedule, or a Tuesday/Thursday schedule, Monday and Tuesday are included to give an idea of their academic commitments. And, to assess a typical leisure day, we ask for a record of their Saturday activities. We chose Saturday over Sunday because most students at BYU are religious, and many abstain from extracurricular activities on Sunday, including studying. The time log completion consists of two parts; the first is recording the time spent on activities of the day, and the second is completing the ratings of each time segment on 17 adjective scales. The time logs take an average of five hours for each respondent to complete.

Recording activities. Each participant assigns each 30 minute segment of time for three specified days (Monday, Tuesday and Saturday) to one of the 21 activity categories — sleep, dining at home, dining out, recreation, studying, teaching, church meeting, reading scripture, reading pleasure, exercise, travel, walking, TV, service, computer, shopping, grooming, visiting, house chores, class, and OTHER. This allows for analysis of the amount of time the participants are spending on various activities and what time of day these activities are taking place. The categories are supplied to provide compatibility across respondents.

Adjective ratings. After completing the activity recording process for each day, the students are asked to rate each half-hour block of time on 17 adjective scales. Each scale consists of nine points and ranges from the anchors of *little* to *much*. Eight of these adjectives focus on how the time was spent — *productive, wasted, pleasant, unpleasant, interesting, boring, unusual,* and *routine.* Four focus on how the participant felt at that time — *tired and weary, alert, confused, clear and focused*. Five focus on how the participant feels about that time in retrospect — *regret, disappointed, ashamed, grateful, satisfied.*

Six Question Survey Materials and Procedure

The six question survey derives from a longer survey used in Scott's (2011) study of BYU students. Included in the longer survey were 11 self-descriptor questions that were the only part of the survey significantly related to GPA. "From an initial factor analysis of the eleven self-descriptors, the six that had the highest communality with the entire set were selected in order to create a more tightly structured factor analytic set" (Scott, 2011, p.26). The six questions measure how much the participant agrees with each of the following statements: "It is important to me to develop the skills necessary to use my time wisely." (skillIMP), "I am an organized person." (IMorg), "I organize my study time carefully to make the best use of it." (Iplan), "I generally prefer to do things spontaneously rather than plan ahead." (Spont), "I have been successful so far in school without having to manage my time carefully." (SWOTM), and "Using time wisely is very important to me." (TMimp). Participants complete the survey on a computer using a response template. This is done after the completion of the time logs.

ASES Materials and Procedure

Participants rate themselves on a five point scale from 0 (Almost Always/Always) to 4 (Never or Rarely), for each of the 48 questions. The completion of this survey is done at the end of the data collection process, after both the time logs and the six question survey are finished. The ASES is expected to combine effectively with time logs and time usage attitudes in accounting for academic success. It is expected that the combined predictive usefulness of these three factors in predicting academic success will exceed an R-squared of .50, far in excess of the .025 that would be estimated from the Robbins et al. (2004) results (from a corrected correlation coefficient of .159 in their Table 6, p. 272).

Results from Study 1 – Canonical Correlation Analysis of the Effects of Five Sets of Predictor Variables on the GPA Set of Criterion Variables

Each of the variable sets undergoes the same process in an effort to examine the holistic structure of the predictors and of GPA, and explore the taxonomy of the types of students in each of the groups. First I look at the internal structure of each of the four predictor variable sets, and GPA. Clustered principal components plots are used to create vectors to define a three-dimensional graph space, and then to cluster participants within that space. Next, the predictive abilities of each variable set, as it relates to GPA, are examined. Canonical correlations are used to assess the strength of the predictions.

GPA Set of Criterion Variables

The GPA data for the 28 participants for whom I have complete time log data is compiled from BYU's academic records. From the raw data, the following nine variables are calculated for each participant: overall GPA, overall GPA for BYU courses only, average GPA for Fall/Winter hours, standard deviation of GPA for Fall/Winter semesters, total number of Fall/Winter credit hours, percent of total hours that were taken during Fall/Winter semesters, total number of Spring/Summer credit hours, percent of total hours that were taken during Spring/Summer terms, and percent of transfer credits.

The 28x9 matrix of GPA data are then standardized in order to make the variables commensurate and comparable to one another in preparation for performing a cluster analysis. Using the statistical program "R", the matrix is analyzed using a hierarchical cluster analysis (complete linkage method), and a dendrogram is produced (see Figure 3). The red line in Figure 3 represents where the dendrogram is separated to produce seven clusters.

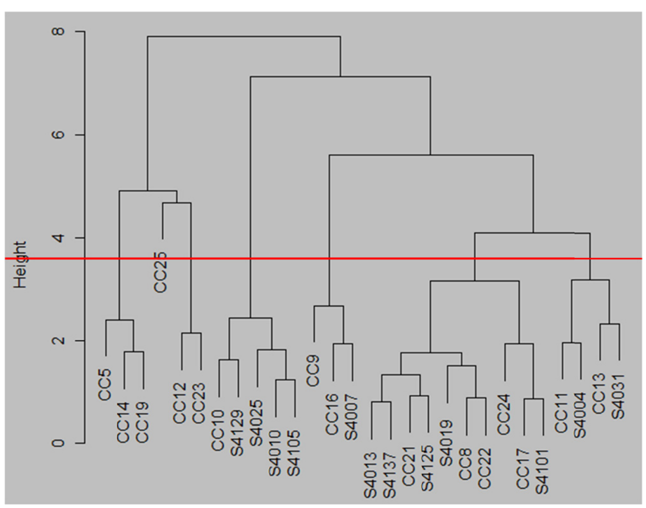


Figure 3. Dendrogram of the structure of 28 persons' GPA variables. A line shows the division of the 28 data points into seven clusters.

A principal component analysis of the data matrix (which now includes the means for each of the seven clusters) is completed. The summary table for the principal component analysis is shown in Table 1. The 9x3 array of factor loadings in this table consists of correlation coefficients between each of the nine GPA-related variables and each of the three factors, and as such they provide the coordinates for plotting the vectors of the nine variables in a three-factor space as shown in Figure 4. The loadings in Table 1 are varimax-rotated factor loadings.

The 9x3 array of communalities (squared factor loadings) are indicator of how much of the variance in each variable is accounted for by each factor. The total communalities indicate what proportion of variance in each of the nine variables is accounted for by the three-factor space, with the uniqueness column indicating the proportion not accounted for. The Fall/Winter standard deviation variable is clearly the one least accounted for in this space as shown by its uniqueness value of 0.2914. In other words, 29.1% of its variance is not accounted for.

The "sum of squares by columns" values[10] for each of the three columns (factors) indicate what proportion of the variance in the XYZ space is accounted for by each factor. Factor 1 accounts for a little less than 40% of the variance. Factor 2 accounts for a little more than 30%, and Factor 3 accounts for a little more than 20%. This total to almost 93%, leaving only a little over 7% variance in the nine variables not accounted for within this space. This is an unusually high percentage of variance accounted for in a three-dimensional principal component plot, indicating that Figure 4 has captured well the pattern of the data for the 28 participants on the nine GPA-related variables.

[10] If this table consisted of the initial factor loadings rather than the rotated factor loadings, these "sums of squares by columns" would be the first three eigenvalues of the correlation matrix. However, once the factor loadings matrix has been rotated, the sums of squares by columns no longer retain this property.

Table 1

Principal Component Analysis Summary Table for Nine GPA Variables, Varimax Rotated

	Loadings			Communalities				Uniqueness
	factor 1	factor 2	factor 3	factor 1	factor 2	factor 3	Total	U
GPA total	.9628	.1530	-.0173	.9270	.0234	.0003	.9507	.0493
Fall/Winter Average	.9634	.2033	-.0248	.9281	.0413	.0006	.9700	.0300
Combined Average	.9555	.2316	.0126	.9129	.0537	.0002	.9667	.0333
Fall/Winter StdDev	-.8356	-.0844	-.0574	.6982	.0071	.0033	.7086	.2914
Percent Transfer	-.2373	-.9494	-.0908	.0563	.9013	.0082	.9659	.0341
Fall/Winter Credits	.0982	.9096	-.2624	.0096	.8274	.0689	.9060	.0940
Fall/Winter Percent	.2279	.9406	-.1514	.0519	.8848	.0229	.9597	.0403
Spring/Summer Credits	-.0479	-.0788	.9737	.0023	.0062	.9482	.9567	.0433
Spring/Summer Percent	.0842	-.1485	.9723	.0071	.0220	.9454	.9746	.0254
Sums of squares by columns:				3.5934	2.7673	1.9980	8.3588	.6412
Percents of sums of squares:				39.93%	30.75%	22.20%	92.88%	7.12%

Using Metrika, the factor loadings from the principal component analysis are utilized to plot the vectors for the nine GPA variables in a three dimensional space. Viewing Figure 4, it is easy to see how the nine variables separate to define three factors. Factor 1 is defined by high total, Fall/Winter, and BYU GPAs, and low standard deviations for Fall/Winter GPA (X-axis). This is the primary GPA dimension. The negative correlation between the standard deviation of GPA and the other three variables in this factor indicates that those with low total GPA also have a high standard deviation of their GPAs across semesters. Those at the right of this XYZ space, high on the X-axis, have high GPAs and those at the left have low GPAs.

Factor 2 is defined by high numbers and percentages of Fall/Winter credit hours, and low percentages of transfer credits (Y-axis). In other words, those who transfer from other schools have a lower proportion of their credit hours attributable to BYU Fall/Winter semesters. Data points at the top of this XYZ space (high on the Y-axis) therefore have a high proportion of their credit hours from BYU, while those at the bottom tend to have a large number of transfer credits.

Factor 3 is defined by high numbers and percentages of Spring/Summer credit hours (Z-axis). In other words those data points at the front of the XYZ space, those high on the Z-axis, have a high proportion of their credit hours from Spring/Summer terms, and those in the back have few or no Spring/Summer credits.

These three axes define the GPA space within which each of the 28 participants can be located.

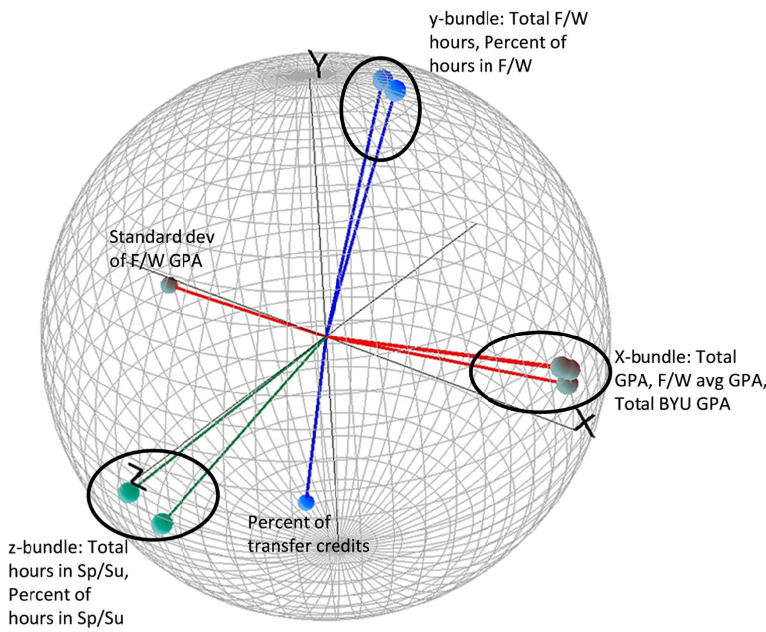
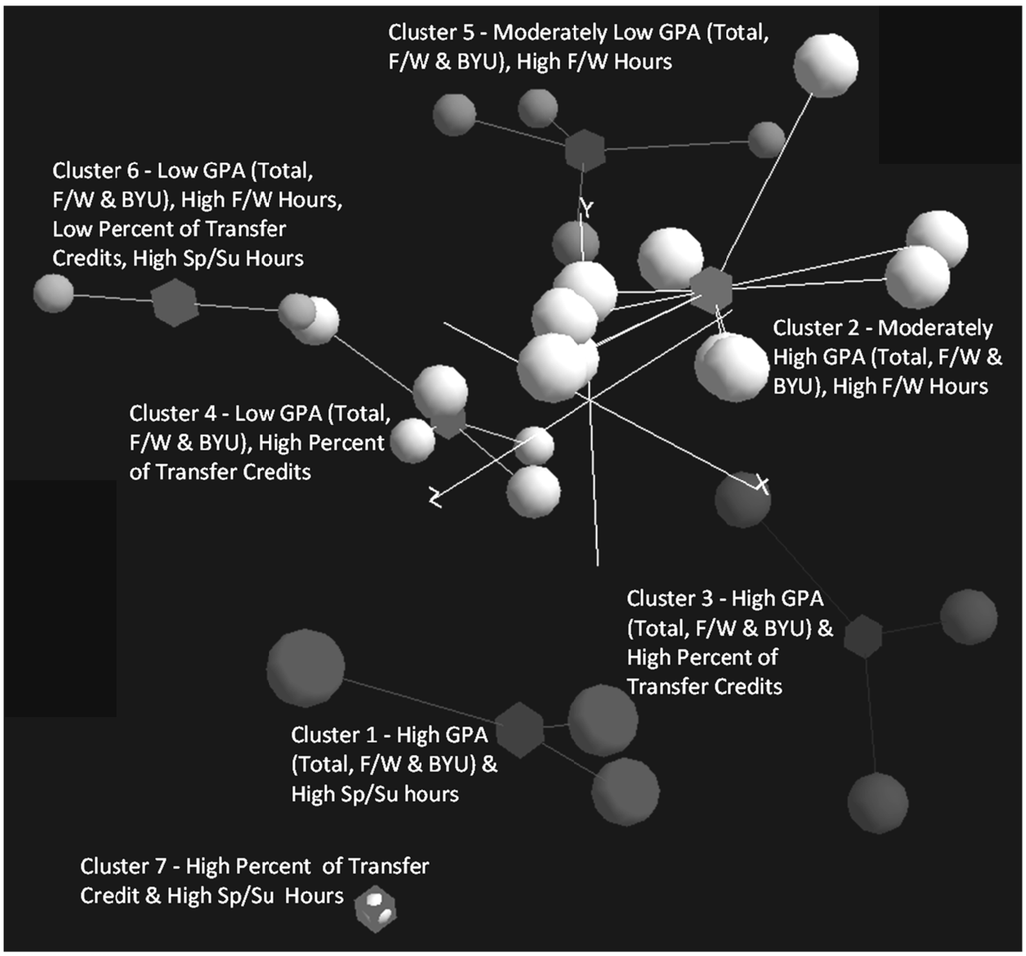


Figure 4. Principal Component Analysis (PCA) vector plot of the nine GPA variables within the three-factor space. Factor loadings (Table 1) are the coordinates from which the vectors for these nine variables are plotted.

The individual factor scores for each of the 28 participants are used to plot their location (see Figure 5) within the space defined by the vector plot of Figure 4. Individuals are connected with lines to their cluster means, represented by cubes. Cluster 1 is made up of three participants who have high total, Fall/Winter, and BYU GPAs. Cluster 2 is made up of 10 participants with moderately high GPAs, and high numbers of Fall/Winter credit hours. Cluster 3 is made up of three participants with high GPAs, and high percents of transfer credits. Cluster 4 is made up of five participants with low GPAs and high percents of transfer credits. Cluster 5 is made up of four participants with moderately low GPAs, and high numbers of Fall/Winter credit hours. Cluster six is made up of two participants with low GPAs, low percents of transfer credits, and high numbers of Spring/Summer credit hours. And Cluster 7 is a lone participant with a high percent of transfer credits and a high number of Spring/Summer hours.



Lambda = 0.002915
Mult R^2 = 0.997085
p = <.0001

Figure 5. Seven GPA clusters of the 28 data points, plotted within the three-factor GPA space defined in Figure 4.

Line plots of each of the seven clusters are created to show the general overall patterns for each cluster. These graphs can also be used to quickly assess how tight each of the clusters truly are, or the goodness of fit for the overall cluster patterns. Figure 6 shows that, for the most part, these seven clusters are relatively tight, and clearly show a general trend for each of the clusters.

These are not ordinary line plots. They are "ordered profiles" (Hendrix and Brown, 1990) in which the nine variables have been ordered and grouped according to correlational similarity to one another, in order to simplify the profiles into flowing patterns rather than the zig-zag patterns that would result from a random ordering. Notice that the first four variables on the left of each graph are the four that define the X-axis of Figure 4, the next three are those that define the Y-axis, and the last two define the Z-axis.

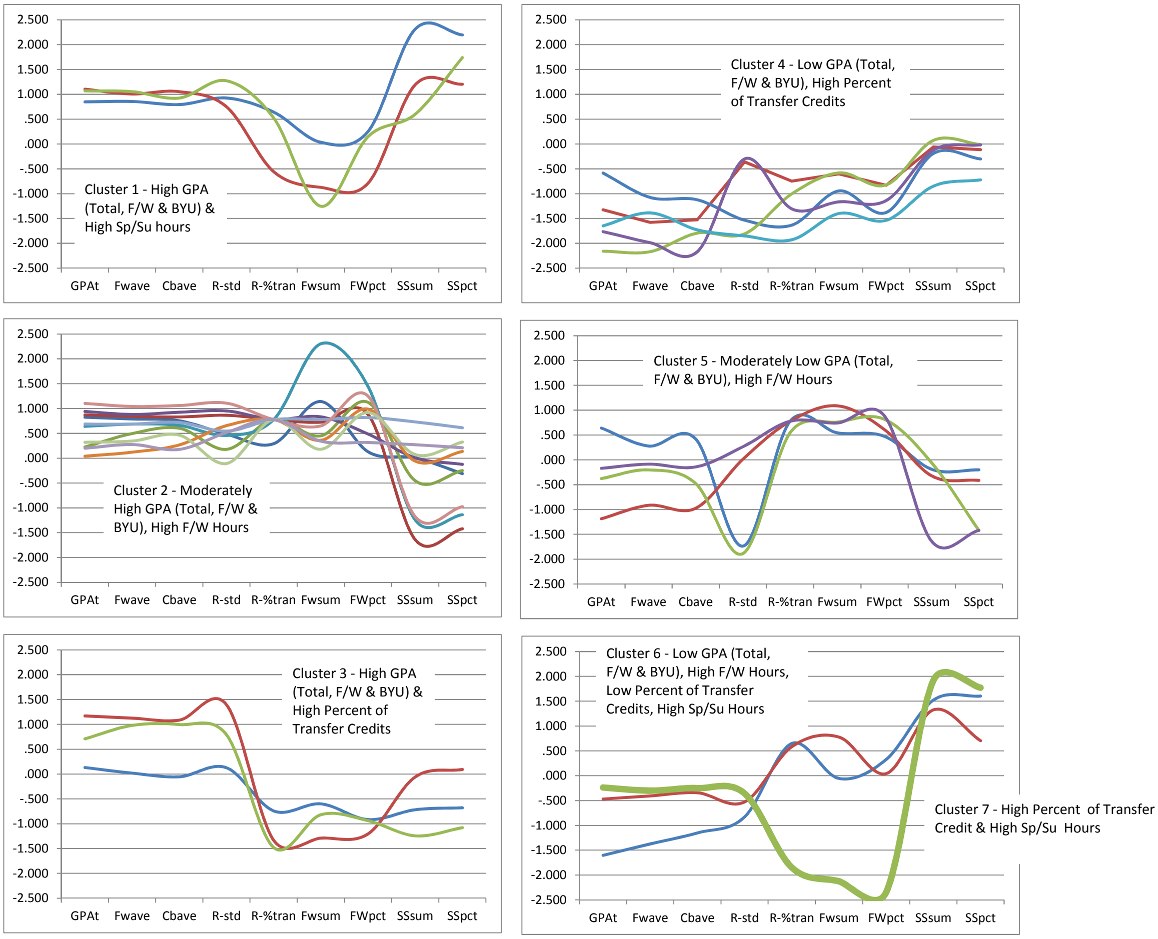


Figure 6. Line plots showing the ordered profiles of the 28 participants in the seven clusters in relation to the nine GPA variables: overall GPA (GPAt), average GPA for Fall/Winter hours (Fwave), overall GPA for BYU courses only (Cbave), reversed standard deviation of GPA for Fall/Winter semesters (R-std), reversed percent of transfer credits (R-%tran), total number of Fall/Winter credit hours (Fwsum), percent of total hours taken during Fall/Winter (FWpct), total number of Spring/Summer credit hours (SS sum), and percent of total hours that were taken during Spring/Summer terms (SSpct). The values on two of the variables (R-std and R-%tran) have been reversed to simplify the profiles.

A one-way MANOVA is used to test the adequacy of the seven clusters in separating the 28 data points within the space of the nine GPA-related variables, as was shown in Figures 5 and 6. The highly significant p-values for both the univariate and multivariate statistics of this MANOVA (Table 2) confirm that the clusters do, indeed, separate well. The multivariate r-squared of 0.999, and the univariate R-squared values ranging from 0.645 to 0.914 indicate that the seven cluster groupings account for a high proportion of the variance in location of each of the 28 participants within the XYZ space defined by Figure 4.

Table 2

One-Way MANOVA as a Test of the Adequacy of the Seven Clusters in Separating the Eighteen Data Points within the Space of the Nine GPA-Related Variables, Multivariate Results at the Bottom of the Table and Univariate Results at the Top

Univariate Statistics

	F(6,21)	p	R2
Nine GPA-Related Variables			
GPA total	13.69	<.0001	0.796
Fall/Winter Average	23.23	<.0001	0.869
Combined Average	23.73	<.0001	0.871
Fall/Winter StdDev	7.73	0.0002	0.688
Percent Transfer	37.10	<.0001	0.914
Fall/Winter Credits	13.89	<.0001	0.799
Fall/Winter Percent	30.11	<.0001	0.896
Spring/Summer Credits	6.35	0.0006	0.645
Spring/Summer Percent	9.35	<.0001	0.728

Multivariate Statistics

	F(6,21)	p	R2
Wilks' Lambda	0.00051	<.0001	0.999
Pillai's Trace	3.218	0.0001	
Hotelling-Lawley Trace	41.453	<.0001	
Roy's Greatest Root	30.735	<.0001	

Note. The multivariate η^2 is calculated as one minus the Wilks' lambda value (Wilks, 1963).

Predictor Variable Set A – Time Spent on Selected Activities

To simplify the analyses, the 21 activity categories given in the time logs are first reduced to focus on seven categories: class, computer, recreation, sleep, study, television, and visiting. These seven were chosen because I felt they were the categories most likely to affect GPA. The total number of hours each participant spent on these activities over the three days (Monday, Tuesday and Saturday) are calculated, and then averaged across the three days. This reduced set of data is then standardized, cluster analyzed, and a dendrogram is created (Figure 7). The red line in Figure 7 represents where the dendrogram is separated to produce eight clusters.

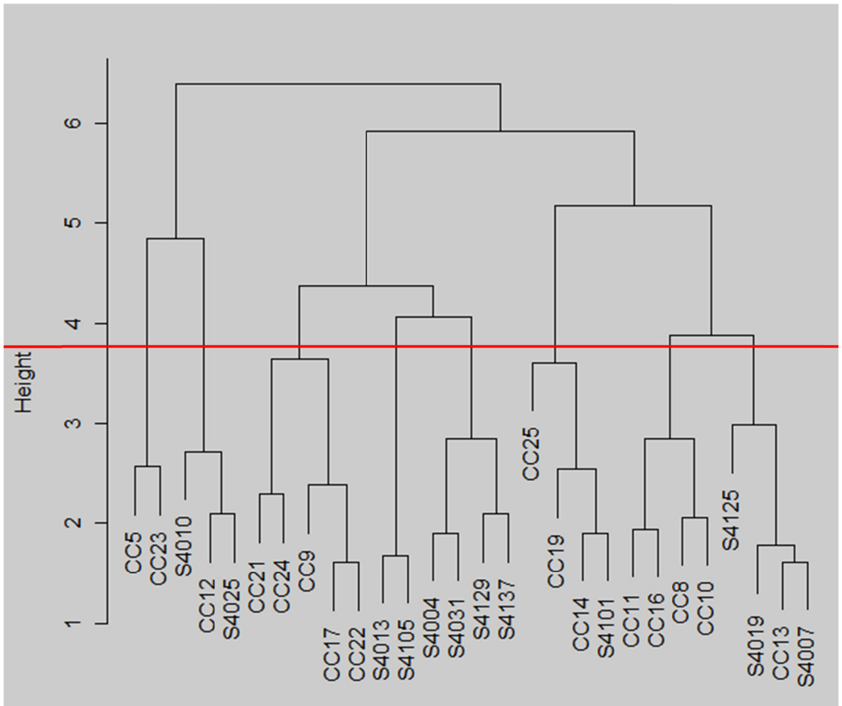


Figure 7. Dendrogram of the structure of 28 persons' relative amount of time spent in each of seven activities: class, computer, recreation, sleep, study, television, and visiting. A line shows the division of the 28 data points into eight clusters.

The data matrix augmented by the means of each of the eight clusters is analyzed using principal component analysis. The summary table for the principal component analysis is shown in Table 3. In the case of the time-spent variables the principal component analysis accounts for about two-thirds of the variance of the seven variables within a three-factor space – reasonably strong, but not nearly so much as with the GPA-related variables. The three varimax-rotated factors are about equal to one another in percent of variance accounted for, at a little over 20% each. Sleep hours and visiting hours are the variables least accounted for within this XYZ space (0.4404 and 0.3966 uniqueness, respectively) with the other five approximately equal to one another at about 0.30 uniqueness.

Table 3

Principal Component Analysis Summary Table for Seven Time-Spent Variables, Varimax Rotated

	Loadings			Communalities				Uniqueness
	factor 1	factor 2	factor 3	factor 1	factor 2	factor 3	Total	U
Class Hours	-.7378	-.3260	-.0929	.5443	.1063	.0086	.6592	.3408
Computer Hours	.8360	-.0499	-.0128	.6989	.0025	.0002	.7015	.2985
Recreation Hours	-.4253	-.0525	.7318	.1809	.0028	.5356	.7192	.2808
Sleep Hours	.4380	.0871	.6001	.1918	.0076	.3602	.5596	.4404
Study Hours	-.1230	-.8232	-.0082	.0151	.6777	.0001	.6929	.3071
Television Hours	.0410	.8415	-.0454	.0017	.7081	.0021	.7118	.2882
Visiting Hours	-.1141	.0460	-.7670	.0130	.0021	.5882	.6034	.3966
Sums of squares by columns:				1.6457	1.5070	1.4948	4.6476	2.3524
Percents of sums of squares:				23.51%	21.53%	21.35%	66.39%	33.61%

Using Metrika, the factor loadings from the principal component analysis are utilized to plot the vectors for the seven time-spent variables. Unlike the GPA variables, which were clearly clustered into three bundles, the time-spent variables have an autoregressive Toeplitz structure. That is, rather than having the variables grouped into tight little bundles as in Figure 4, they are more evenly spaced throughout the XYZ space. A path through the vector plot is drawn in Figure 8. The vector order of this path is used to create ordered profiles that comprise the line plots of Figure 10. Ordered profile plots increase the ease with which the results can be interpreted (Hendrix & Brown, 1990).

Comparing Table 3 to its graphical rendition, Figure 8, one can see that the structure is characterized by three oppositions. First, the vertical dimension is defined by TV hours at the top and study hours at the bottom. The horizontal X-axis is defined by computer hours at the right, with class hours at the left (and somewhat downward). The horizontal Z-axis is defined by recreation hours and sleep hours in the front (positive on Z), with recreation somewhat to the left on X and sleep somewhat to the right on X; and the negative end of the Z-axis is defined by visiting hours in opposition to these two.

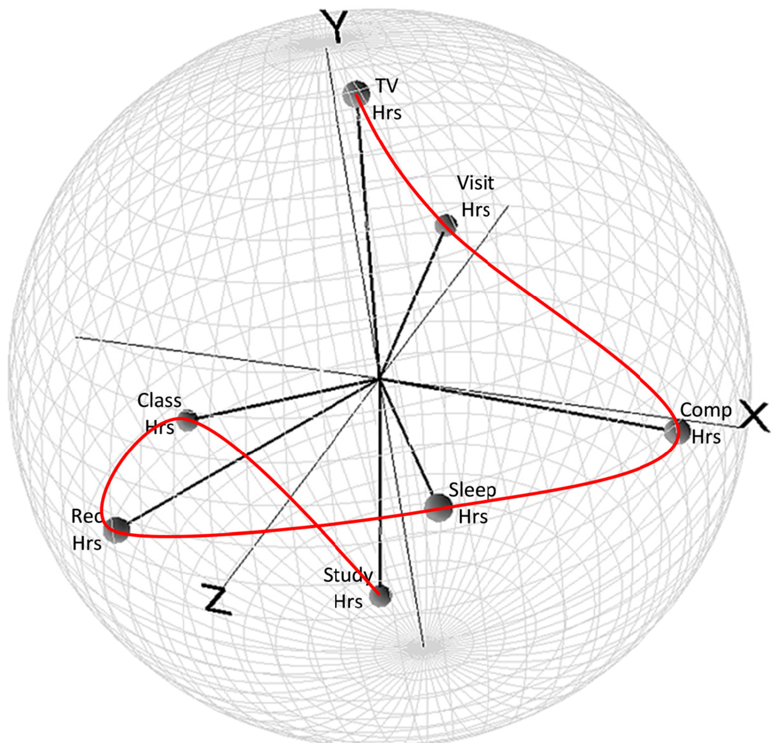


Figure 8. PCA vector plot, within the three-factor space, of time spent on each of seven activities: class, computer, recreation, sleep, study, television, and visiting.

The individual factor scores for each of the 28 participants are used to plot their location within the space (Figure 9) defined by Figure 8. Individuals are connected with lines to their cluster means. Cluster 1 is made up of two participants who have a high number of hours spent using the computer. Cluster 2 is made up of four participants who have a high number hours spent in class and studying. Cluster 3 is made up of five participants who have a moderately high number of hours spent visiting, and watching television. Cluster 4 is made up of three participants who have a high number of hours spent watching television. Cluster 5 is made up of five participants who have a high number of hours spent in class and participating in recreation.

Cluster six is made up of four participants who have a high number of hours spent using the computer and sleeping. Cluster 7 made up of four participants who have a high number of hours spent visiting. Cluster 8 is made up of two participants who have a high number of hours spent studying.

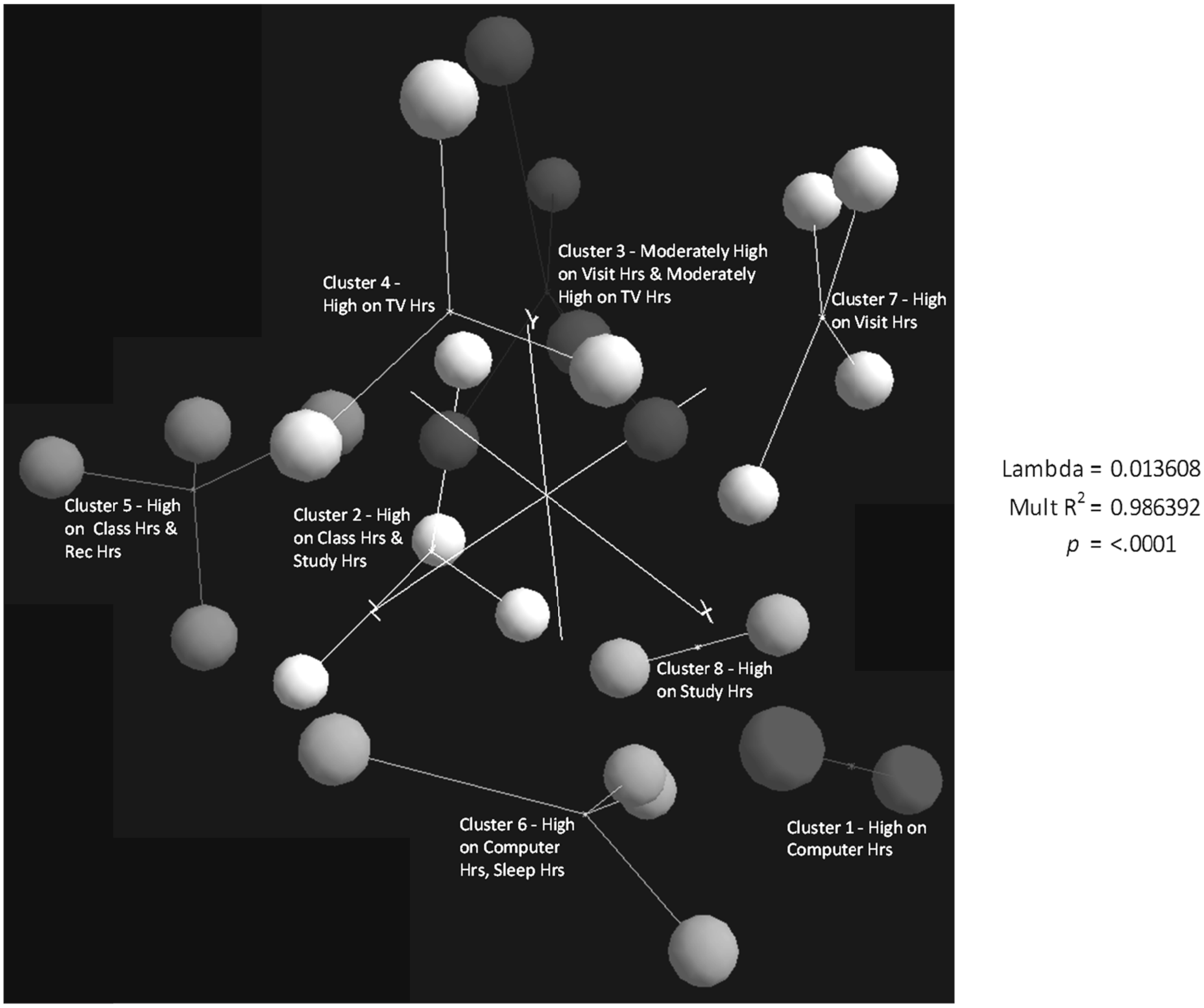


Figure 9. Eight clusters of the 28 data points, plotted within the three-factor space, based on time spent on seven activities, as seen in Figure 8.

Line plots of each of the eight clusters are created to show the general overall patterns for each cluster. Figure 10 clarifies the precise location of each participant with respect to the seven time-spent variables, and shows that, for the most part, these eight clusters are tight, and clearly show the same general trend within each of the clusters.

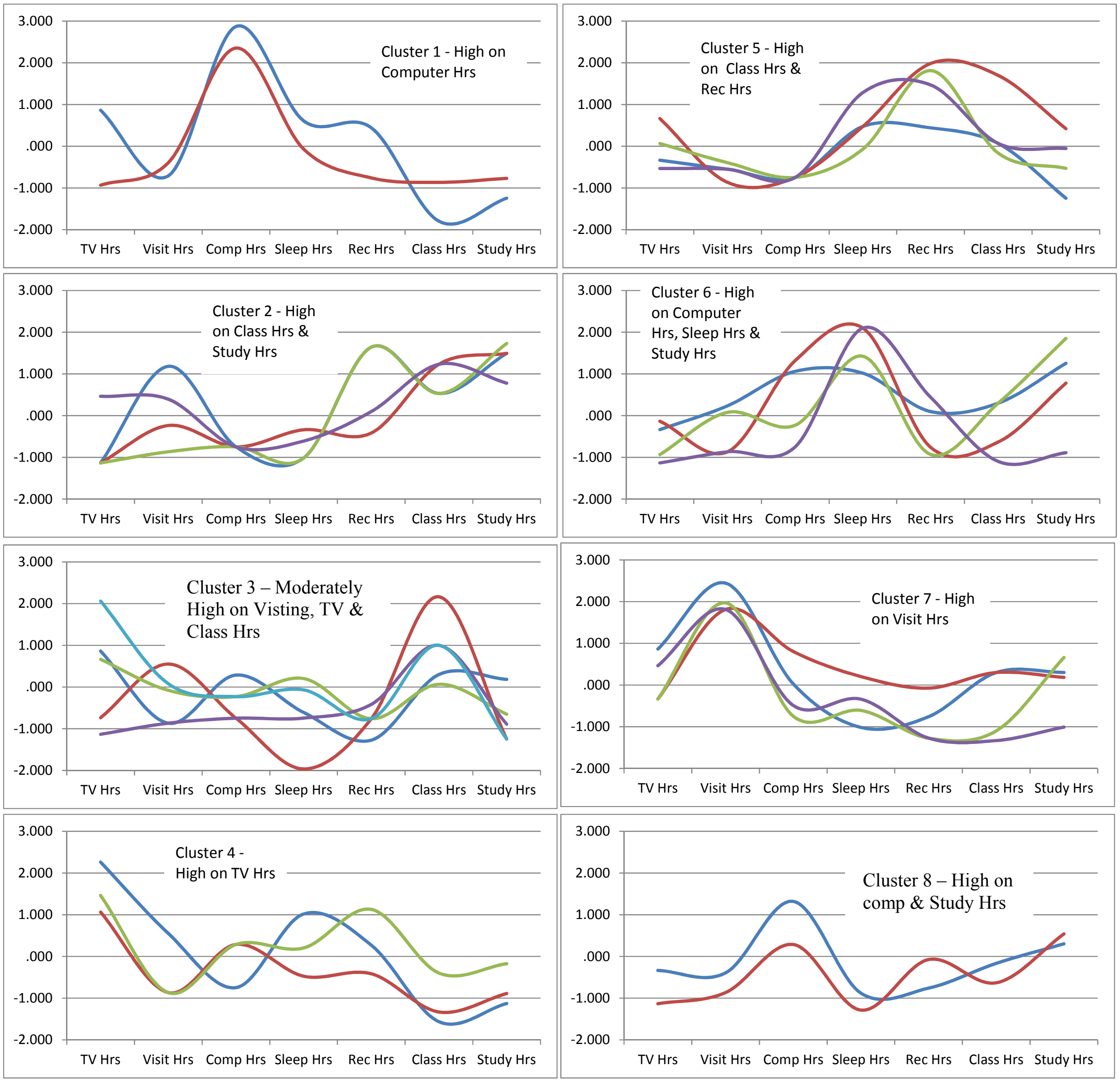


Figure 10. Line plots showing the order profiles of the 28 participants within the eight clusters in relation to time spent on seven different activities.

A one-way MANOVA is used to test the adequacy of the eight clusters in separating the 28 data points within the space of the seven time-spent variables. The highly significant p-values for both the univariate and multivariate statistics in Table 4 confirm that the clusters separate well.

Table 4

One-Way MANOVA as a Test of the Adequacy of the Eight Clusters in Separating the Eighteen Data Points within the Space of the Seven Time-Spent Variables, Multivariate Results at the Bottom of the Table and Univariate Results at the Top

Univariate Statistics

	F(7,20)	p	R2
Seven Time-Spent Variables			
Class Hours	4.51	0.0037	0.612
Computer Hours	8.99	<.0001	0.759
Recreation Hours	5.17	0.0018	0.644
Sleep Hours	7.96	0.0001	0.736
Study Hours	5.04	0.0020	0.638
Television Hours	2.72	0.0373	0.488
Visiting Hours	8.52	<.0001	0.749

Multivariate Statistics

	F(7,20)	p	R2
Wilks' Lambda	0.00047	<.0001	1.000
Pillai's Trace	4.058	<.0001	
Hotelling-Lawley Trace	19.154	<.0001	
Roy's Greatest Root	7.406	<.0001	

Note. The multivariate η2 is calculated as one minus the Wilks' lambda value (Wilks, 1963).

A canonical correlation analysis is used to evaluate the multivariate relatedness of the nine GPA-related variables (the Y set) and the seven time-spent variables (the X set). The results are shown in Table 5. Only one of the multivariate tests, Roy's Greatest Root, is significant. However, if any one of the multivariate tests is significant, that is usually sufficient to avoid a Type I error (Rencher, 1990). Roy's Greatest Root is typically the multivariate test most likely to obtain significant results. It is possible to have multivariate significance without univariate significance. This simply means that there is a significant match in the overall pattern or structure between the two variable sets without a clearly defined connection between parts. When, however, when there is univariate significance without multivariate significance, one cannot trust the results. In other words, the multivariate test is a filter to protect against alpha inflation in running several univariate tests. Although there is multivariate significance, in the relationship between the GPA-related variables and the time-spent variables, the connections are not very strong.

Actually, there are three sets of links to be considered in canonical correlation: the links between the X set of observed variables and their latent variables, the links between the Y set of observed variables and their latent variables, and finally, the links between the X and Y latent variables as expressed in the canonical correlation coefficients. The first canonical correlation coefficient, .8437 in this case (Table 5), can be thought of as the upper limit in the value of multiple R that could be expected in a multiple regression (either in predicting a Y-set variable from a group of X-set variables, or vice versa). For the nine GPA-related variables and the seven time-spent variables of Table 5, this indicates that the strongest multiple regression one could obtain would have a multiple R of .8437, and therefore an R-squared value (percent variance accounted for) of .7118.

The layout of the canonical correlation summary table shown in Table 5 in intended to emphasize the similarity between factor analysis/principal component analysis (PCA), and canonical correlation analysis. Canonical correlation analysis can be thought of as a double factor analysis. Brown, Hendrix, Hedges, and Smith (2012) have summarized this approach to canonical correlation:

> Like factor analysis and PCA, canonical correlation analysis also finds latent variables that are linear combinations of the observed/manifest variables. However, the criterion by which we obtain the linear combination differs. Rather than seeking a factor or component that has the least amount of squared distance from the internal set of variables, canonical correlation seeks two linear combinations simultaneously, one on the

> X set of variables and one on the Y set of variables, subject to the criterion that the correlation coefficient between the two paired latent variables is *maximized.* (p. 284)

The canonical correlation summary table, Table 5, gives loadings, squared loadings (comparable to communalities in PCA or factor analysis), and uniqueness, sums of squares by columns and their percents, interpreted in the same way as in a factor analysis or PCA summary table, but with two of them, one (for the Y set) above the other (for the X set). From Table 5 it can be seen that the connection between the GPA-related variables (the Y set) and their underlying three latent variables is not particularly strong, with only 31.97% variance accounted for. The connection between the time-spent observed variables (the X set) and their underlying three latent variables is only slightly stronger, with 34.59% variance accounted for. Like factor analysis and PCA, one can see in the total squared loadings which observed variables are most strongly related to their latent variables (Spring/Summer credits and Spring/Summer percents in the Y set with values of .4676 and .7171 respectively, and visiting hours in the X set with a value of .9399), and in the uniqueness values those that are highly unrelated (Fall/Winter credits and Fall/Winter percents in the Y set with values of .9154 and .9214, and class hours and study hours in the X set with values of .8846 and .8609).

Table 5

Canonical Correlation Summary Table with the Y Set of GPA Variables (Dependent) at the Top of the Table, and the X Set of Time-Spent Variables (Independent) at the Bottom of the Table

	Loadings			Squared Loadings				Uniqueness
	LV1	LV2	LV3	LV1	LV2	LV3	Total	U
Y Set (GPA)	*(eta1)*	*(eta2)*	*(eta3)*	*(eta1)*	*(eta2)*	*(eta3)*		
GPA total	.0074	.3824	.4820	.0001	.1462	.2323	.3786	.6214
Fall/Winter Average	.0785	.4513	.4323	.0062	.2037	.1869	.3967	.6033
Combined Average	.0706	.3594	.4805	.0050	.1292	.2309	.3650	.6350
Fall/Winter StdDev	-.1372	-.1307	-.4908	.0188	.0171	.2409	.2768	.7232
Percent Transfer	.0850	-.2464	-.2111	.0072	.0607	.0446	.1125	.8875
Fall/Winter Credits	-.1249	.0902	-.2467	.0156	.0081	.0609	.0846	.9154
Fall/Winter Percent	-.1820	.1877	.1013	.0331	.0352	.0103	.0786	.9214
Spring/Summer Credits	.6365	-.1513	.1989	.4051	.0229	.0396	.4676	.5324
Spring/Summer Percent	.6605	-.1748	.5003	.4363	.0306	.2503	.7171	.2829
Sum of squares by columns:				.9274	.6537	1.2965	2.8776	6.1224
Percents of sums of squares:				10.30%	7.26%	14.41%	31.97%	68.03%
X Set (time spent)	*(chi1)*	*(chi2)*	*(chi3)*	*(chi1)*	*(chi2)*	*(chi3)*		
Class	-.1313	.1831	.2542	.0172	.0335	.0646	.1154	.8846
Computer	.4803	.0701	.3026	.2307	.0049	.0916	.3272	.6728
Recreation	.4320	-.4024	-.0647	.1866	.1619	.0042	.3527	.6473
Sleep	.3498	.1348	.4934	.1224	.0182	.2434	.3840	.6160
Study	-.2666	.1737	.1945	.0711	.0302	.0378	.1391	.8609
Television	-.2994	-.0276	.2696	.0896	.0008	.0727	.1631	.8369
Visiting	-.2614	.7877	-.5011	.0683	.6205	.2511	.9399	.0601
Sum of squares by columns:				.7860	.8699	.7654	2.4213	4.5787
Percents of sums of squares:				11.23%	12.43%	10.93%	34.59%	65.41%

	Coefficient	Multivariate Statistics	Index	p Value
First Canonical Correlation	.8437	Wilks' Lambda	.0260	.3926
Second Canonical Correlation	.7263	Pillai's Trace	2.5445	.2624
Third Canonical Correlation	.7025	Hotelling-Lawley Trace	5.7619	.5361
		Roy's Greatest Root	2.4705	.0020

These tabular results can be expressed graphically with the linked vector plots for the GPA and time-spent variables shown in Figure 11. The plots show the X-set vectors and the Y-set vectors within their respective latent variable spaces. The two spaces are linked by a canonical correlation of .844 for the two x-axes, .726 for the two y-axes, and .703 for the two z-axes. In the time-spent vector plot on the left of Figure 11 one can see the visiting hours variable (which has XYZ coordinates of .2614, .7877, and -.5011 respectively) extending up near the y-axis and into the background on the x-axis and the z-axis as indicated by these coordinates. The bounding spheres for these two linked plots represent the maximum length of vectors, that is, a vector would extend to the sphere if all of the variance were accounted for by the latent variables. In both the X set and also the Y set of variables for this canonical correlation analysis, nearly all of the vectors fall far short, indicating what is also seen in the large uniqueness values and percent of sums of squares—that only about a third of the variance in the variables of each set is accounted for by the latent variables.

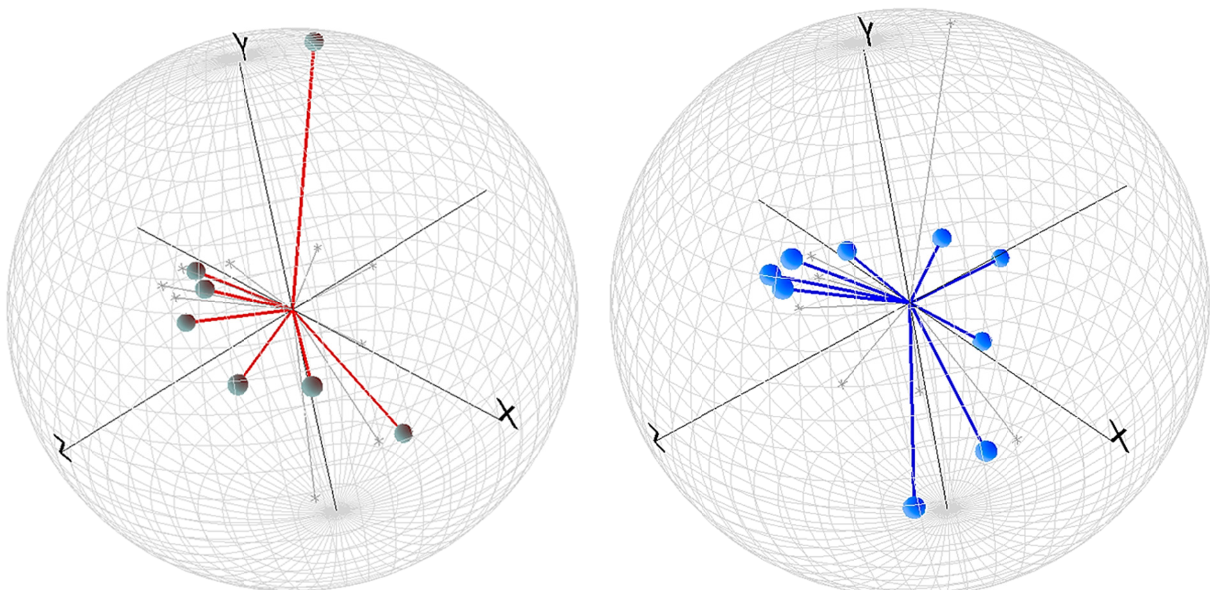


Figure 11. Linked vector plots showing the time-spent vectors within their latent variable space, and the GPA vectors within their latent variable space. The two spaces are linked by a canonical correlation of .844 for the two x-axes, .726 for the two y-axes, and .703 for the two z-axes. On the left, the “time spent” vectors are emphasized in red, and on the right the GPA vectors are emphasized in blue.

Linked factor score plots are also generated for this canonical correlation analysis, as shown in Figure 12. The clusters are shown within their respective spaces (time-spent clusters in time-spent spaces), as well as in the other variable space (time-spent clusters in GPA space). The factor score plots make it easy to see that even within their own spaces the clusters are not tightly grouped. And when placed in the other variable space, the clusters overlap even more, and become difficult to distinguish. Four MANOVAs are used to evaluate the relative effectiveness of the four combinations of cluster structure and latent variable space shown in Figure 12: the time-spent cluster structure within the time-spent (X set) latent variable space as shown in the upper left panel, the GPA cluster structure within the GPA (Y set) latent variable space as shown in the upper right panel, the time-spent cluster structure within the GPA (Y set) latent variable space as shown in the lower left panel, and the GPA cluster structure within the time-spent (X set) latent variable space as shown in the lower right panel. The results of each MANOVA are shown in Figure 12 next to the panel to which they apply. The strongest of the four is the first, the one in the upper left panel for the time-spent cluster structure within its own latent variable space, with a Wilk's lambda value of .06791 and therefore an R-squared value of .9321 (since one minus Wilk's lambda is an index of multivariate R-squared). The weakest of the four is the GPA cluster structure within this same time-spent latent variable space (lower left panel), and it is also the only one of the four that is not statistically significant. This analysis has an R-squared of .6508, which seems reasonably strong by univariate standards, but for multivariate structure it is not.[11]

[11]To put this in context, recall that the original clustering of GPA variables within their own latent variable space as shown in Figures 5 and 6, had very high MANOVA statistics, $\Lambda(6,21)=.00051$, $p<.0001$, est $\eta^2=.9995$, as reported in Table 2. The original clustering of time-spent variables within their own latent variable space as shown in Figures 9 and 10 were also very high on the MANOVA statistics, $\Lambda(7,20)=.00047$, $p<.0001$, est $\eta^2=.9995$, as reported in Table 4. These two latent variable spaces are created by principal component analysis and are therefore fitted to only one dataset each. The corresponding latent variable space by cluster structure combination (GPA clusters in GPA latent variable space and time-spent clusters in time-spent latent variable space) shown in Figure 12 are fitted to both sets of variables simultaneously by canonical correlation, and the cluster structure is slightly less effective (multivariate R-squared values of .9321 and .8326 respectively). And, of course, the crossed cluster structures with latent variable spaces shown in the lower panels of Figure 12 have lower values (.6508 for one).

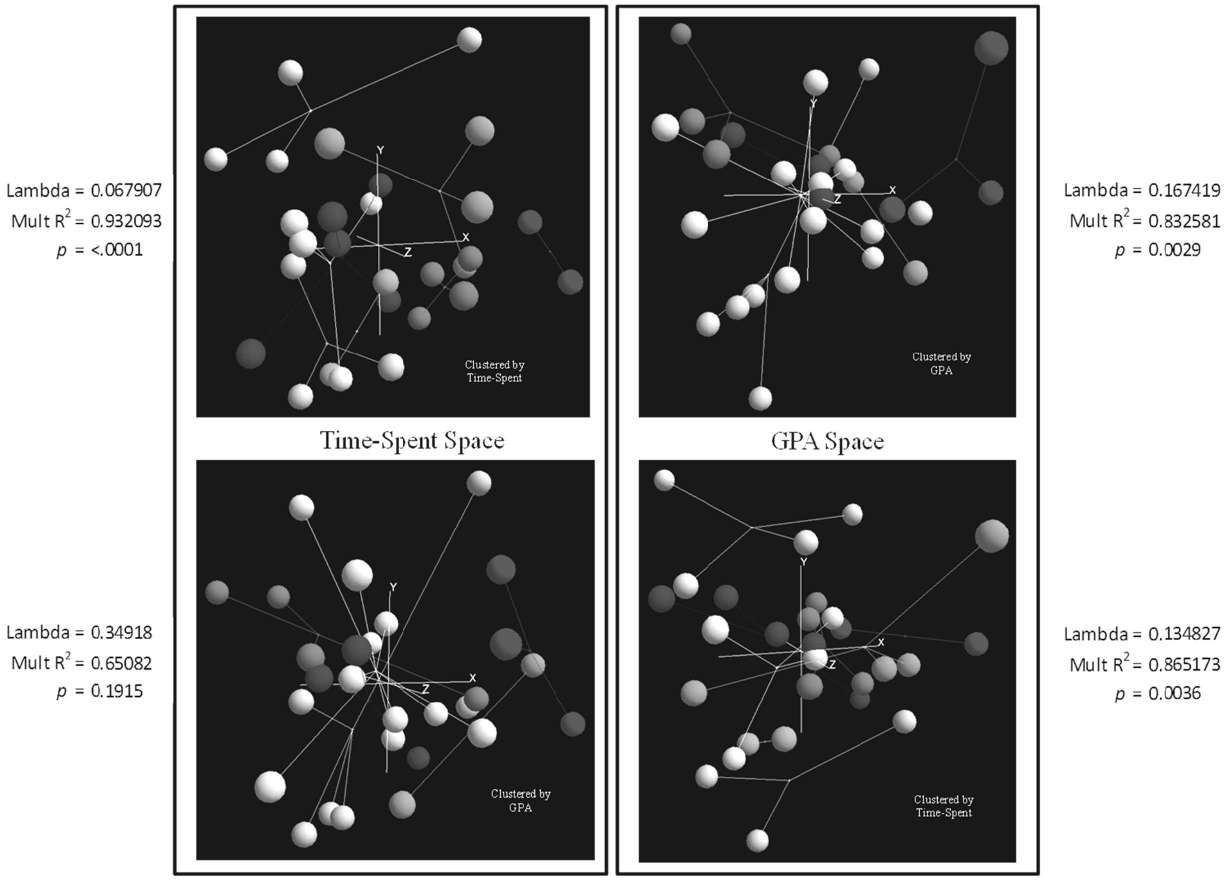


Figure 12. Linked factor score plots for time spent and GPA. On the left, the time-spent and GPA clusters are shown in the time-spent space. On the right, the GPA and time-spent clusters are shown in the GPA space.

Predictor Variable Set B – Time Evaluations

Not every participant engaged in every one of the 21 activity categories over the three day recording period. Therefore, there is incomplete adjective rating data for many of the categories. Due to statistical restraints regarding degrees of freedom, only three of the categories (class, sleep and study) had a sufficient number of adjective ratings to be utilized in this analysis.[12]

[12] In the next section, Variable Set C combines time-spent with activity evaluations. There are many possible ways to combine these two sets of variables for analysis. I did explore the canonical correlations among all possible

To ease the process of analyzing the adjective ratings, a factor analysis is performed (see Table 6). Factor 1 is categorized by positive adjectives, or the use of time was 'good'. It includes high positive factor loadings on 'pleasant', 'interesting', 'grateful' and 'satisfied', and high negative factor loadings on 'unpleasant' and 'boring'. Factor 2 is categorized as 'wasted', or the time was not well spent. It has high positive loadings on the following adjectives: 'wasted', 'regret', 'disappointed', and 'ashamed'. And it has relatively high negative factor loadings on 'productive' and 'routine'. Finally, Factor 3 focuses on how alert a person was during that particular time. It has high positive factor loadings on 'alert' and 'focused', and a high negative loading on 'tired'.

Table 6

Factor Analysis Summary Table of Rotated Three Factor Solution Calculated on the Three-Way Person by Activity Category by Day Means

	Loadings			Communalities			Uniqueness
	factor 1	factor 2	factor 3	factor 1	factor 2	factor 3	U
prodct1	.165	-.668	.078	.4465	.0273	.0061	.4799
wast2	-.160	.754	-.041	.5685	.0256	.0017	.5958
pleas3	.861	-.091	.020	.0083	.7420	.0004	.7507
unpleas4	-.754	.178	.097	.0317	.5679	.0093	.6089
interst5	.660	.114	.444	.0130	.4353	.1969	.6452
borng6	-.713	.054	-.143	.0030	.5080	.0205	.5315
unus7	.242	.499	.368	.2492	.0588	.1354	.4434
routn8	-.091	-.503	-.373	.2531	.0082	.1393	.4006
tired9	.003	.105	-.708	.0111	.0000	.5018	.5129
alert10	.115	-.040	.882	.0016	.0132	.7774	.7923
conf11	-.089	.354	-.199	.1256	.0078	.0397	.1731
focsd12	.116	-.094	.848	.0089	.0134	.7188	.7411
regret13	-.177	.794	-.075	.6299	.0312	.0057	.6668
disapp14	-.380	.653	-.047	.4266	.1441	.0022	.5729
ashmd15	-.105	.723	-.026	.5232	.0110	.0007	.5350
gratef16	.675	-.265	.077	.0702	.4556	.0059	.5317
satis17	.673	-.433	.180	.1874	.4535	.0326	.6734
Sums of squares by columns:				3.5579	3.5030	2.5944	9.6553
Percents of sums of squares:				20.93%	20.61%	15.26%	56.80%

groupings of the two variables. The three chosen variables were selected because of their completeness and relevance. Appendix A shows the canonical table.

The factor scores for each of the three activity categories (class, sleep, and study) for each participant are standardized, and a dendrogram is created (Figure 13). The red line in Figure 13 represents where the dendrogram is separated to produce five clusters.

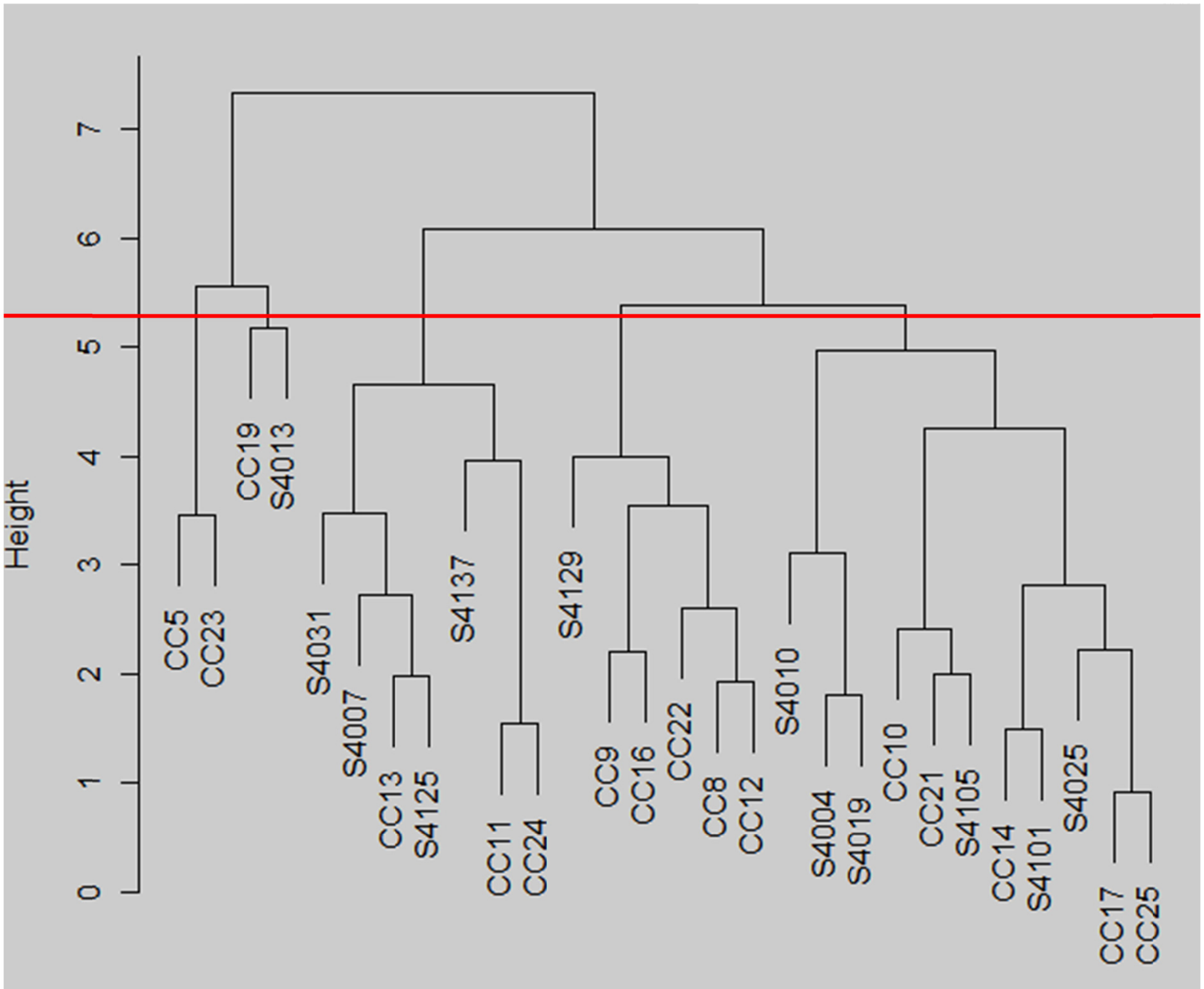


Figure 13. Dendrogram of the structure of 28 persons' evaluative factor scores for CLASS time, SLEEP time, and STUDY time. A line shows the division of the 28 data points into five clusters.

The data matrix augmented by the means of each of the five clusters is analyzed using principal component analyses. The summary table for the analysis is shown in Table 7. The three factor solution for this time evaluation data is comparable to the one in Table 3 for the time-spent set of variables, with about two-thirds of the variance accounted for with three factors.

Table 7

Principal Component Analysis Summary Table for Nine Time Evaluation Factor Score Variables, Varimax Rotated

	Loadings			Communalities				Uniqueness
	factor 1	factor 2	factor 3	factor 1	factor 2	factor 3	Total	U
Factor 1 ("good") Eval of Class	.8686	.0679	.3318	.7544	.0046	.1101	.8691	.1309
Factor 2 ("wasted") Eval of Class	-.0216	.6726	-.4876	.0005	.4524	.2378	.6906	.3094
Factor 3 ("alert") Eval of Class	-.6220	-.0836	.2608	.3869	.0070	.0680	.4619	.5381
Factor 1 ("good") Eval of Sleep	.3725	.3397	.6149	.1388	.1154	.3781	.6323	.3677
Factor 2 ("wasted") Eval of Sleep	.2819	.1803	-.6538	.0794	.0325	.4274	.5394	.4606
Factor 3 ("alert") Eval of Sleep	.0698	-.0512	.6307	.0049	.0026	.3978	.4053	.5947
Factor 1 ("good") Eval of Study	.7995	-.2858	.1122	.6391	.0817	.0126	.7334	.2666
Factor 2 ("wasted") Eval of Study	-.0554	.8786	.0169	.0031	.7719	.0003	.7752	.2248
Factor 3 ("alert") Eval of Study	-.5904	.5254	.1741	.3485	.2760	.0303	.6549	.3451
Sums of squares by columns:				2.3556	1.7441	1.6624	5.7621	3.2379
Percents of sums of squares:				26.17%	19.38%	18.47%	64.02%	35.98%

The vector plot of the nine time evaluation variables shown in Figure 14 is created from the factor loadings of Table 7. Like the time-spent variables, these vectors have a Toeplitz structure. A path is drawn through the vector plot, to be used in creating the ordered profile line plots of Figure 16.

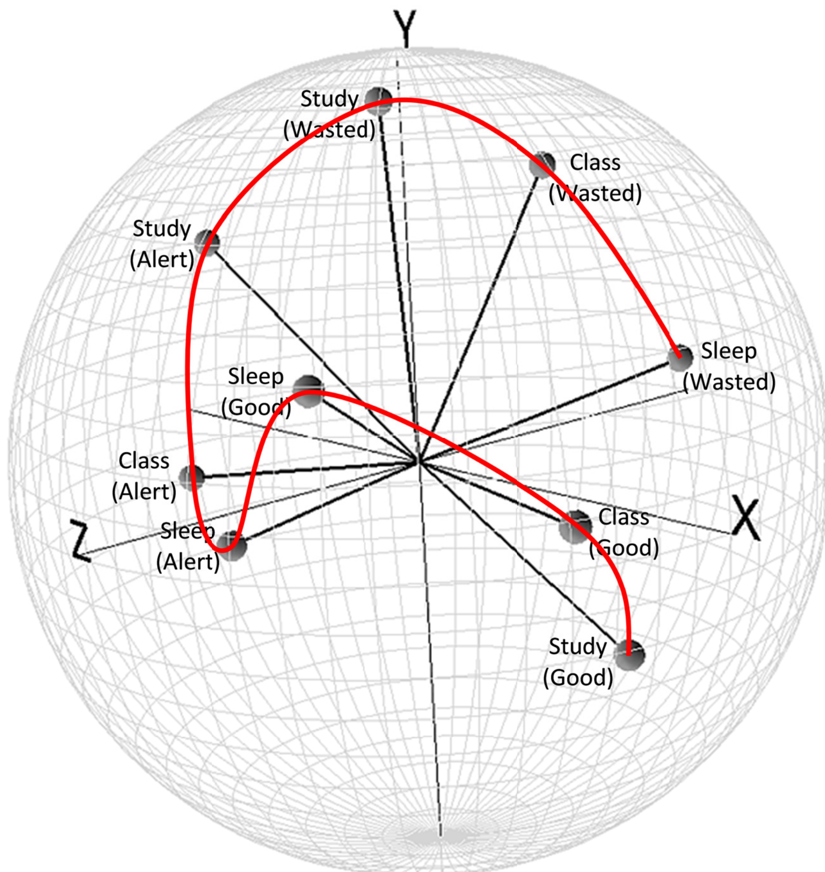


Figure 14. PCA vector plot of nine time evaluation variables with three evaluations of each of the three activities: time spent in class, time spent sleeping, and time spent studying.

The individual factor scores for each of the 28 participants are used to plot them (Figure 15) within the space defined by the vectors of Figure 14. Individuals are connected with lines to their cluster means. Cluster 1 is made up of two participants who, overall, evaluated all three activities positively. Cluster 2 is made up of six participants who evaluated their class and study time as good, but felt their sleep was wasted. Cluster 3 is made up of 11 participants who evaluated both their class time and study time as wasted. Cluster 4 is made up of seven participants who evaluated their class time as wasted, and felt very "alert" while sleeping (usually not a good thing). Cluster 5 is made up of two participants who evaluated their class and study time positively, but again felt "alert" while sleeping.

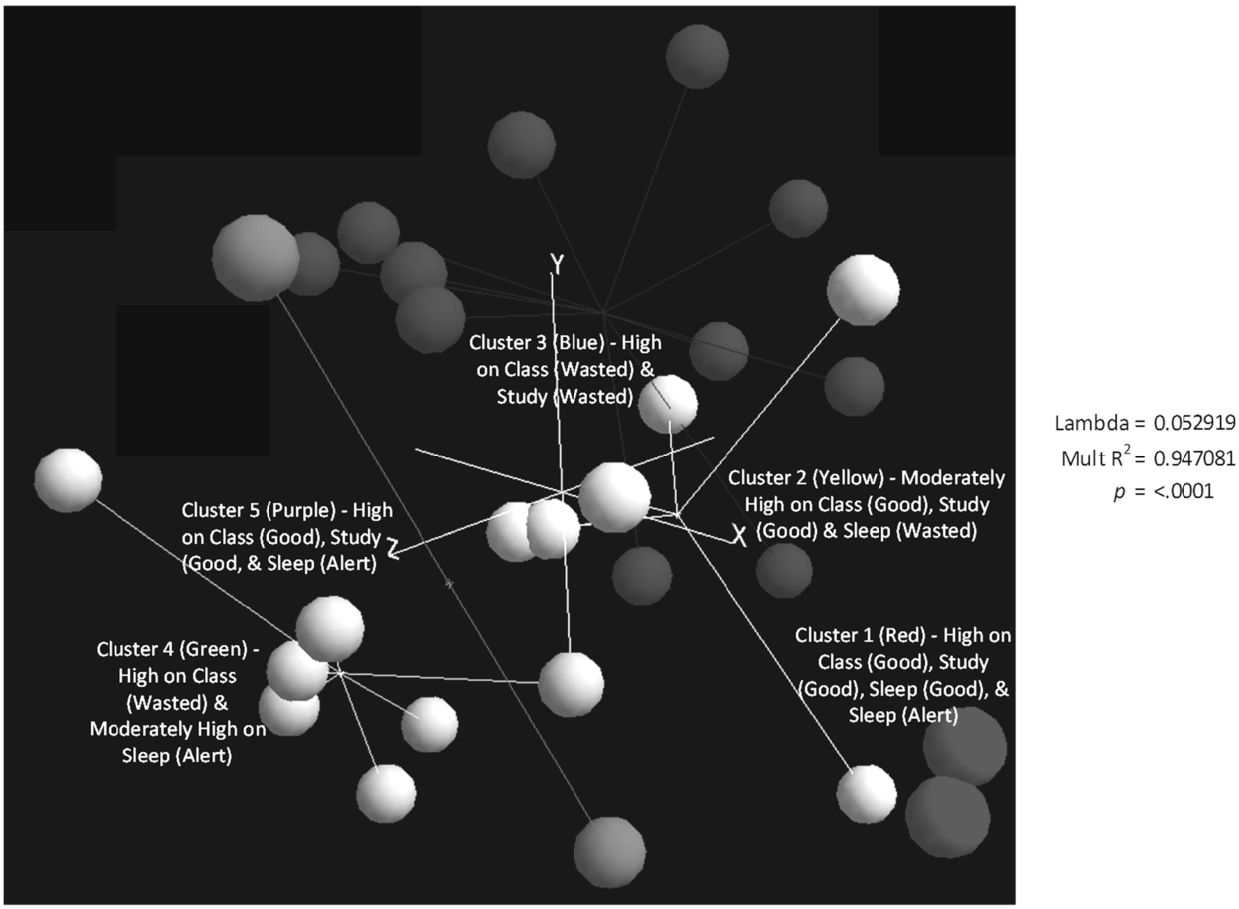


Figure 15. Five clusters, based on time evaluations, in the three-factor space defined in Figure 14.

Line plots of each of the five clusters are created to show the general overall patterns for each cluster. Figure 16 shows that, unlike the GPA and time-spent clusters, the time evaluation clusters do not separate quite as nicely, and it is more difficult to see a clear pattern in the clusters.

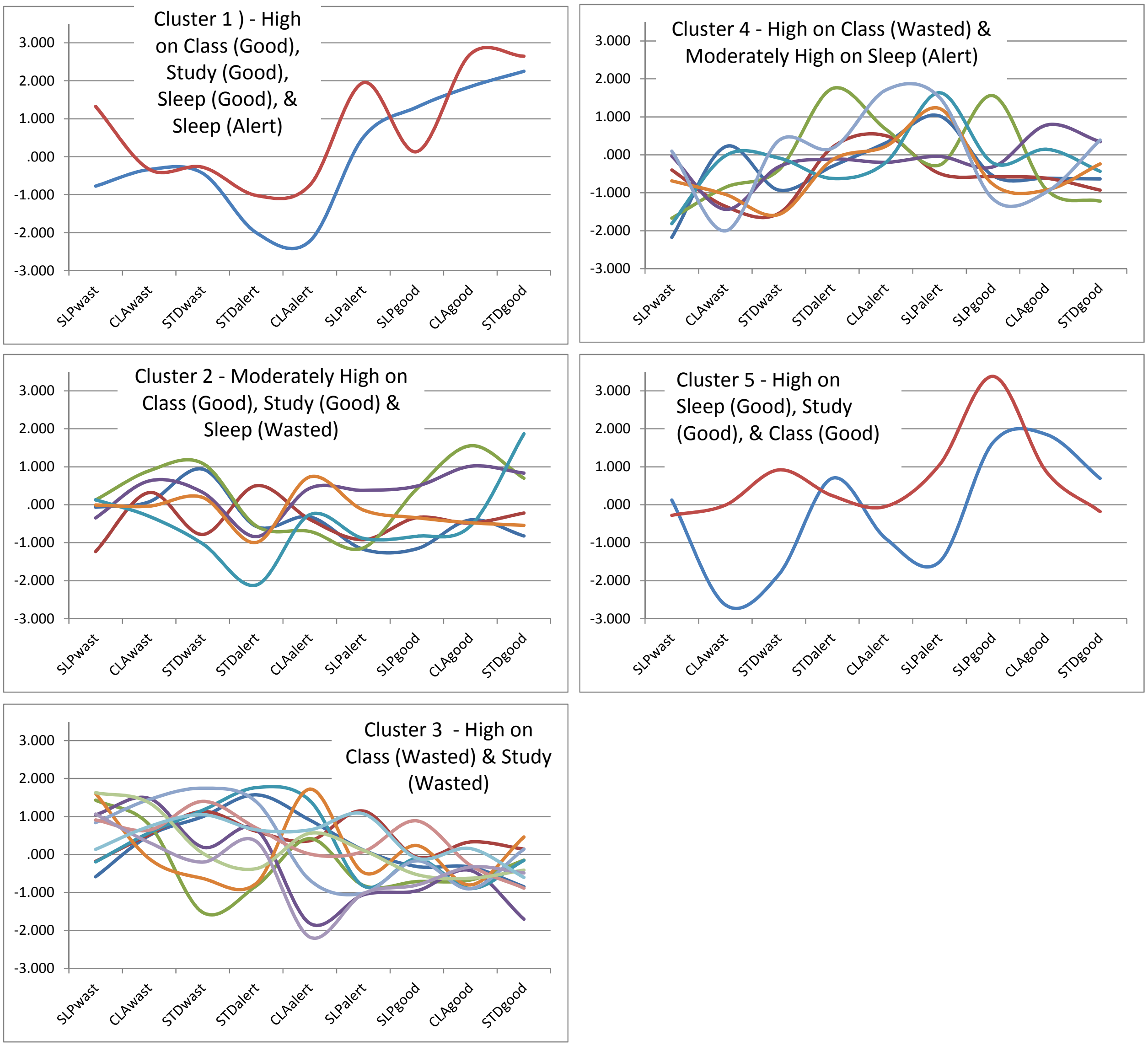


Figure 16. Line plots showing the five clusters related to the evaluations of class, sleep and study.

A one-way MANOVA is used to test the adequacy of the five clusters in separating the 18 data points within the space of the nine time evaluation variables. Although, most of the p-values are significant, showing that the clusters separate fairly well (see Table 8), these clusters are not as tight as the GPA and time-spent clusters.

Table 8

One-Way MANOVA as a Test of the Adequacy of the Five Clusters in Separating the Eighteen Data Points within the Space of the Nine Time Evaluation Variables, Multivariate Results at the Bottom of the Table and Univariate Results at the Top

Univariate Statistics

	F(6,21)	p	R2
Nine Time Evaluation Variables			
Factor 1 ("good") Eval of Class	10.69	<.0001	0.650
Factor 2 ("wasted") Eval of Class	8.85	0.0002	0.606
Factor 3 ("alert") Eval of Class	1.78	0.1664	0.237
Factor 1 ("good") Eval of Sleep	7.58	0.0005	0.569
Factor 2 ("wasted") Eval of Sleep	4.76	0.0060	0.453
Factor 3 ("alert") Eval of Sleep	3.02	0.0386	0.344
Factor 1 ("good") Eval of Study	7.82	0.0004	0.576
Factor 2 ("wasted") Eval of Study	1.72	0.1804	0.230
Factor 3 ("alert") Eval of Study	4.33	0.0094	0.429

Multivariate Statistics

	F(6,21)	p	R2
Wilks' Lambda	0.00518	<.0001	0.995
Pillai's Trace	2.786	<.0001	
Hotelling-Lawley Trace	13.047	<.0001	
Roy's Greatest Root	6.997	<.0001	

Note. The multivariate η2 is calculated as one minus the Wilks' lambda value (Wilks, 1963).

A canonical correlation analysis is used to evaluate the relatedness of the X set of nine time evaluation variables to the Y set of GPA-related variables. The results are shown in Table 9. Again, only Roy's Greatest Root is significant. And, once again, although there is multivariate significance, the first, second and third canonical correlations are only moderately strong, and the link between the nine time-evaluation variables in the X set and their corresponding latent variables (36.62%) is nearly as weak as those in Table 5 in the preceding section, and the link for the nine GPA-related variables to their latent variables (37.51%) is only slightly stronger than those in Table 5.

Table 9

Canonical Correlation Summary Table with the Y Set of GPA Variables (Dependent) at the Top of the Table, and the X Set of Time Evaluation Variables (Independent) at the Bottom of the Table

	Loadings			Squared Loadings				Uniqueness
	LV1	LV2	LV3	LV1	LV2	LV3	Total	U
Y Set (GPA)	*(eta1)*	*(eta2)*	*(eta3)*	*(eta1)*	*(eta2)*	*(eta3)*		
GPA total	-.7210	.3649	.0745	.5198	.1332	.0056	.6585	.3415
Fall/Winter Average	-.7596	.2806	.0574	.5770	.0787	.0033	.6590	.3410
Combined Average	-.7434	.3432	.0942	.5526	.1178	.0089	.6793	.3207
Fall/Winter StdDev	.4968	-.4784	.1543	.2468	.2289	.0238	.4995	.5005
Percent Transfer	.3348	.2075	-.1724	.1121	.0431	.0297	.1849	.8151
Fall/Winter Credits	-.2090	-.3473	.5351	.0437	.1206	.2863	.4506	.5494
Fall/Winter Percent	-.2396	-.2758	.1260	.0574	.0761	.0159	.1493	.8507
Spring/Summer Credits	-.0160	.0377	.0884	.0003	.0014	.0078	.0095	.9905
Spring/Summer Percent	-.1540	.1499	-.1982	.0237	.0225	.0393	.0855	.9145
			Sum of squares by columns:	2.1334	.8222	.4206	3.3762	5.6238
			Percents of sums of squares:	23.70%	9.14%	4.67%	37.51%	62.49%
X Set (evaluation)	*(chi1)*	*(chi2)*	*(chi3)*	*(chi1)*	*(chi2)*	*(chi3)*		
Class, Factor 1 ("good")	-.3839	.2400	-.0517	.1474	.0576	.0027	.2077	.7923
Class, Factor 2 ("wasted")	.5490	.2626	.5163	.3014	.0690	.2666	.6369	.3631
Class, Factor 3 ("alert")	.1105	.3292	-.2493	.0122	.1084	.0622	.1827	.8173
Sleep, Factor 1 ("good")	-.0130	.3666	-.4078	.0002	.1344	.1663	.3009	.6991
Sleep, Factor 2 ("wasted")	.7045	.0013	-.2327	.4963	.0000	.0541	.5505	.4495
Sleep, Factor 3 ("alert")	-.0802	.0283	.4291	.0064	.0008	.1841	.1914	.8086
Study, Factor 1 ("good")	-.1387	-.1520	-.2173	.0192	.0231	.0472	.0896	.9104
Study, Factor 2 ("wasted")	.4089	.6713	.4318	.1672	.4506	.1865	.8043	.1957
Study, Factor 3 ("alert")	.1082	.5661	-.0133	.0117	.3205	.0002	.3324	.6676
			Sum of squares by columns:	1.1621	1.1643	.9698	3.2962	5.7038
			Percents of sums of squares:	12.91%	12.94%	10.78%	36.62%	63.38%

	Coefficient	Multivariate Statistics	Index	p Value
First Canonical Correlation	.8739	Wilks' Lambda	.0125	.7119
Second Canonical Correlation	.8204	Pillai's Trace	2.9435	.5500
Third Canonical Correlation	.6633	Hotelling-Lawley Trace	7.5341	.7530
		Roy's Greatest Root	3.2319	.0004

Linked vector plots are created for the GPA and time evaluation variables (Figure 17). The plots show the vectors within their respective latent variable space. The two spaces are linked by a canonical correlation of 0.874 for the two x-axes, 0.820 for the two y-axes, and 0.663 for the two z-axes. Again the short vectors in these two linked spaces are indicative of the weak connections, in both the X set and also the Y set, between the observed variables and their corresponding latent variables. These short vectors in the linked vector plots of Figure 17 (and the concomitant small amount of variance accounted for by the latent variables in both the X set and the Y set in Table 9) are indicative that although the two sets of latent variables have a reasonably strong link between them (with the first two canonical correlations being 0.8739 and 0.8204), neither set of latent variables represents its manifest variables very well. The X set of latent variables (chi 1, chi 2, and chi 3) only accounts for 36.62% of the variance in the X set of nine observed time evaluation variables, and the Y set of latent variables (eta 1, eta 2, and eta 3) only accounts for 37.51% of the variance in the Y set of nine observed GPA-related variables.

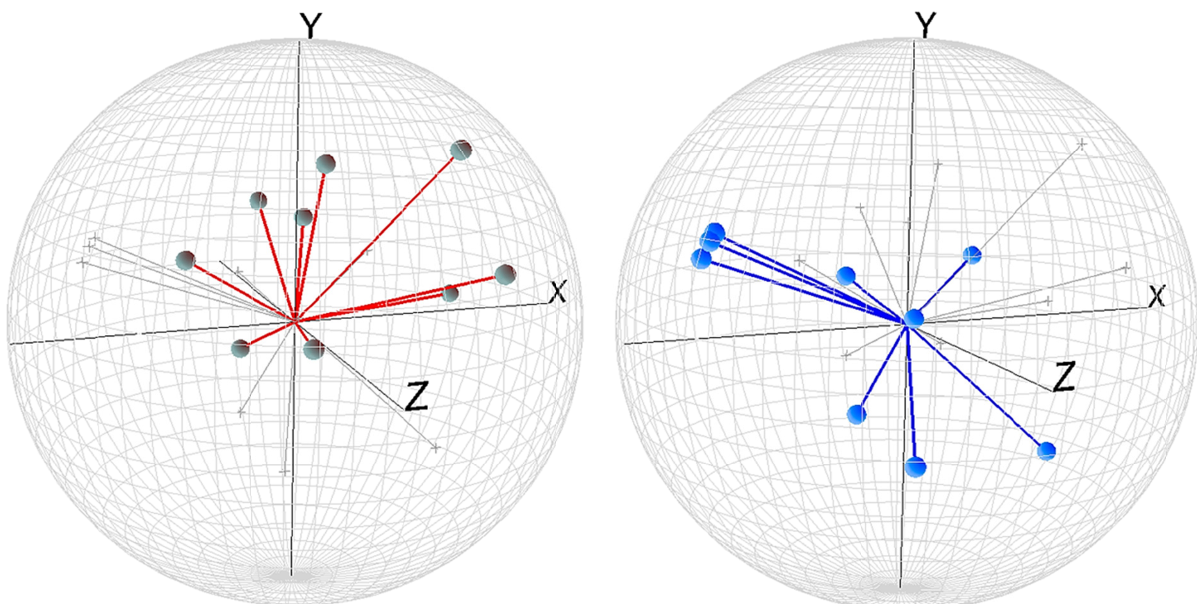


Figure 17. Linked vector plots with the time evaluation vectors emphasized in red, and the GPA vectors emphasized in blue (as explained in Figure 11).

Figure 18 shows the linked factor score plots of the 28 participants within the linked time evaluation space and GPA space. The clusters are shown within their respective spaces (time evaluation clusters in time evaluation spaces), as well as in the other variable space (time evaluation clusters in GPA space). As was the case with Variable Set A, the factor score plots make it easy to see that these two variable sets are not very predictive of one another. They have a strong enough link between the two sets of latent variables, but neither set of latent variables has a strong link to its observed variables.

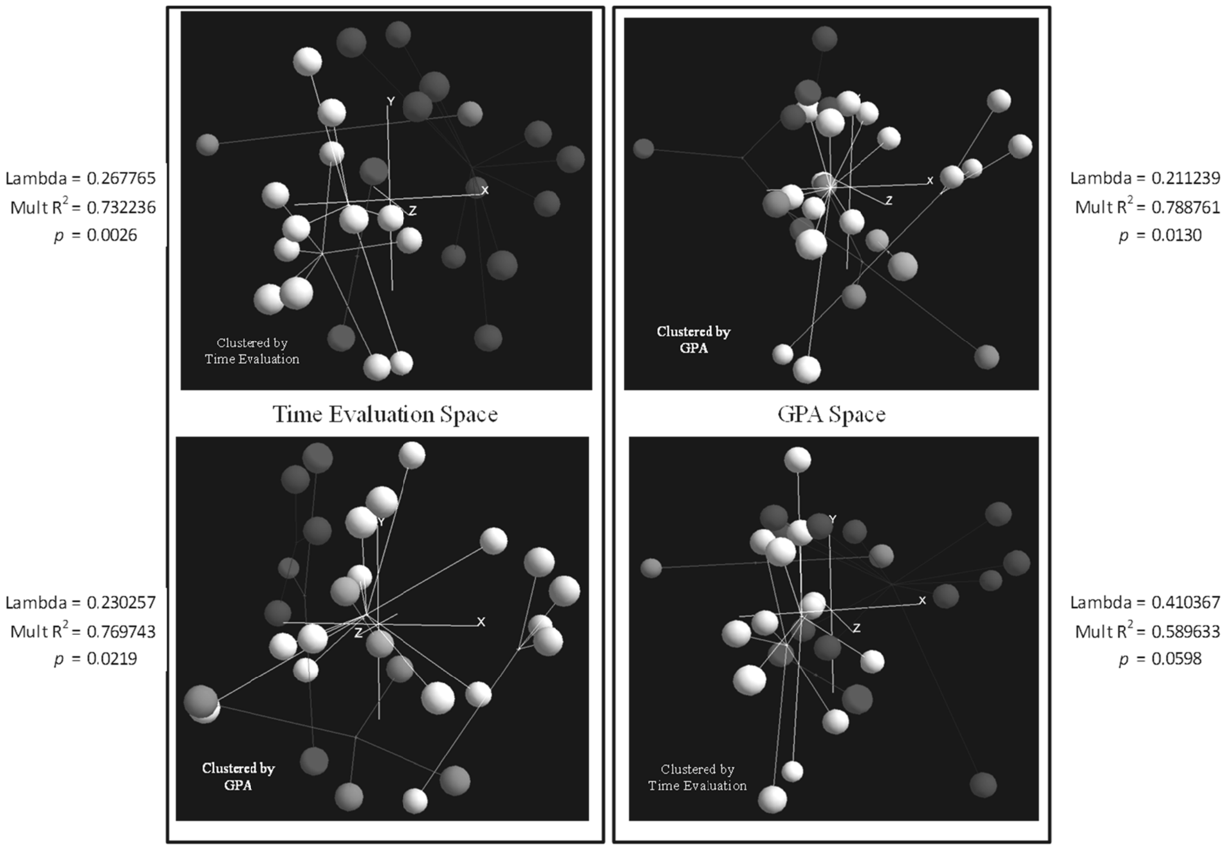


Figure 18. Linked factor score plots for time evaluation and GPA. On the left, the time evaluation and GPA clusters are shown in the time evaluation space. On the right, the GPA and time evaluation clusters are shown in the GPA space.

Predictor Variable Set C – Combination of Time Spent and Activity Evaluations

Variable Set C is a combination of the time-spent variables and the time evaluation variables. The data are standardized, then cluster analyzed using “R”, and a dendrogram is created (Figure 19). The red line in Figure 19 represents where the dendrogram is separated to produce six clusters.

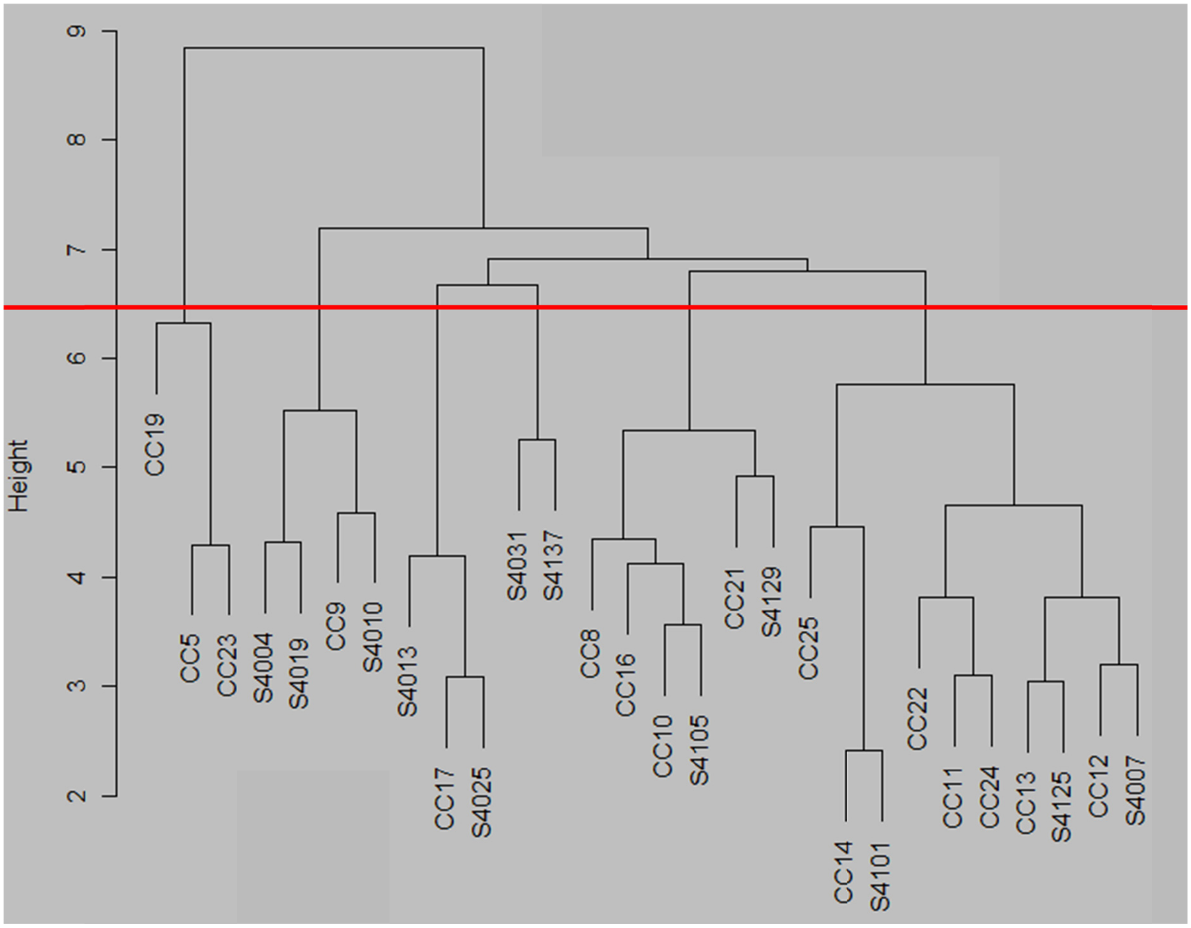


Figure 19. Dendrogram of the cluster structure of the 28 participants within the space of the combined seven time-spent variables from Predictor Variable Set A and the nine time evaluation variables from Predictor Variable Set B. A line shows the division of data points into six clusters.

The data matrix augmented by means of each of the six clusters is analyzed using principal component analysis. The principal component summary table is given in Table 10. It is notable that when the seven time-spent variables are combined with the nine time evaluation variables, a principal component analysis of the combined set of sixteen variables only has 46.52% of the variance accounted for by three factors. In contrast, three factors account for 66.39% of the variance in a principal component analysis of the seven time-spent variables by themselves (Table 3), and 64.02% of the variance in a principal component analysis of the nine time evaluation variables by themselves (Table 7). Obviously the combined dataset is more factorially complex.

Table 10

Principal Component Analysis Summary Table of Sixteen Variables from a Combined Dataset of Time Spent and Time Evaluation, Varimax Rotated

	Loadings			Communalities				Uniqueness
	factor 1	factor 2	factor 3	factor 1	factor 2	factor 3	Total	U
Class Hours	-.3274	-.6271	-.0938	.1072	.3932	.0088	.5092	.4908
Computer Hours	.6310	.2645	.5085	.3981	.0700	.2586	.7266	.2734
Recreation Hours	-.0980	-.4479	-.0526	.0096	.2006	.0028	.2130	.7870
Sleep Hours	-.0479	.3248	.3780	.0023	.1055	.1429	.2506	.7494
Study Hours	-.4184	-.3308	.2227	.1750	.1094	.0496	.3340	.6660
Television Hours	.0578	.5526	-.0443	.0033	.3054	.0020	.3107	.6893
Visiting Hours	-.1648	.0276	-.2401	.0272	.0008	.0576	.0856	.9144
Factor 1 ("good") Eval of Class	.7232	.1515	.4455	.5230	.0229	.1984	.7444	.2556
Factor 2 ("wasted") Eval of Class	-.0238	.3139	-.6578	.0006	.0985	.4327	.5318	.4682
Factor 3 ("alert") Eval of Class	-.6145	-.2693	.1693	.3776	.0725	.0287	.4788	.5212
Factor 1 ("good") Eval of Sleep	.1718	.3786	.5881	.0295	.1433	.3459	.5187	.4813
Factor 2 ("wasted") Eval of Sleep	.3582	.0531	-.5425	.1283	.0028	.2943	.4254	.5746
Factor 3 ("alert") Eval of Sleep	.0834	-.0445	.4564	.0070	.0020	.2083	.2172	.7828
Factor 1 ("good") Eval of Study	.7901	-.0995	.2891	.6243	.0099	.0836	.7178	.2822
Factor 2 ("wasted") Eval of Study	-.1832	.6973	-.2196	.0336	.4862	.0482	.5680	.4320
Factor 3 ("alert") Eval of Study	-.6987	.5646	.0694	.4882	.3188	.0048	.8117	.1883
Sums of squares by columns:				2.9347	2.3418	2.1671	7.4436	8.5564
Percents of sums of squares:				18.34%	14.64%	13.54%	46.52%	53.48%

Using Metrika, the factor loadings from the principal component analysis are utilized to plot the vectors for the seven time-spent variables and the nine evaluative factor score variables. To ease the visual understanding of the vector plots, two figures are created, with both showing top, front and side views. Figure 20 shows the time-spent variables bolded, with a path through those specific seven vectors. Figure 21 shows the evaluative factor score variables bolded, with a path through those specific nine vectors.

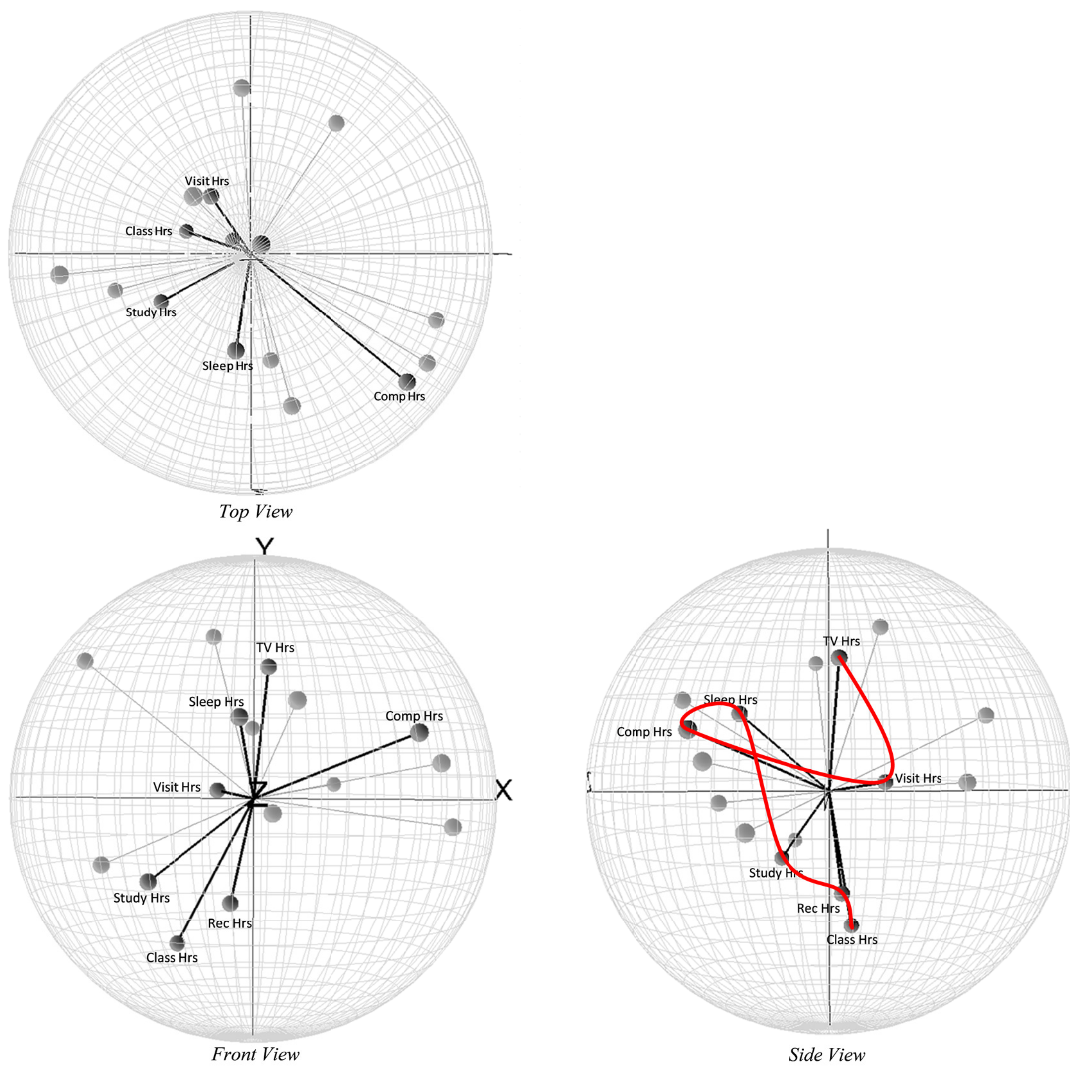


Figure 20. PCA vector plot, within the three-factor space, of time spent on seven activities, and evaluative factor scores for class, sleep and study. The time-spent variables are bolded.

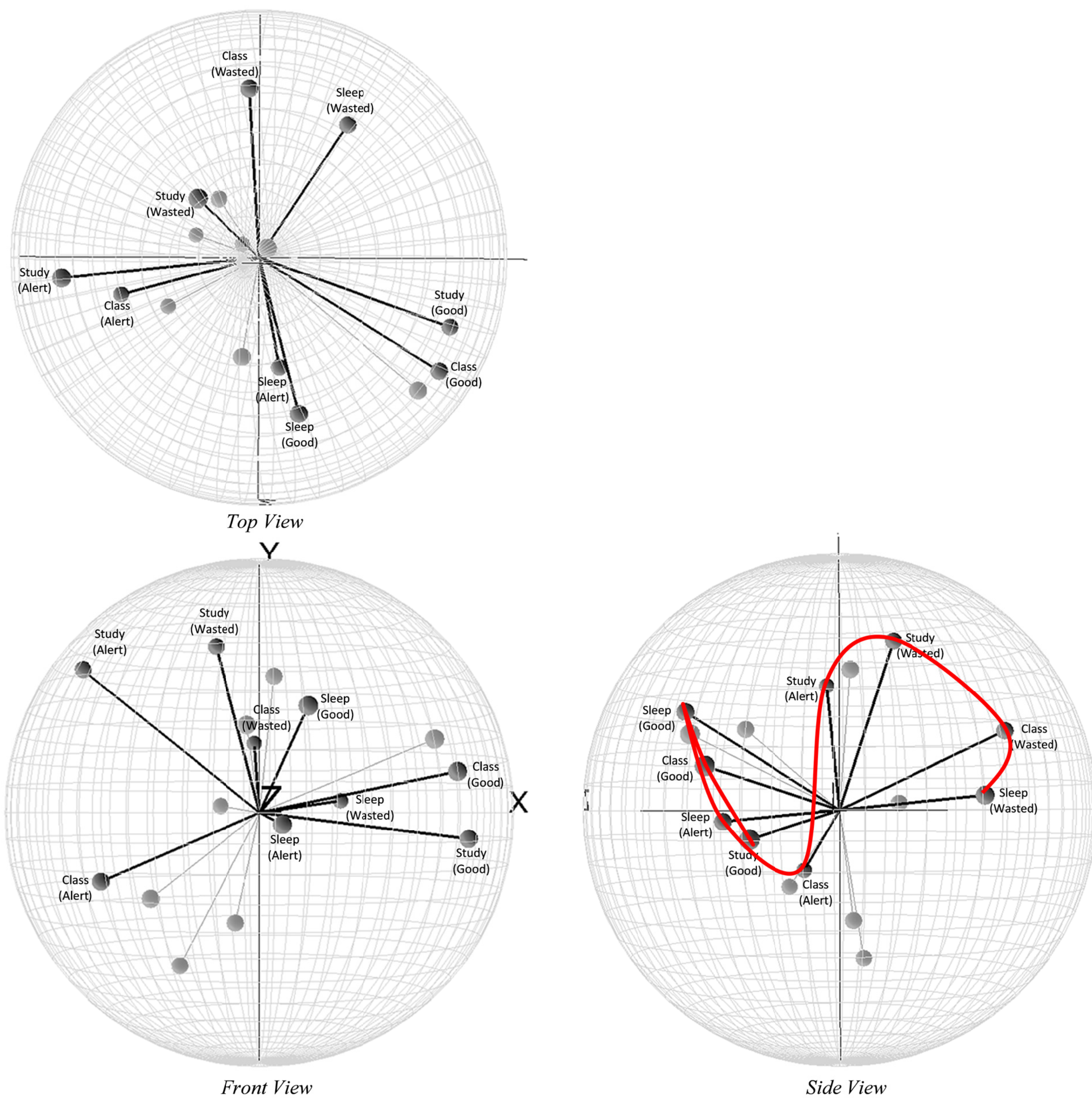


Figure 21. PCA vector plot, within the three-factor space, of time spent on seven activities, and evaluative factor scores for class, sleep and study. The evaluative factor score variables are bolded.

In Figure 22, the individual factor scores for each of the 28 participants are used to plot each participant's location within the space defined by Figures 20 & 21. Individuals are connected with lines to their cluster means. Cluster 1 is made up of three participants. Cluster 2 is made up of six participants. Cluster 3 is made up of four participants. Cluster 4 is made up of nine participants. Cluster 5 is made up of three participants, and cluster six is made up of two participants.

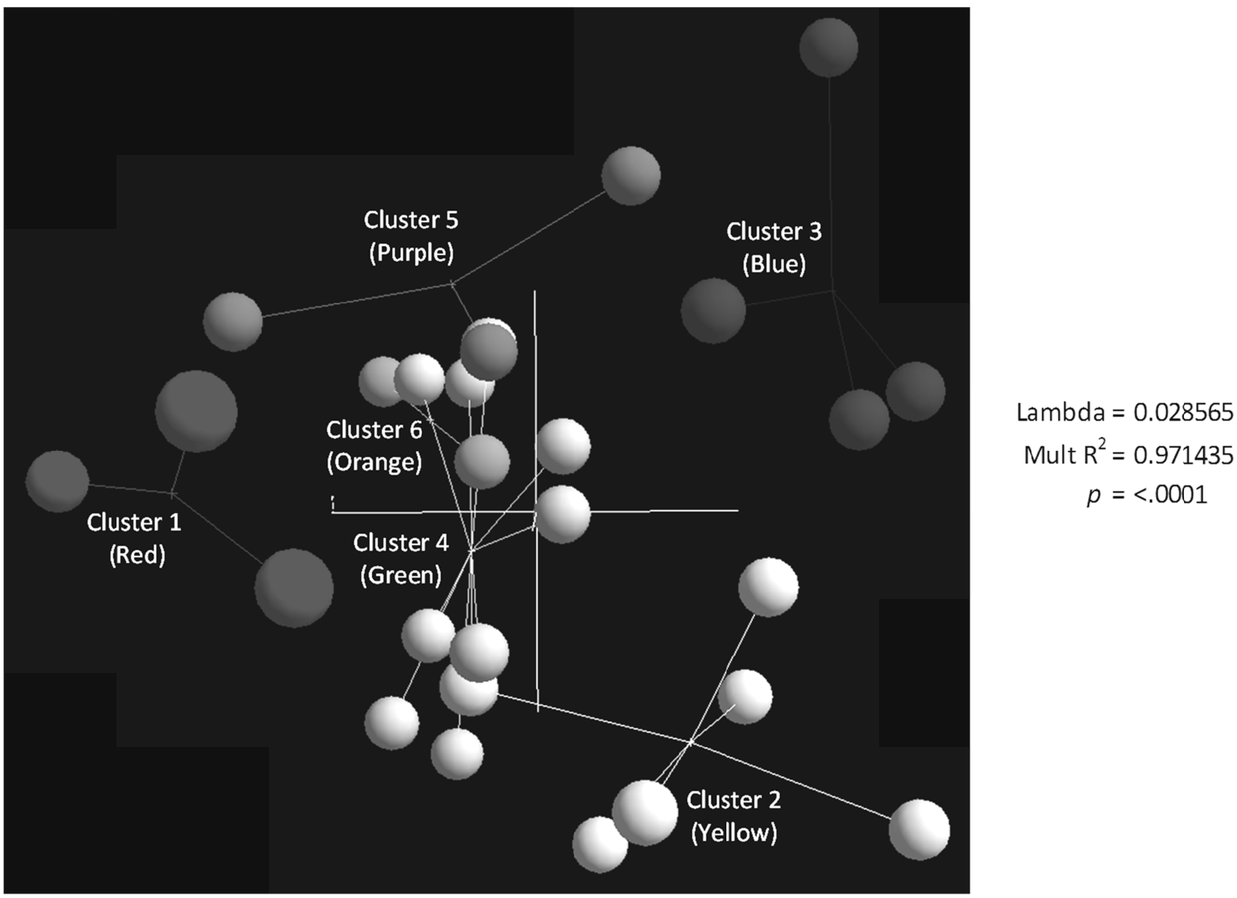


Figure 22. Five clusters, based on time spent on seven activities, and time evaluations, in the three-factor space, as seen in Figures 20 & 21.

A one-way MANOVA is used to test the adequacy of the six clusters in separating the 18 data points within the space of the 16 combined time variables. Most of the p-values are significant, the univariate R-squared values range from 0.224 to 0.703 and the multivariate statistics are very strong, showing that the clusters separate fairly well (see Table 11).

Table 11

One-Way MANOVA as a Test of the Adequacy of the Six Clusters in Separating the Eighteen Datapoints within the Space of the Set of Sixteen Combined Time Variables, Multivariate Results at the Bottom of the Table and Univariate Results at the Top

Univariate Statistics	F(6,21)	p	R2
Sixteen Combined Time Variables			
Class Hours	2.20	0.0910	0.333
Computer Hours	10.42	<.0001	0.703
Recreation Hours	1.84	0.1471	0.295
Sleep Hours	3.72	0.0137	0.458
Study Hours	1.27	0.3109	0.224
Television Hours	2.73	0.0455	0.383
Visiting Hours	5.28	0.0025	0.545
Factor 1 ("good") Evaluation of Class	8.07	0.0002	0.647
Factor 2 ("wasted") Evaluation of Class	4.52	0.0055	0.507
Factor 3 ("alert") Evaluation of Class	8.38	0.0001	0.656
Factor 1 ("good") Evaluation of Sleep	3.54	0.0169	0.446
Factor 2 ("wasted") Evaluation of Sleep	3.47	0.0183	0.441
Factor 3 ("alert") Evaluation of Sleep	2.34	0.0754	0.348
Factor 1 ("good") Evaluation of Study	4.62	0.0049	0.512
Factor 2 ("wasted") Evaluation of Study	2.22	0.0884	0.336
Factor 3 ("alert") Evaluation of Study	2.99	0.0332	0.404

Multivariate Statistics	F(6,21)	p	R2
Wilks' Lambda	0.00003	<.0001	1.000
Pillai's Trace	4.141	<.0001	
Hotelling-Lawley Trace	53.190	0.0059	
Roy's Greatest Root	23.404	<.0001	

Note. The multivariate η2 is calculated as one minus the Wilks' lambda value (Wilks, 1963).

A canonical correlation analysis is run with the sixteen combined time variables as the X set and the nine GPA-related variables as the Y set. The results are shown in Table 12. While the first, second and third canonical correlations are very high (.9878, .9565, and .9482, respectively), Roy's Greatest Root is, once again, the only significant multivariate statistic, presumably because of the somewhat small N of 28. Almost half of the variance (47.79%) in the Y set of variables (GPA) is accounted for by the X set of variables (time-spent and activity evaluation). However, only 20.07% of the variance in the X set of variables is accounted for by the Y set of variables. This indicates that the X set includes a lot of information about the 28 participants' individual lives that is not relevant to GPA-related performance.

One can use a canonical correlation summary table such as Table 12 to understand the subtle patterns of relationships between the two sets of variables, and presumably to even build theory that can be spot-tested with multiple regression. For example, one might begin in Table 12 to examine the variables with the largest uniqueness values, indicating a poor fit with the latent variables, and also the variables with the largest total squared loadings (communalities) which indicates a strong relationship to the latent variables. Study hours in the X set has a strong uniqueness value of 0.9744, which indicates, somewhat surprisingly, that it does not enter into the prediction of GPA-related variables. Also, on the Y set of variables, Fall/Winter standard deviation has a large uniqueness and does not enter much into the predictive relationship.

On the other hand, Spring/Summer credits and Spring/Summer percent of credit hours have a high total communality, primarily due to the high squared loadings in the first latent variable, eta 1. This appears to be a student lifestyle variable, whether they like the summer off, or would like to vigorously pursue a degree. We can now look at the corresponding squared loadings in the X set to find reasonable predictors. The three highest loadings are class hours, computer hour, and an evaluation of one's sleep hours as "wasted". The theory goes that students who spend a relatively high proportion of their time in class and in using a computer, and who rate sleep as "wasted" will be more likely to attend school during Spring/Summer terms. The other two GPA-related variables in the Y set that have high total communality, due to the first latent variable, chi 1, are total GPA, and Fall/Winter average GPA. We could add to our theory that these same students with high class hours, high computer hours, and "wasted" sleep have higher GPAs. We can formulate this theory deduced from Table 12 for multiple regression analyses. We first hypothesize that total GPA can be predicted from these three X set variables (class hours, computer hours, and sleep "wasted"), and test it with multiple regression. We do, in fact, obtain a significant multiple regression result for this hypothesis, $F(3,24)=3.52$, $p=0.0302$, $R^2=0.3058$. We test the hypothesis that a second primary academic performance measure, Fall/Winter average GPA, can be predicted from these same three variables and obtain a second positive result, $F(3,24)=3.76$, $p=0.0241$, $R^2=0.3198$.

We now test the "academic lifestyle" hypothesis by first using multiple regression of Spring/Summer credits onto the same three predictor variables, and almost obtain a positive result, $F(3,24)=2.87$, $p=0.0574$, $R^2=0.2641$. We similarly test the second lifestyle variable, the prediction of Spring/Summer percent of credit hours from these three variables and obtain a positive result, $F(3,24)=3.05$, $p=0.0481$, $R^2=0.2759$.

Table 12

Canonical Correlation Summary Table with the Y Set of GPA Variables (Dependent) at the Top of the Table, and the X Set of Combined Time Spent and Time Evaluations Variables (Independent) at the Bottom of the Table

	Loadings			Squared Loadings				Uniqueness
	LV1	LV2	LV3	LV1	LV2	LV3	Total	U
Y Set (GPA)	*(eta1)*	*(eta2)*	*(eta3)*	*(eta1)*	*(eta2)*	*(eta3)*		
GPA total	.5521	.3548	.0651	.3048	.1259	.0042	.4349	.5651
Fall/Winter Average	.5568	.4487	.0298	.3100	.2013	.0009	.5122	.4878
Combined Average	.5640	.4021	.0550	.3181	.1617	.0030	.4828	.5172
Fall/Winter StdDev	-.4001	-.2068	-.2300	.1601	.0428	.0529	.2557	.7443
Percent Transfer	-.2293	-.3058	.4153	.0526	.0935	.1725	.3186	.6814
Fall/Winter Credits	.5352	.1809	-.1896	.2864	.0327	.0359	.3551	.6449
Fall/Winter Percent	.4191	.2290	-.4429	.1756	.0524	.1962	.4242	.5758
Spring/Summer Credits	-.7302	.2794	.4447	.5332	.0781	.1978	.8090	.1910
Spring/Summer Percent	-.6625	.3304	.4003	.4389	.1092	.1602	.7083	.2917
Sum of squares by columns:				2.5798	.8976	.8236	4.3010	4.6990
Percents of sums of squares:				28.66%	9.97%	9.15%	47.79%	52.21%
X Set (time & evaluation)	*(chi1)*	*(chi2)*	*(chi3)*	*(chi1)*	*(chi2)*	*(chi3)*		
Class Hours	.5257	.1656	-.1291	.2764	.0274	.0167	.3205	.6795
Computer Hours	-.4121	.3136	.1174	.1698	.0983	.0138	.2820	.7180
Recreation Hours	-.0767	.0994	.4269	.0059	.0099	.1822	.1980	.8020
Sleep Hours	-.3028	.2260	.1217	.0917	.0511	.0148	.1576	.8424
Study Hours	.0832	-.0827	-.1089	.0069	.0068	.0119	.0256	.9744
Television Hours	-.1810	-.2221	-.3142	.0328	.0493	.0987	.1808	.8192
Visiting Hours	.0301	.1357	-.4458	.0009	.0184	.1987	.2181	.7819
Class ("good")	-.1525	.2855	.1649	.0233	.0815	.0272	.1320	.8680
Class ("wasted")	-.0423	-.5038	.3934	.0018	.2538	.1548	.4104	.5896
Class ("alert")	.2301	-.3405	-.0460	.0529	.1159	.0021	.1710	.8290
Sleep ("good")	-.2129	-.0523	.0286	.0453	.0027	.0008	.0489	.9511
Sleep ("wasted")	-.3982	-.4270	.0087	.1586	.1823	.0001	.3410	.6590
Sleep ("alert")	.0809	-.0123	.0710	.0065	.0002	.0050	.0117	.9883
Study ("good")	-.1590	.2243	.0354	.0253	.0503	.0013	.0768	.9232
Study ("wasted")	.0069	-.6365	.2389	.0000	.4051	.0571	.4623	.5377
Study ("alert")	.1096	-.3794	-.1346	.0120	.1439	.0181	.1741	.8259
Sum of squares by columns:				.9101	1.4972	.8033	3.2106	12.7894
Percents of sums of squares:				5.69%	9.36%	5.02%	20.07%	79.93%

	Coefficient	Multivariate Statistics	Index	p Value
First Canonical Correlation	.9878	Wilks' Lambda	.000002	.2977
Second Canonical Correlation	.9565	Pillai's Trace	5.6446	.2204
Third Canonical Correlation	.9482	Hotelling-Lawley Trace	68.5305	.2105
		Roy's Greatest Root	40.1201	<.0001

Linked vector plots are created for the GPA and time-spent/time evaluation variables (Figure 23). Again, in an effort to ease the visual understanding of the vector plots, three figures are created. One set of variables is emphasized in each of the plots. The plots show the vectors within their respective latent variable space. The two spaces are linked by a canonical correlation of .988 for the two x-axes, .957 for the two y-axes, and .948 for the two z-axes, truly a strong link.

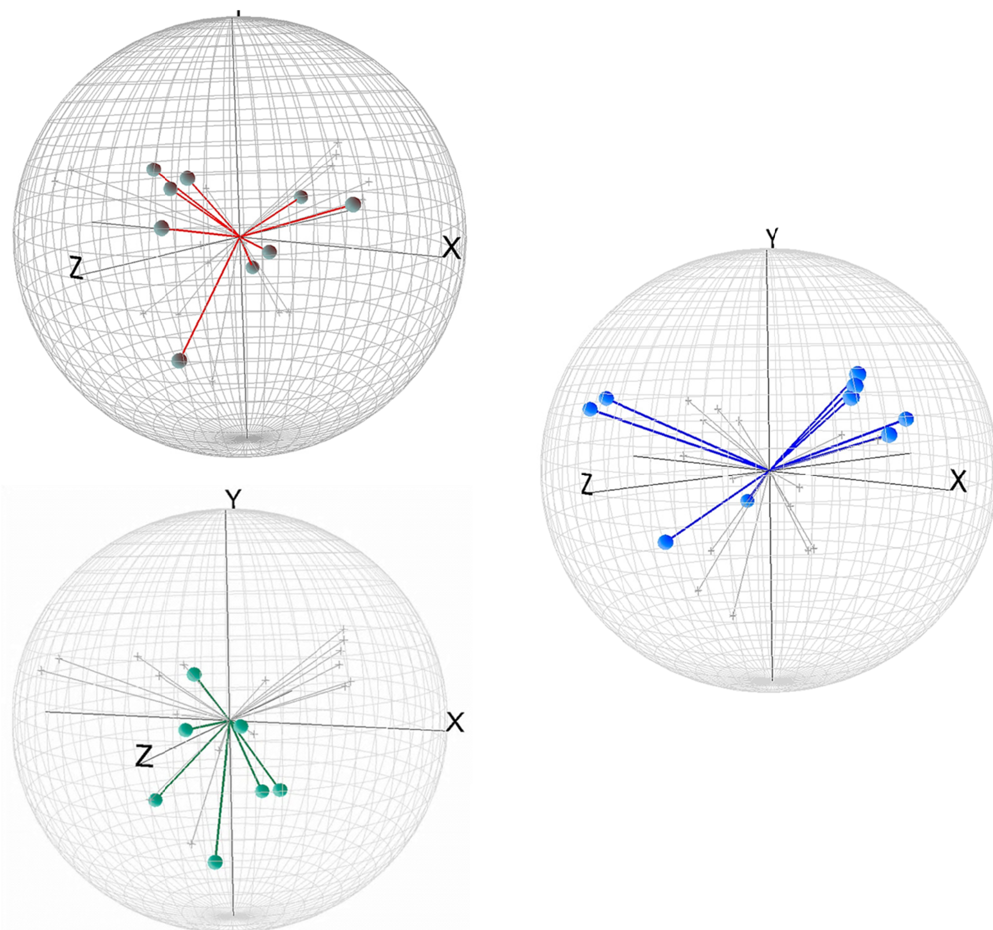


Figure 23. Linked vector plots with the "time evaluation" vectors emphasized in red, "time spent" vectors emphasized in green, and the GPA vectors emphasized in blue (as explained in Figure 11).

Linked factor score plots are then generated (Figure 24). Despite the multivariate significance, and the high canonical correlations, the clusters do not separate well, even within their respective spaces. (Because the lack of separation is compounded when the clusters are shown in the other variable space, those pictures have been omitted.) There is a strong connection between the two sets of latent variables, but neither set of latent variables represents the multivariate information in its observed variables well. And one could not argue that is because the two manifest variable spaces are factorially complex. Table 1 shows that three factors account for 92.88% of the variance in the nine GPA-related variables, creating a very clear and simple vector space (Figure 4). Even though the combined time-spent and time evaluation space is admittedly more factorially complex, one can still account for 46.52% of the variance in its 16 variables with three factors (Table 10), which is substantially more than the 20.07% accounted for by its canonical correlation latent variables in the linked space (Table 12).

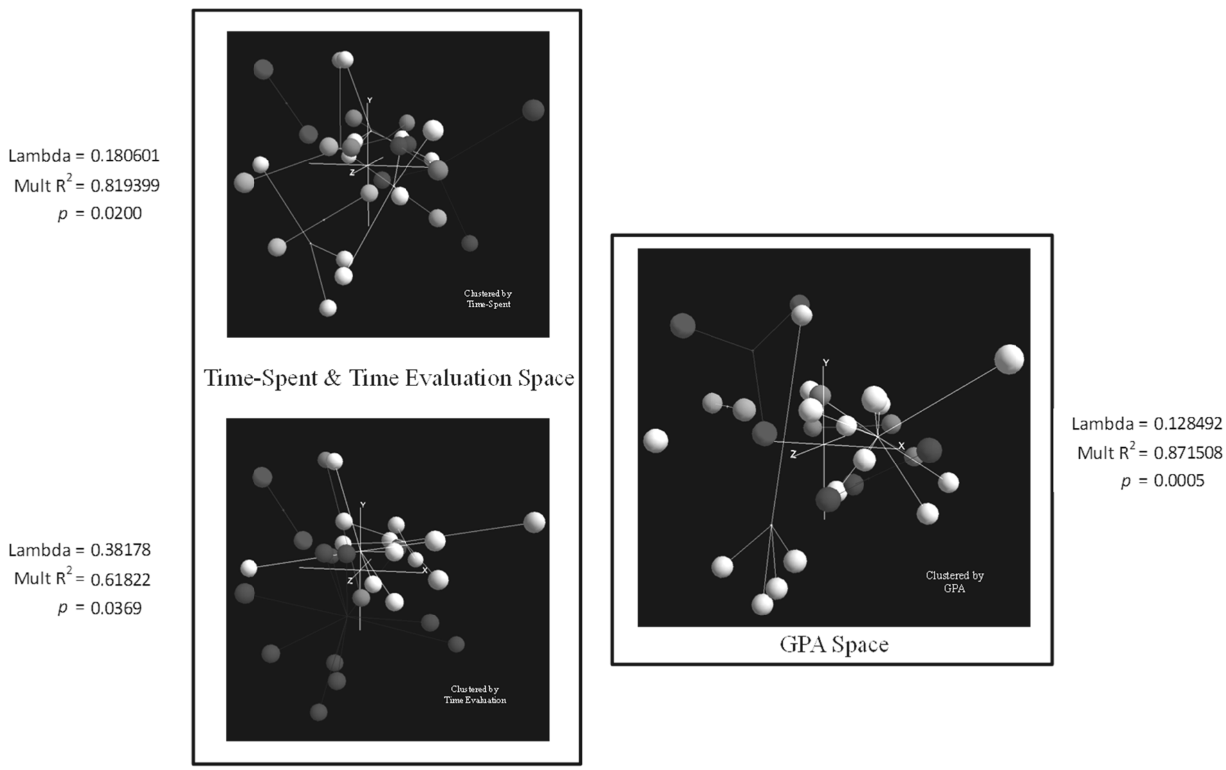


Figure 24. Linked factor score plots for the combination of time-spent and time evaluation, and GPA. On the left, the time-spent and time evaluation clusters are shown in the combination space. On the right, the GPA cluster is shown in the GPA space. Due to the small predictive value of these variables, the clusters do not separate well, and overlap significantly even within their own respective spaces. The lack of separation is compounded when the clusters are shown in the opposite variable's space, so those figures have been omitted.

While the canonical correlation summary table shows that the combined time log data does a fairly good job of predicting GPA (47.79% of variance accounted for), it is important to recognize that the predictive possibilities of the time log data have not been exhausted with this one statistical test. We must recognize that the total list of 21 activities was narrowed down to only the seven that were most pertinent to GPA for the time-spent analyses. Then the data were narrowed even further to analyze the adjective evaluations, due to insufficient data for the majority of the activities. Figure A1 in Appendix A shows the range of possible canonical correlations, but restricted to only the seven selected activities. It includes every combination of evaluation factors and number of hours spent on each activity for this subset of variables. The first, and always strongest, canonical correlation for the activity evaluations range from 0.713 to 1. And the first canonical correlation for the frequencies range from 0.847 to 1. Because the first canonical correlation gives the maximum possible multiple regression, it is likely there are some better combinations of variables to predict GPA than the ones utilized above. However, finding those successful combinations would be quite a time consuming undertaking.

Several regression analyses are run in an effort to test the canonical correlation results found in Figure A1. Table 13 shows the results from one of the most obvious possible regressions, predicting total GPA from class time spent, study time spent, and the three factors for the respondents' subjective evaluations for these two. This significant regression ($p=0.048$) has an R-squared value of 0.513, meaning more than 50% of the variance in predicting GPA is accounted for by the eight time-spent and evaluation variables.

Table 13

Regression Analysis Summary for the Prediction of Total GPA from the Eight Variables of Class Time Spent, Study Time Spent, and the Three Factors for the Respondents' Subjective Evaluations for Each of These

Source	SS	df	MS
Model	7.6276	8	0.9535
Residual	7.2367	19	0.3809
Total	14.8643	27	0.5505

N of obs	=	28
F(8,19)	=	2.50
Prob > F	=	0.0481
R-squared	=	0.5131
Adj R-squared	=	0.3082
Root MSE	=	0.6172

Predictors	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
Class Time Spent	0.3448	0.1207	2.86	0.010	0.0921	0.5975
"Good" Evaluation of Class Time	0.2687	0.2360	1.14	0.269	-0.2252	0.7626
"Wasted" Evaluation of Class Time	-0.2710	0.2405	-1.13	0.274	-0.7743	0.2324
"Alert" Evaluation of Class Time	-0.3691	0.2761	-1.34	0.197	-0.9470	0.2088
Study Time Spent	0.0279	0.0478	0.58	0.567	-0.0722	0.1279
"Good" Evaluation of Study Time	0.1161	0.3080	0.38	0.710	-0.5286	0.7607
"Wasted" Evaluation of Study Time	0.1800	0.2695	0.67	0.512	-0.3841	0.7441
"Alert" Evaluation of Study Time	0.6746	0.3455	1.95	0.066	-0.0485	1.3977
Regression Constant	-1.1459	0.3988	-2.87	0.010	-1.9807	-0.3111

Predictor Variable Set D – Six Question Survey

Only the 18 participants specifically recruited for the hypothesis testing portion of this project complete the six question survey. These data are standardized, cluster analyzed, and a dendrogram is created (Figure 25). The red line in Figure 25 represents where the dendrogram is separated to produce four clusters.

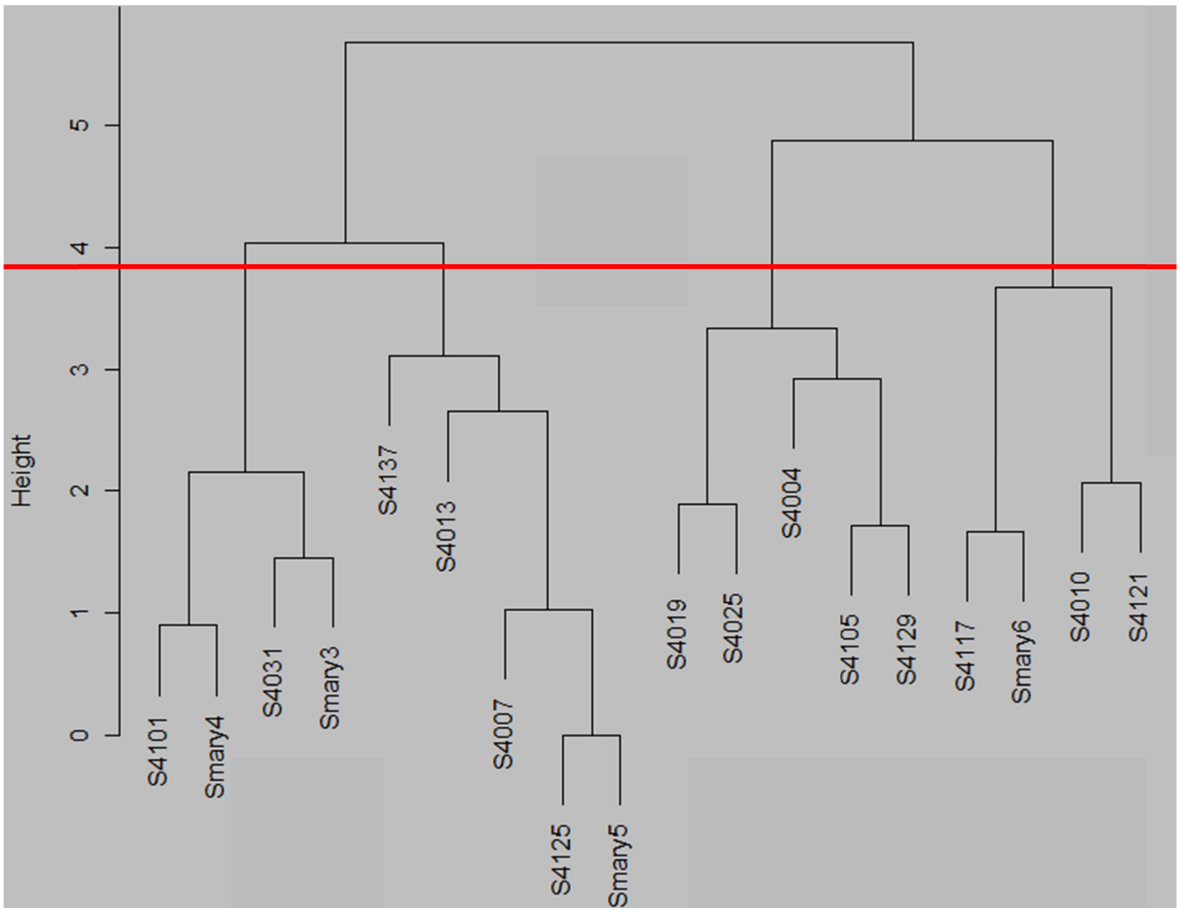


Figure 25. Dendrogram of the structure of 18 persons' scores for the six question survey about time management attitudes. A line shows the division of the 18 data points into four clusters.

A principal component analysis of the data matrix, including the means of the clusters, is completed. The summary table for the analysis is shown in Table 14. The three factors account for 82.12% of the variance in these six variables, an indication that we are likely to have a simple and clearly-defined vector space.

Table 14

Principal Component Analysis Summary Table for Six Time Management Attitude Question Variables, Varimax Rotated

	Loadings			Communalities				Uniqueness
	factor 1	factor 2	factor 3	factor 1	factor 2	factor 3	Total	U
TM skill is important.	-.4039	.8668	.0280	.1631	.7513	.0008	.9152	.0848
I am organized.	.8717	-.1116	.0617	.7598	.0125	.0038	.7761	.2239
I organize carefully.	.7920	-.0586	.2120	.6273	.0034	.0449	.6756	.3244
I am spontaneous.	-.7658	-.2671	.2540	.5865	.0713	.0645	.7223	.2777
I am successful without TM.	.0558	.0175	.9748	.0031	.0003	.9501	.9536	.0464
Using time wisely IMP.	.3660	.8662	-.0168	.1339	.7503	.0003	.8845	.1155
Sums of squares by columns:				2.2737	1.5891	1.0645	4.9273	1.0727
Percents of sums of squares:				37.90%	26.49%	17.74%	82.12%	17.88%

The factor loadings from the principal component analysis are plotted using Metrika, to obtain the PCA vector plot of Figure 26. Question four, which asks about spontaneity, is reversed to create tight XYZ vector bundles. The X-axis is defined by questions two, three and four, ("I am an organized person.”, "I organize my study time carefully to make the best use of it.", and the reverse of "I generally prefer to do things spontaneously rather than plan ahead.", respectively). The Y-axis is defined by questions one and six, ("It is important to me to develop the skills necessary to use my time wisely.", "Using time wisely is very important to me.", respectively). And the Z-axis is defined by question five, ("I have been successful so far in school without having to manage my time carefully.”) Participants whose data points are on the right side of this space (high X-axis values) rate themselves as being well-organized and planning things out, while those on the left see themselves as spontaneous. Those at the top of the space consider time management important while those at the bottom do not. Those at the front of the space (high Z-axis values) consider themselves to be successful without time management. A path through the vector plot is used to create ordered profiles utilized later in the line plots (see Figure 28).

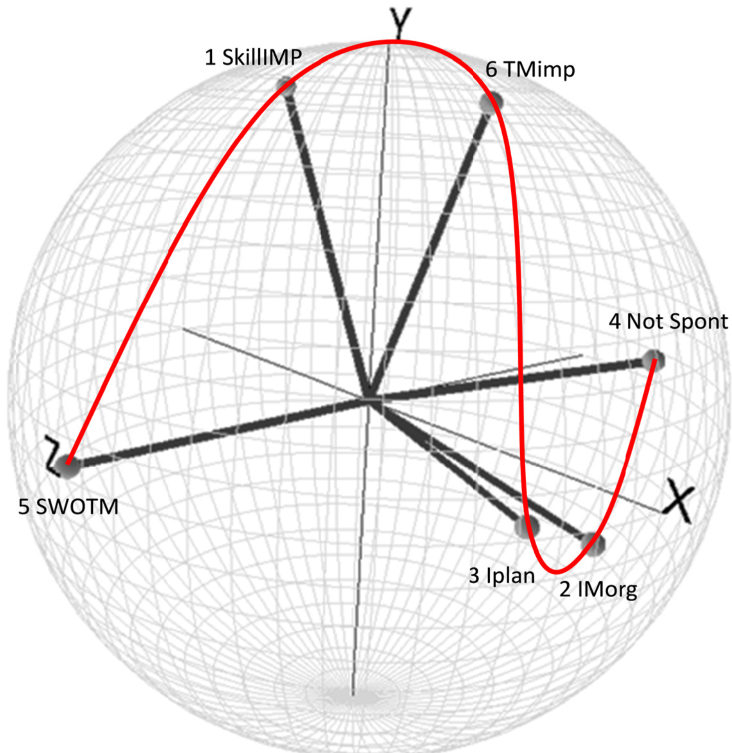


Figure 26. PCA vector plot of the six question survey within the three-factor space.

The individual factor scores for each of the 18 participants are used to plot them within the space defined in Figure 26 (see Figure 27). Individuals are connected with lines to their cluster means, represented by cubes. Cluster 1 is made up of five participants who reported being spontaneous, and needing time management skills to be successful in school. Cluster 2 is made up of five participants who agreed strongly with the "I am organized" self-descriptor. Cluster 3 is made up of four participants who reported that they are spontaneous and are successful in school without time management skills. Cluster 4 is made up of four participants who report being moderately organized and moderately successful without time management skills.

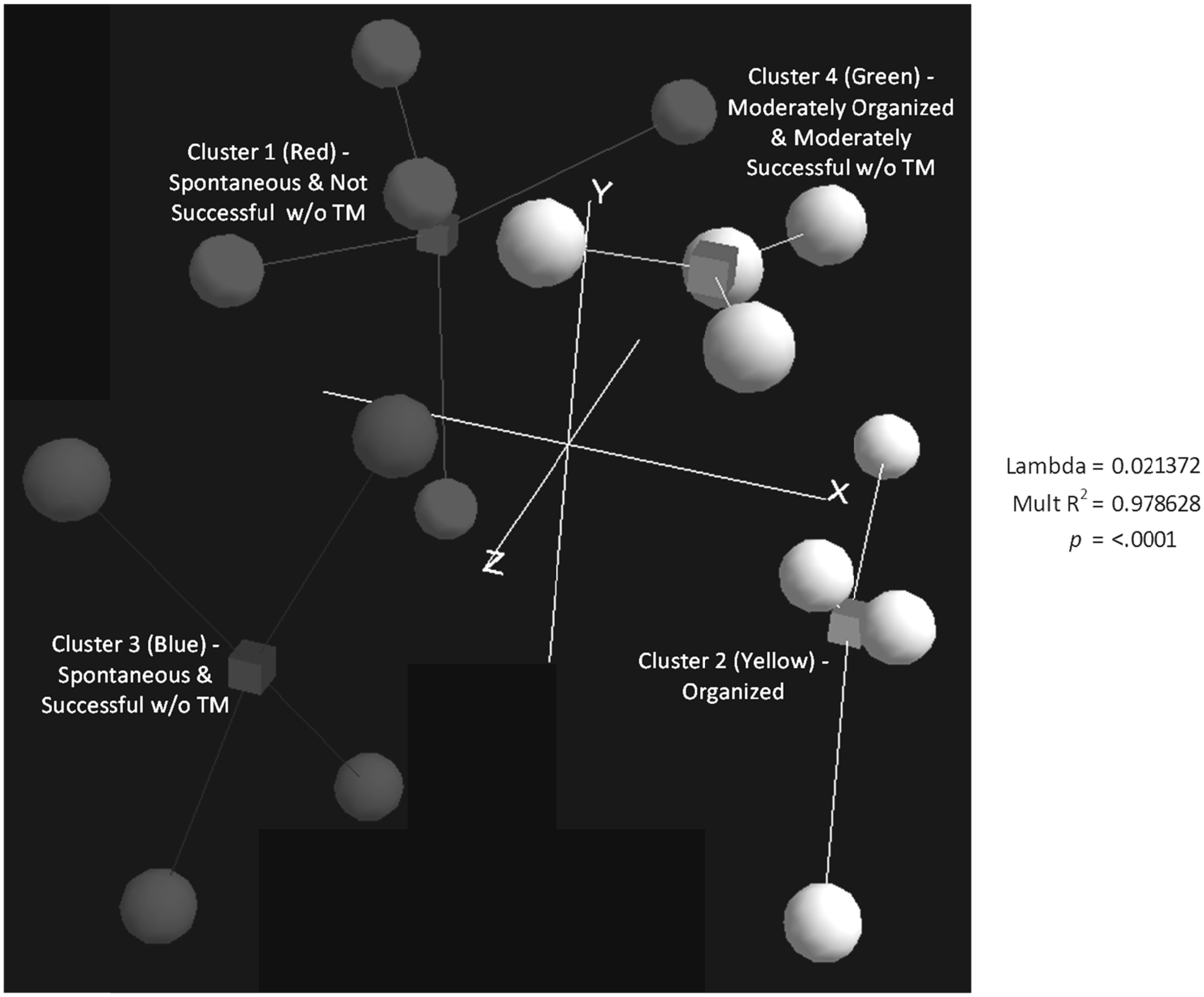


Figure 27. Four clusters, based on the six-question survey, in the three-factor space, as seen in Figures 26.

Line plots of each of the four clusters are created to show the general overall patterns for each cluster (see Figure 28). Although the cluster groupings of these line plots are not as compelling as some, it is primarily because of the small sample size, the sparsity of the data.

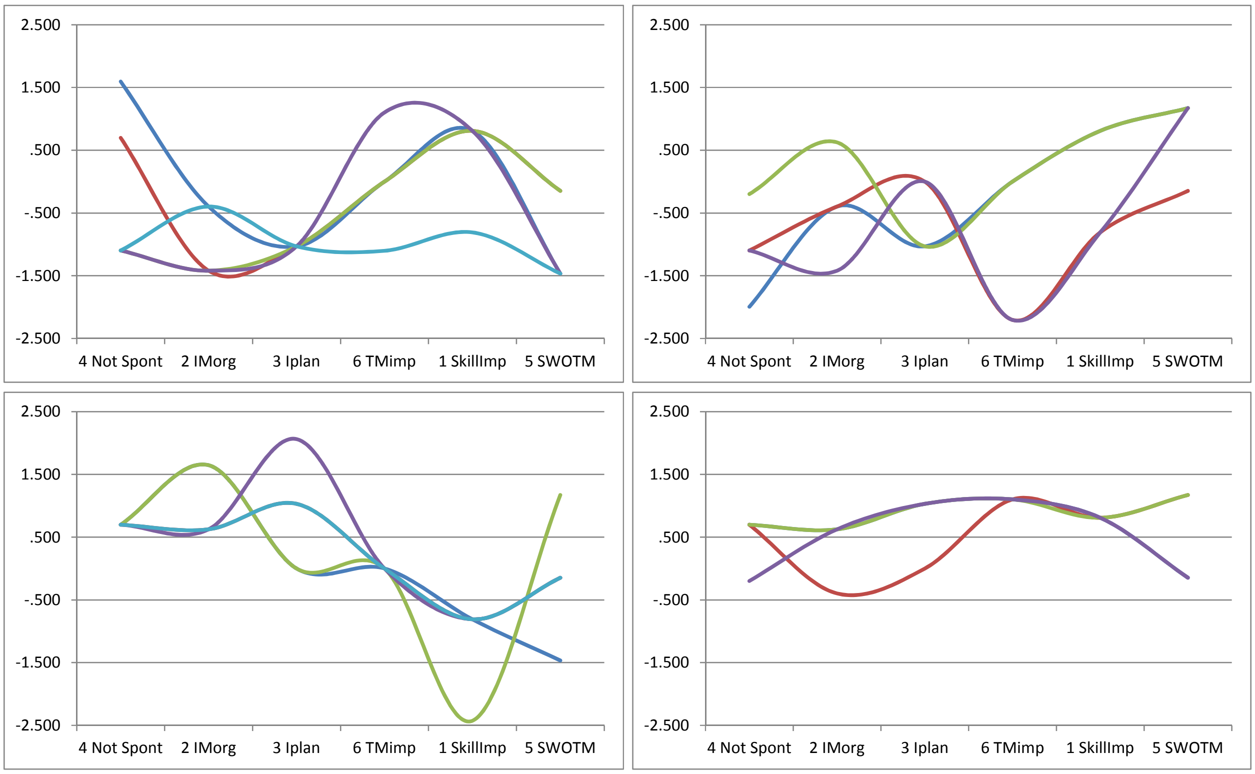


Figure 28. Line plots of the four clusters related to the six question survey.

A one-way MANOVA is used to test the adequacy of the four clusters in separating the 18 data points within the space of the six time-management attitude question survey variables. The highly significant p-values for both the univariate and multivariate statistics in Table 15 show that the clusters separate well, despite the small sample size.

Table 15

One-Way MANOVA as a Test of the Adequacy of the Four Clusters in Separating the Eighteen Data Points within the Space of the Six Time-Management Attitude Question Variables, Multivariate Results at the Bottom of the Table and Univariate Results at the Top

Univariate Statistics	F(6,21)	p	R2
Six Time-Management Attitude Question Variables			
TM skill is important.	7.00	0.0041	0.600
I am organized.	10.08	0.0008	0.684
I organize carefully.	11.74	0.0004	0.716
I am spontaneous.	4.50	0.0207	0.491
I am successful without TM.	4.55	0.0200	0.494
Using time wisely is important.	6.22	0.0066	0.571

Multivariate Statistics	F(6,21)	p	R2
Wilks' Lambda	0.00381	<.0001	0.996
Pillai's Trace	2.350	<.0001	
Hotelling-Lawley Trace	23.266	<.0001	
Roy's Greatest Root	16.258	<.0001	

Note. The multivariate η2 is calculated as one minus the Wilks' lambda value (Wilks, 1963).

A canonical correlation analysis is calculated on these data with the six question survey results as the X set (the predictors) and the nine GPA-related variables as the Y set (the criteria). The results are shown in Table 16. No multivariate tests could be run due to insufficient degrees of freedom. Because of the small sample size, all three of the canonical correlations are perfect, and all are statistically significant.[13] Also, 60.1% of the variance in the GPA variables is accounted for by the six question survey. And 57.3% of the variance amidst the six question survey variables is accounted for by the GPA variables. Despite the problems due to inadequate sample size, this analysis is a good example of a strong predictive canonical correlation. All

[13] When the number of observations in a canonical correlation dataset is not sufficient to support the number of variables in the analysis, the multivariate tests cannot be run due to matrix singularity.

three links are reasonably strong. The GPA-related variables (which are the target of prediction) are over 60% accounted for by their latent variables, the six questions are also nearly 60% accounted for by their latent variables, and the link between the two sets of latent variables is perfect. Even though this perfect link is spurious, due to small sample size and matrix singularity, it is expected that a replication of this study with a robust sample size would have strong results.

Table 16

Canonical Correlation Summary Table with the Y Set of GPA Variables (Dependent) at the Top of the Table, and the X Set of Six Time Management Questions Variables (Independent) at the Bottom of the Table

	Loadings			Squared Loadings				Uniqueness
	LV1	LV2	LV3	LV1	LV2	LV3	Total	U
Y Set (GPA)	*(eta1)*	*(eta2)*	*(eta3)*	*(eta1)*	*(eta2)*	*(eta3)*		
GPA total	-.4906	.6744	.2190	.2407	.4548	.0480	.7435	.2565
Fall/Winter Average	-.4800	.6921	.1602	.2304	.4790	.0257	.7351	.2649
Combined Average	-.5280	.7001	.2503	.2788	.4901	.0627	.8316	.1684
Fall/Winter StdDev	.3200	-.5995	-.3927	.1024	.3594	.1542	.6160	.3840
Percent Transfer	.6425	-.0917	-.2968	.4128	.0084	.0881	.5093	.4907
Fall/Winter Credits	-.6087	.0697	.3523	.3705	.0049	.1241	.4995	.5005
Fall/Winter Percent	-.5844	.2324	.3463	.3415	.0540	.1199	.5155	.4845
Spring/Summer Credits	-.6110	-.5704	-.0406	.3733	.3254	.0016	.7003	.2997
Spring/Summer Percent	-.4227	-.2995	.2010	.1787	.0897	.0404	.3088	.6912
Sum of squares by columns:				2.5291	2.2657	.6647	5.4595	3.5405
Percents of sums of squares:				28.10%	25.17%	7.39%	60.66%	39.34%
X Set (six questions)	*(chi1)*	*(chi2)*	*(chi3)*	*(chi1)*	*(chi2)*	*(chi3)*		
TM skill is important.	.6726	-.2635	.6108	.4524	.0694	.3731	.8949	.1051
I am organized.	-.6708	.5693	-.1054	.4500	.3241	.0111	.7852	.2148
I organize carefully.	-.1207	.9614	-.0102	.0146	.9243	.0001	.9390	.0610
I'm spontaneous.	.4870	-.3656	-.5512	.2372	.1337	.3038	.6747	.3253
Successful w/o TM.	.2031	.0470	-.0142	.0412	.0022	.0002	.0437	.9563
Using time wisely IMP.	.6449	.3032	.4078	.4159	.0919	.1663	.6741	.3259
Sum of squares by columns:				1.6112	1.5456	.8546	4.0115	1.9885
Percents of sums of squares:				23.02%	22.08%	12.21%	57.31%	28.41%

	Coefficient	p Value
First Canonical Correlation	1.0000	<.0001
Second Canonical Correlation	1.0000	<.0001
Third Canonical Correlation	1.0000	<.0001

No multivariate tests due to insufficient degrees of freedom.

Linked vector plots are created for the GPA and six question variables (Figure 29). The plots show the vectors within their respective latent variable space. However, because the canonical correlations are perfect, the space is the same for both sets of variables.

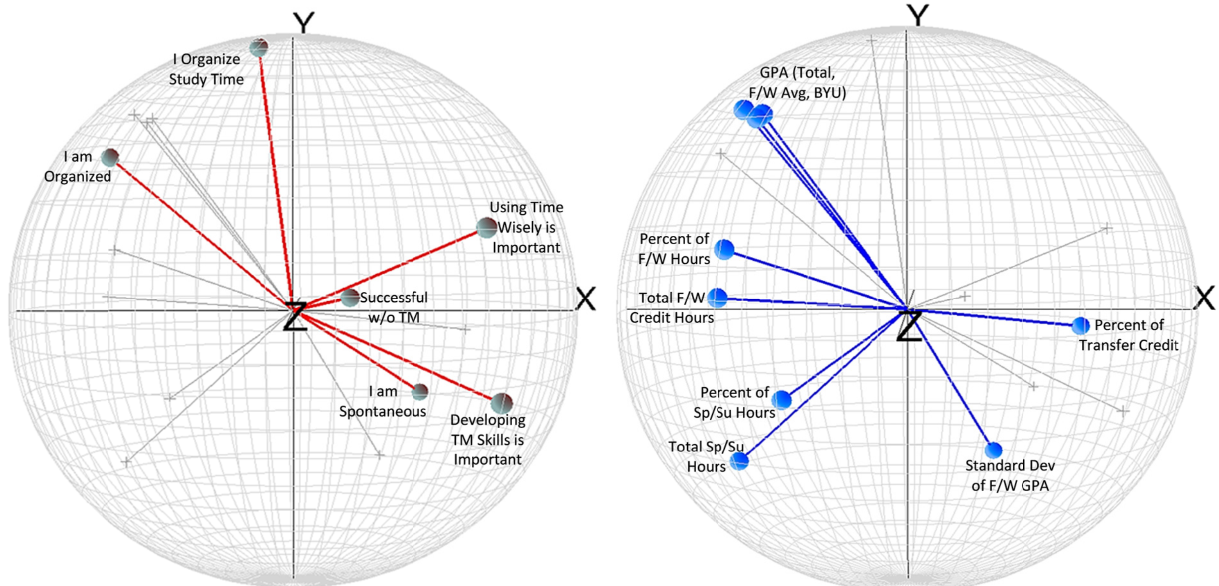


Figure 29. Linked vector plots with the six question survey vectors emphasized in red, and the GPA vectors emphasized in blue (as explained in Figure 11).

The linked factor score plots for this canonical correlation analysis are shown in Figure 30. Once again, because of the perfect canonical correlations, the spaces for the two sets of variables are the same. Therefore, only one view of the clusters is shown in the figure.

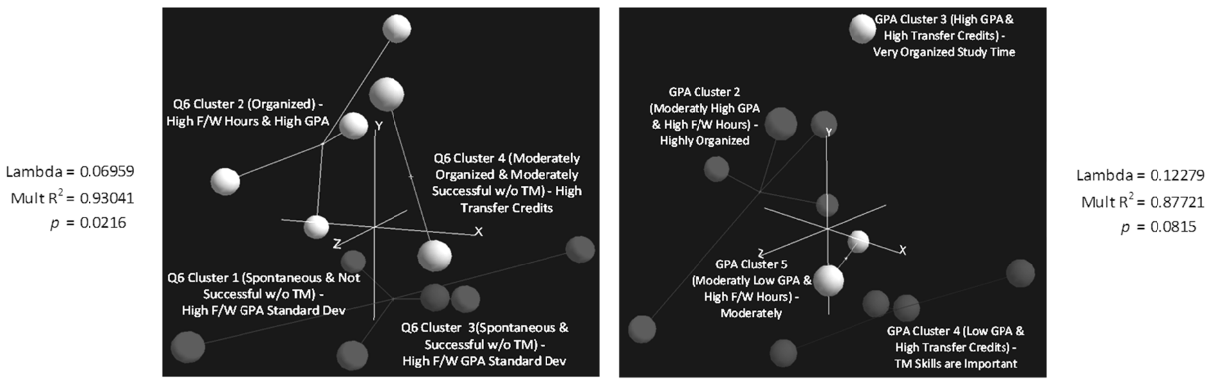


Figure 30. Linked factor score plots for the six-question survey and GPA. Because the canonical correlations for the x, y and z-axes are all 1.00, the three-factor spaces for both sets of variables are the same. Therefore, the factor score plots are identical regardless of the space they are shown in. The six question survey clusters are on the left, and the GPA clusters are on the right.

Predictor Variable Set E – ASES Behaviors and ASES Situations

Only the 18 participants specifically recruited for the hypothesis testing portion of this project complete the ASES. The whole ASES is analyzed holistically, including both the behavioral and situational subscales. The data are standardized, cluster analyzed, and a dendrogram is created (Figure 32). The red line in Figure 31 represents where the dendrogram is separated to produce eight clusters.

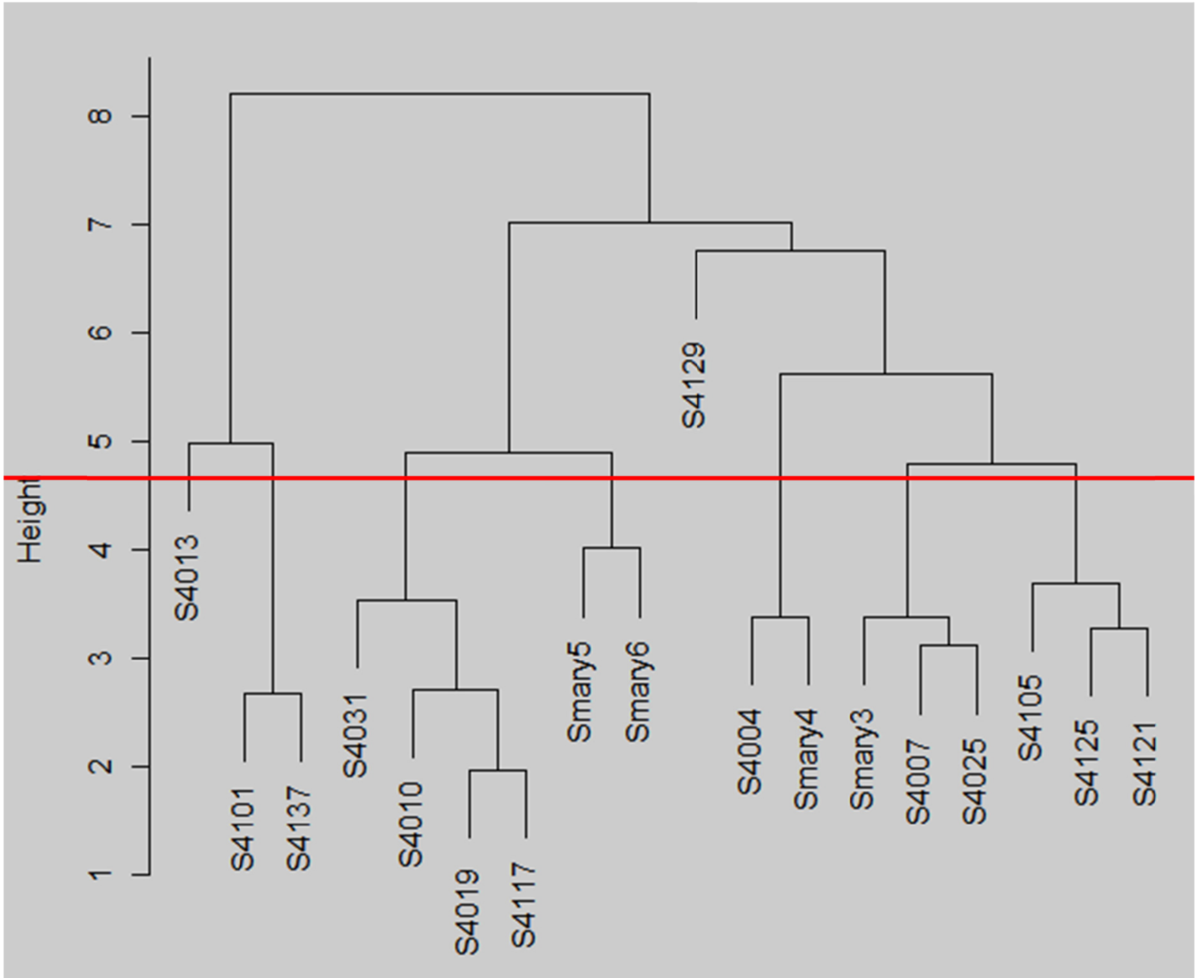


Figure 31. Dendrogram of the structure of 18 persons' scores for the 14 ASES variables, six situational variables, seven behavioral, and one total score. A line shows the division of the 18 data points into eight clusters.

A principal component analysis of the data matrix, including the means for the clusters, is completed. The summary table for the analysis is shown in Table 17. Even though this dataset has a relatively large number of variables, the principal component analysis accounts for over 70% of the variance in the 14 variables with three factors.

Table 17

Principal Component Analysis Summary Table of Fourteen Subscale Score Variables of the ASES, with Seven Behavioral Subscale Variables, Six Situational Subscale Variables, and One Total ASES Variable, Varimax Rotated

	Loadings			Communalities				Uniqueness
	factor 1	factor 2	factor 3	factor 1	factor 2	factor 3	Total	U
Behavioral-Favors	.7161	.0986	-.0131	.5127	.0097	.0002	.5226	.4774
Behavioral-Initiative	.3891	-.2856	-.6399	.1514	.0816	.4094	.6424	.3576
Behavioral-Negative Feelings	.1464	.8098	.1390	.0214	.6558	.0193	.6965	.3035
Behavioral-Opinions	.8515	.2812	-.1778	.7250	.0791	.0316	.8357	.1643
Behavioral-Positive Feelings	.6986	.1997	.2108	.4880	.0399	.0445	.5723	.4277
Behavioral-Requests	.3451	.0412	.7472	.1191	.0017	.5583	.6791	.3209
Behavioral-Rights	.4240	.6547	.1427	.1797	.4286	.0203	.6287	.3713
Situational-Authorities	.6900	.5217	.2134	.4761	.2722	.0455	.7938	.2062
Situational-Friends	.8137	.2938	.2328	.6620	.0863	.0542	.8026	.1974
Situational-Global	.7082	.2105	-.3794	.5016	.0443	.1439	.6898	.3102
Situational-Intimate/Close	.3519	.6659	.1511	.1238	.4434	.0228	.5900	.4100
Situational-Parents	.0075	-.6383	.4917	.0001	.4074	.2418	.6492	.3508
Situational-Public	.5059	.6950	-.1141	.2559	.4830	.0130	.7519	.2481
ASES Total	.8282	.5323	.1292	.6859	.2833	.0167	.9859	.0141
Sums of squares by columns:				4.9027	3.3162	1.6216	9.8406	4.1594
Percents of sums of squares:				35.02%	23.69%	11.58%	70.29%	29.71%

Using Metrika, the factor loadings from the principal component analysis are utilized to plot the vectors for the seven behavioral variables, the six situational variables, and the total ASES score. To ease the visual understanding of the vector plots, two figures are created; Figure 32 shows the behavioral variables bolded, and Figure 33 shows the situational variables bolded.

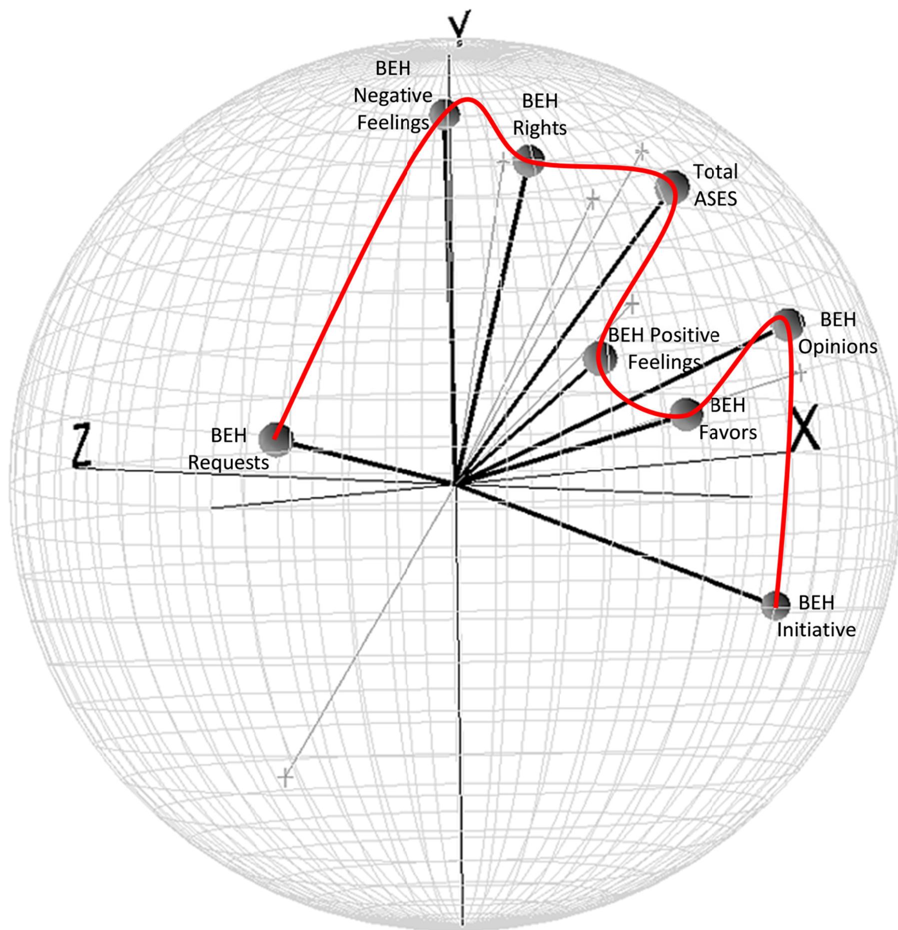


Figure 32. PCA vector plot, within the three-factor space, of the situational and behavioral variables of the ASES. The behavioral variables are bolded.

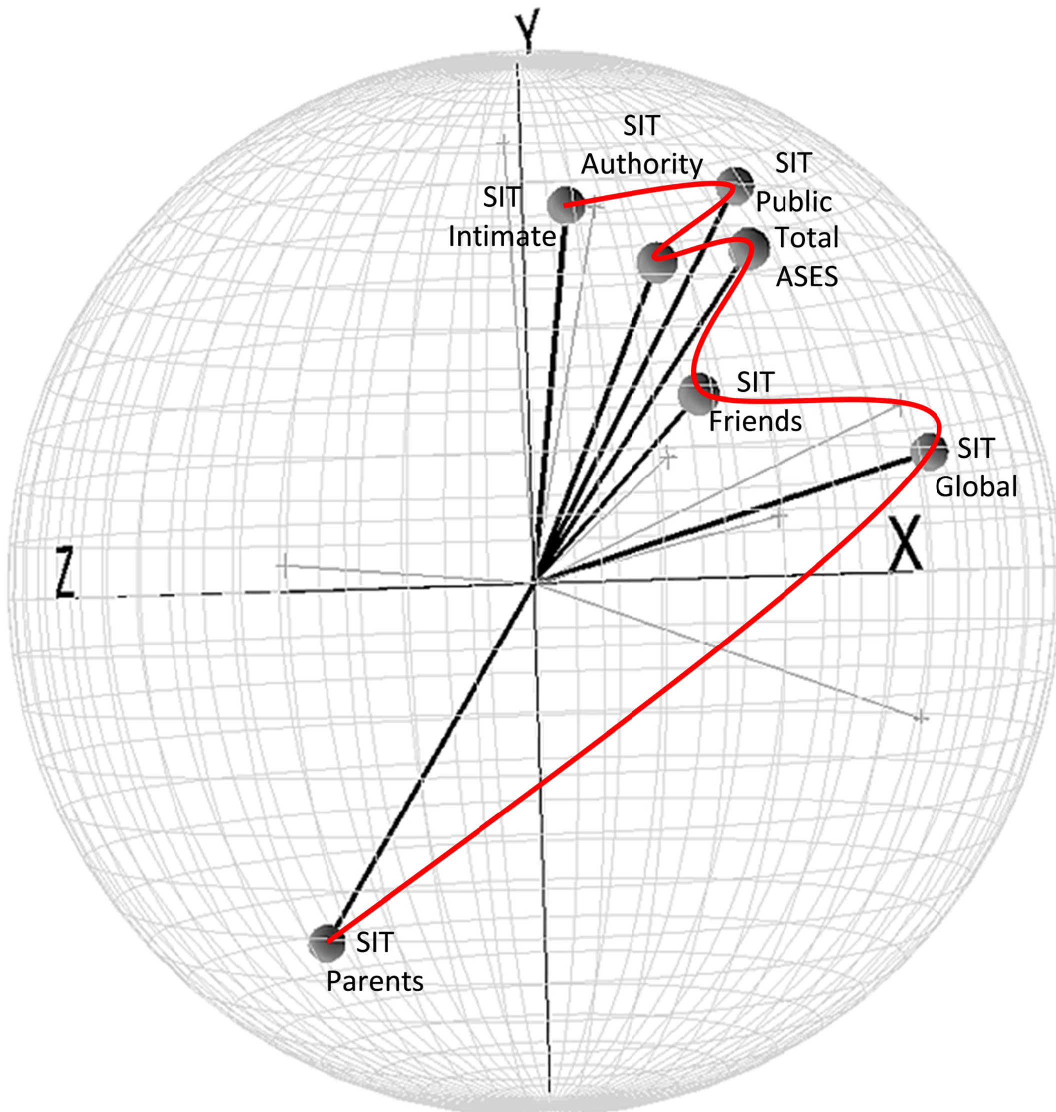


Figure 33. PCA vector plot, within the three-factor space, of the situational and behavioral variables of the ASES. The situational variables are bolded.

The individual factor scores for each of the 18 participants are used to plot them within the space defined in Figures 32 and 33 (see Figure 34). Individuals are connected with lines to their cluster means. Cluster 1 is made up of two participants. Cluster 2 is made up of three participants. Cluster 3 is made up of four participants. Cluster 4 is made up of one participant.

Cluster 5 is made up of two participants. Cluster six is made up of three participants. Cluster 7 is made up of one participant. And cluster 8 is made up of two participants.

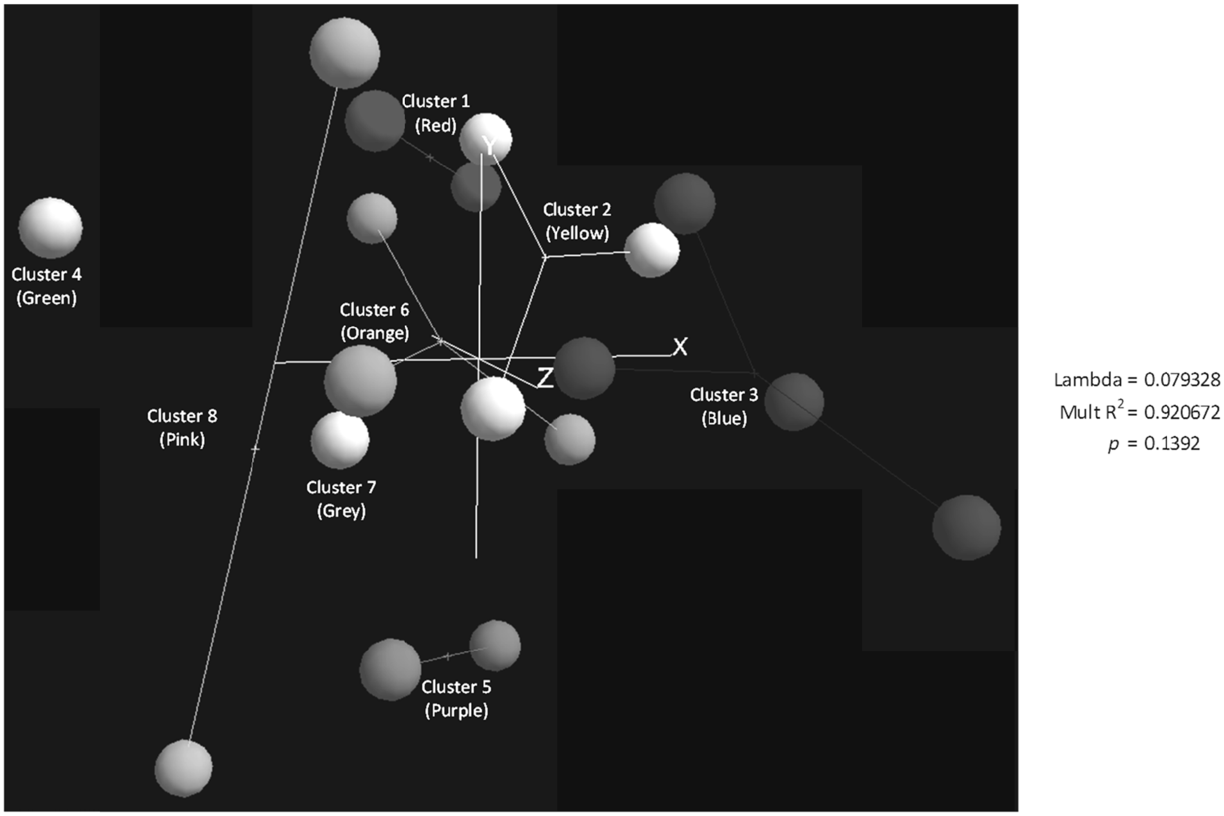


Figure 34. Eight clusters, based on situational and behavioral dimensions of the ASES, in the three-factor space, as seen in Figures 32 & 33.

Line plots of each of the eight clusters are created to show the general overall patterns for each cluster. Figure 35 shows that, for the most part, these eight clusters are do not separate very well, and it is difficult to interpret a general trend for several of the clusters.

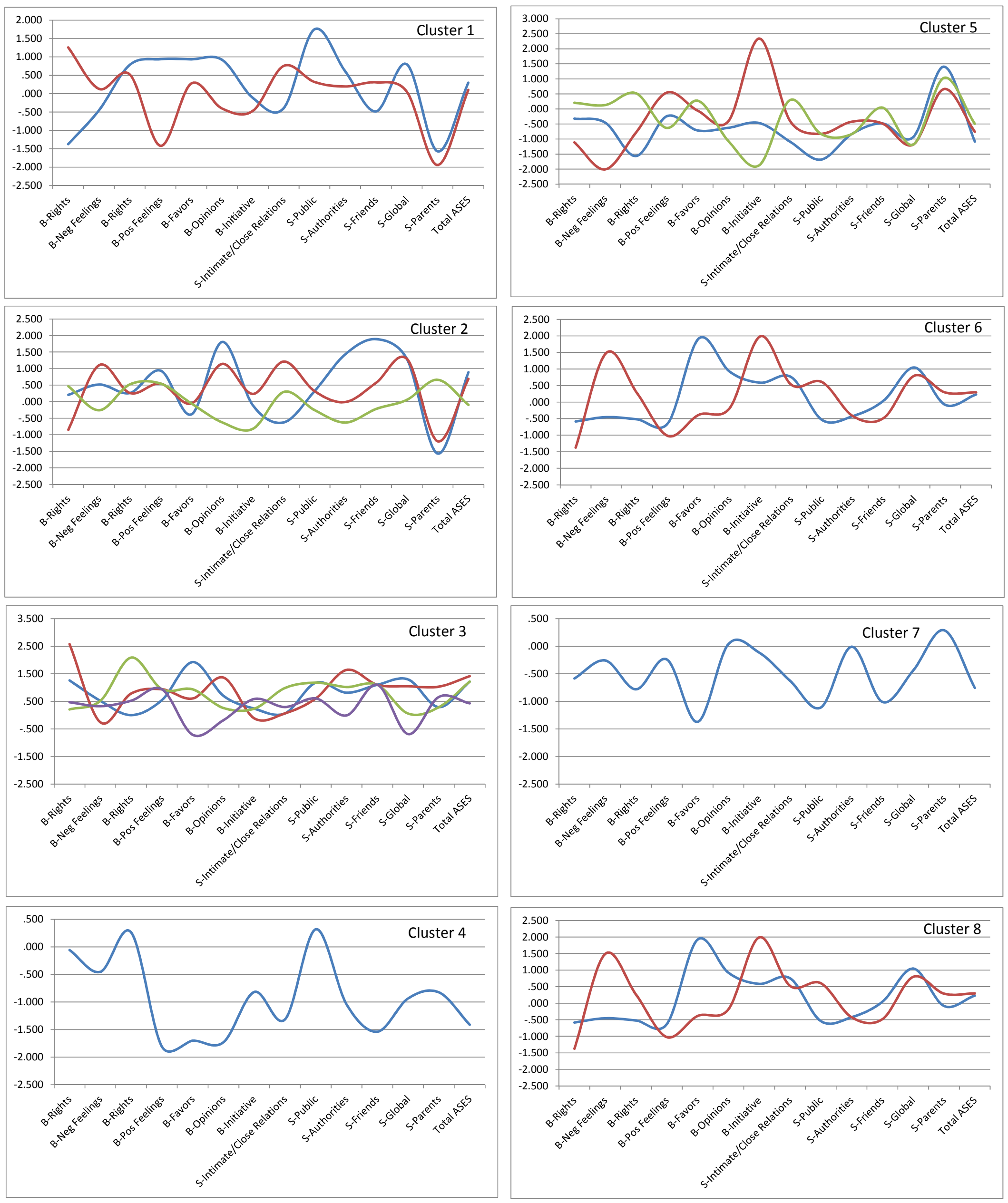


Figure 35. Line plots for eight clusters related to both subscales, behavioral and situational of the ASES.

A one-way MANOVA is used to test the adequacy of the eight clusters in separating the 18 data points within the space of the 14 ASES variables, including both the behavioral and the situational subscales. The high number of non-significant p-values in Table 18 signifies the poor separation of the clusters, which may be attributed to the large number of variables. Surprisingly, the multivariate R^2 value calculated from the Wilks' Lambda is still quite strong (0.921) even though the cluster separation is not very good, testifying to the relative optimism of this index.

Table 18

One-Way MANOVA as a Test of the Adequacy of the Eight Clusters in Separating the Eighteen Data Points within the Space of the Set of Fourteen Combined ASES Variables Plus Three Factor Scores, Multivariate Results at the Bottom of the Table and Univariate Results at the Top

Univariate Statistics

	F(6,21)	p	R2
Fourteen Combined ASES Variables Plus Three Factor Score Variables			
Behavioral-Favors	1.99	0.1566	0.582
Behavioral-Initiative	0.44	0.8580	0.234
Behavioral-Negative Feelings	0.55	0.7786	0.279
Behavioral-Opinions	1.41	0.2987	0.498
Behavioral-Positive Feelings	1.95	0.1626	0.578
Behavioral-Requests	1.15	0.4081	0.445
Behavioral-Rights	3.90	0.0261	0.732
Situational-Authorities	0.98	0.4946	0.407
Situational-Friends	5.87	0.0065	0.804
Situational-Global	1.89	0.1748	0.569
Situational-Intimate/Close	0.62	0.7264	0.304
Situational-Parents	3.97	0.0246	0.735
Situational-Public	3.35	0.0414	0.701
ASES Total	3.40	0.0394	0.704
Factor 1	3.43	0.0386	0.706
Factor 2	0.81	0.6001	0.361
Factor 3	1.45	0.2869	0.504

Multivariate Statistics

	F(6,21)	p	R2
Wilks' Lambda	0.07855	0.1362	0.921
Pillai's Trace	1.571	0.1264	
Hotelling-Lawley Trace	4.657	0.2037	
Roy's Greatest Root	2.471	0.0353	

Note. The multivariate ?2 is calculated as one minus the Wilks' lambda value (Wilks, 1963).

A canonical correlation analysis is run on the latent variables of the X and Y sets. The results are shown in Table 19. As was the case with the six question survey, no multivariate tests could be run due to insufficient degrees of freedom. All three of the canonical correlations are perfect, and statistically significant. Unlike the six question survey, however, the variance accounted for between these two sets of variables is very low. Only 15.1% of the variance in the GPA variables can be accounted for by the ASES variables. And only 18% of the variance in the ASES variables can be accounted for by the GPA variables.

Table 19

Canonical Correlation Summary Table with the Y set of GPA Variables (Dependent) at the Top of the Table, and the X Set of Fourteen ASES Subscale Variables (Independent) at the Bottom of the Table

	Loadings			Squared Loadings				Uniqueness
	LV1	LV2	LV3	LV1	LV2	LV3	Total	U
Y Set (GPA)	*(eta1)*	*(eta2)*	*(eta3)*	*(eta1)*	*(eta2)*	*(eta3)*		
GPA total	-.1065	-.0182	.2554	.0113	.0003	.0652	.0769	.9231
Fall/Winter Average	-.0339	.0054	.2280	.0011	.0000	.0520	.0532	.9468
Combined Average	-.0009	.0136	.3622	.0000	.0002	.1312	.1314	.8686
Fall/Winter StdDev	.1719	-.3208	-.2560	.0295	.1029	.0655	.1980	.8020
Percent Transfer	-.0295	.3931	-.1638	.0009	.1545	.0268	.1822	.8178
Fall/Winter Credits	.0502	-.3330	.2287	.0025	.1109	.0523	.1657	.8343
Fall/Winter Percent	-.0257	-.3551	.2490	.0007	.1261	.0620	.1888	.8112
Spring/Summer Credits	.2851	-.4653	-.1914	.0813	.2165	.0366	.3344	.6656
Spring/Summer Percent	.1330	-.0725	-.0849	.0177	.0053	.0072	.0302	.9698
			Sum of squares by columns:	.1451	.7167	.4989	1.3607	7.6393
			Percents of sums of squares:	1.61%	7.96%	5.54%	15.12%	84.88%
X Set (ASES)	*(chi1)*	*(chi2)*	*(chi3)*	*(chi1)*	*(chi2)*	*(chi3)*		
B-Favors	-.2683	-.1353	-.1683	.0720	.0183	.0283	.1186	.8814
B-Initiative	.2844	.2004	-.3905	.0809	.0402	.1525	.2735	.7265
B-Negative Feelings	-.0553	.3477	.5534	.0031	.1209	.3063	.4302	.5698
B-Opinions	-.0544	.1826	.0874	.0030	.0333	.0076	.0439	.9561
B-Positive Feelings	-.0519	.0126	.1374	.0027	.0002	.0189	.0217	.9783
B-Requests	-.3752	.2077	.2173	.1408	.0431	.0472	.2311	.7689
B-Rights	.2437	-.0520	.2309	.0594	.0027	.0533	.1154	.8846
S-Authorities	-.0384	.2410	.1001	.0015	.0581	.0100	.0696	.9304
S-Friends	-.1751	.3370	.4102	.0307	.1136	.1683	.3125	.6875
S-Global	.0511	.2067	.1504	.0026	.0427	.0226	.0680	.9320
S-Intimate/Close Rel	-.0753	.0561	.1015	.0057	.0031	.0103	.0191	.9809
S-Parents	-.7200	-.0272	-.1501	.5184	.0007	.0225	.5417	.4583
S-Public	.4036	-.0833	.1180	.1629	.0069	.0139	.1838	.8162
ASES Total	-.0939	.2040	.2017	.0088	.0416	.0407	.0911	.9089
			Sum of squares by columns:	1.0923	.5255	.9025	2.5203	11.4797
			Percents of sums of squares:	7.80%	3.75%	6.45%	18.00%	82.00%

	Coefficient	p Value
First Canonical Correlation	1.0000	<.0001
Second Canonical Correlation	1.0000	<.0001
Third Canonical Correlation	1.0000	<.0001

No multivariate tests due to insufficient degrees of freedom.

Linked vector plots are created for the GPA and ASES variables (Figure 36). Again, in an effort to ease the visual understanding of the vector plots, three figures are created. The ASES subscale variables are each emphasized in their own plot.

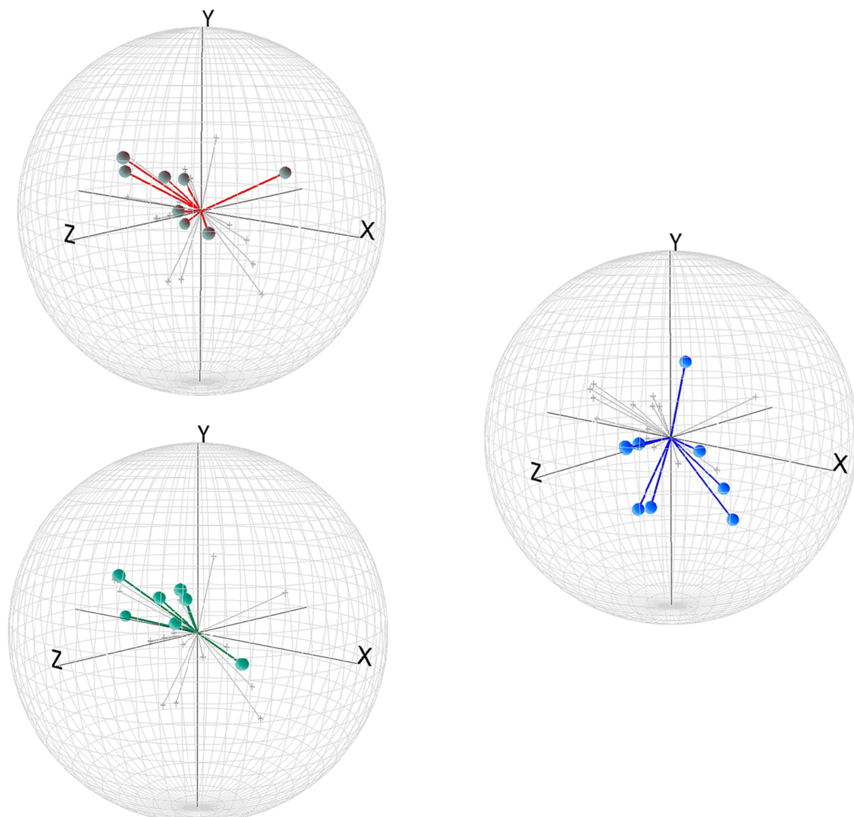


Figure 36. Linked vector plots with the ASES Behavioral vectors emphasized in red, ASES Situational vectors emphasized in green, and the GPA vectors emphasized in blue (as explained in Figure 12).

Linked factor score plots for this canonical correlation analysis are shown in Figure 37. Once again, because of the perfect canonical correlations, the two sets of variables' spaces are the same. Therefore, only one view of the clusters is shown in the figure. Neither set of clusters is visually compelling.

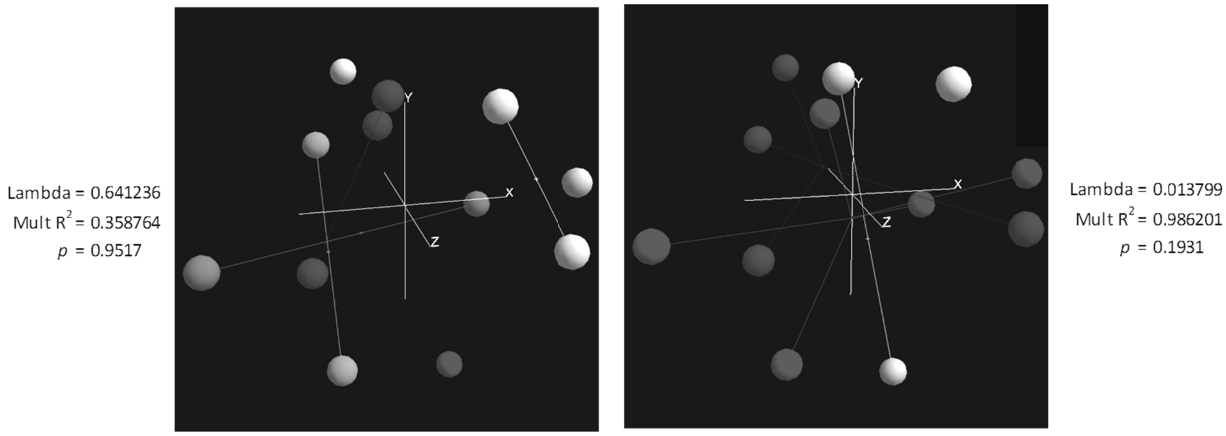


Figure 37. Linked factor score plots for the six-question survey and GPA. Because the canonical correlations for the x, y and z-axes are all 1.00, the three-factor spaces for both sets of variables are the same. Therefore, the factor score plots are identical regardless of the space they are shown in. The ASES clusters are on the left, and the GPA clusters are on the right.

Results from Study 2 – Hypothesis Tests of Effects of Academic Probation and Gender on Four Sets of Variables

Variable Set A – Time Spent on Selected Activities

Hypotheses.

1. The time-spent data from the time logs will produce substantially greater effect sizes in predicting academic performance than those reported from the studies from either of the two subcategories (IC and EM) from the Robbins et al. (2004) meta-analysis.
2. The high performing group of students study more hours outside of class for every hour in class, than the students on academic probation. In accord with Britton & Tesser's findings, this will account for substantially more variance in the difference between the two groups than ACT performance.
3. Women report spending more time on academic related activities than men.

Results. Of the 18 participants specifically recruited for the hypothesis testing in this study, Study 2, only 12 had the complete data needed for variable set A, time-spent on selected activities. Four of the participants are high performing males, three are high performing females, three are low performing males, and two are low performing females.

A two-way MANOVA is run on the time-spent data with gender group and academic performance group as main effects, and with their two-way interaction. The only significant multivariate statistic is Roy's Greatest Root for the entire model ($p=0.015$). Undoubtedly, this is due to the small sample size since there are a number of fairly robust univariate R-squared values (reported in Table 20). Also the single significant multivariate test is enough to protect against alpha inflation, and therefore, the univariate results will still be discussed.

The amount of time spent in class is statistically significant for the entire model ($p=0.0204$, $R^2=0.687$), academic group ($p=0.0347$, $R^2=0.252$), and gender ($p=0.0131$, $R^2=0.395$). Students in the high performing group report spending more time in class ($\bar{X}=3.500$ hours) than students in the low performing group ($\bar{X}=2.167$ hours). Females also report spending more time in class ($\bar{X}=3.667$ hours), than males ($\bar{X}=2.000$ hours), supporting hypothesis three. Females furthermore report spending significantly more time studying ($p=0.0382$, $R^2=0.393$) than males (7.195 hours and 3.986 hours, respectively).

Hypothesis two, stating that the high performing students study more hours outside of class for every hour in class, is not supported by the results. In fact, the number of study hours for both the high performing group and the low performing group are almost equal (5.820 and 5.361, respectively), despite the fact that the high performers spend significantly more time in class.

Hypothesis one is also not supported by the time-spent data. The effect sizes for Robbins et al. (2004) academic related skills category is 0.238. The effect sizes for the internal conceptions and external manifestations subcategories from my meta-analysis are 0.260 and 0.343, respectively. The R-squared statistics of the academic group main effect for the time-spent variables range from 0.001(Television Hours) to 0.252 (Class Hours). Although the time spent in class has a greater effect size than Robbins et al. original reported effect size, it is not larger than either of the subscale effect sizes from my meta-analysis.

Table 20

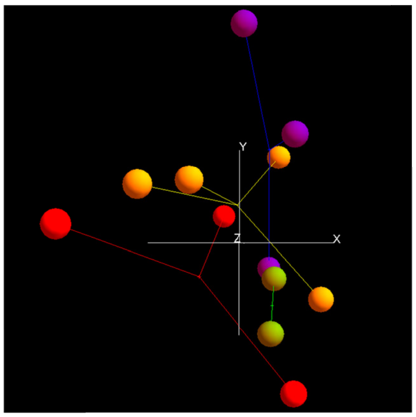
Two-Way Multivariate Analysis of Variance of the Time-Spent Variables, with Main Effects for Gender and for Academic Group, and Also the Two-Way Interaction, Showing Multivariate Results at the Bottom of the Table and Univariate Results for the Seven Time-Spent Variables at the Top

Univariate Statistics	Entire Model			Gender			Academic Group			Gender X Academic Group		
	F (3,8)	p	R^2	F(1,8)	p	R^2	F(1,8)	p	R^2	F(1,8)	p	R^2
Seven Time-Spent Variables												
Class Hours	5.85	.0204	.687	10.08	.0131	.395	6.45	.0347	.252	0.00	.9996	.000
Computer Hours	0.80	.5289	.230	0.86	.3796	.083	0.53	.4871	.051	1.64	.2359	.158
Recreation Hours	0.14	.9345	.049	0.09	.7710	.011	0.23	.6467	.027	0.06	.8143	.007
Sleep Hours	0.36	.7815	.120	0.00	.9841	.000	0.36	.5649	.040	0.87	.3786	.096
Study Hours	2.54	.1298	.488	6.14	.0382	.393	0.13	.7323	.008	0.52	.4927	.033
Television Hours	1.69	.2452	.388	2.09	.1867	.159	0.01	.9256	.001	3.58	.0950	.274
Visiting Hours	0.07	.9734	.026	0.04	.8444	.005	0.04	.8444	.005	0.09	.7771	.010

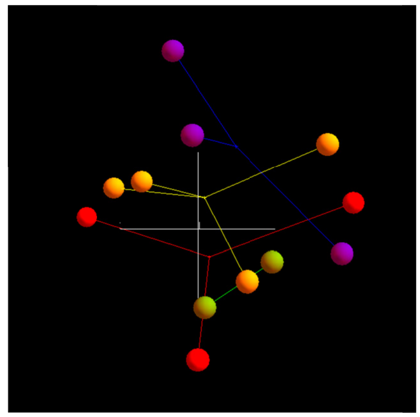
Multivariate Statistics	Entire Model			Gender		Academic Group		Gender X Academic Group	
	Value	p	$\eta 2$	Value	p	Value	p	Value	p
Wilks' Lambda	.00875	.4095	.991	.23979	.6169	.17638	.4930	.05979	.1941
Roy's Greatest Root	20.80	.0153							

Note. Only Wilks' Lambda is reported here in the multivariate section for the main effects and interaction, since with one degree of freedom in the numerator the other three multivariate significance tests yield the same p value. The multivariate η2 is calculated as 1-Λ from a one-way MANOVA analysis (Wilks, 1963) of the four categorized groups (gender x hi/lo academics).

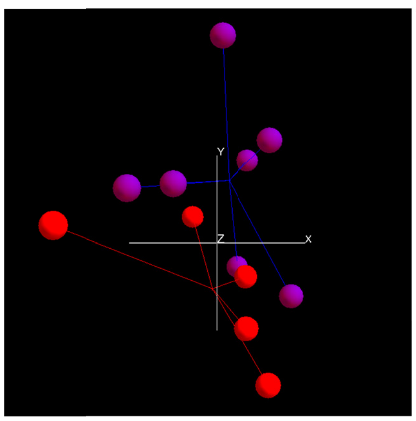
The individual factor scores for each of the 12 participants are used to plot them in Figure 38, which is the vector plot, defined in Figure 8, for these seven time-spent variables. Individuals are connected with lines to their respective group means (academic, gender, academic by gender). The male group is much higher on the Y-axis signifying that they spend more time watching television than the female group. The high performing groups are more negative on the X-axis and slightly more positive on the Z-axis, meaning they spend more hours in class, and less hours visiting.



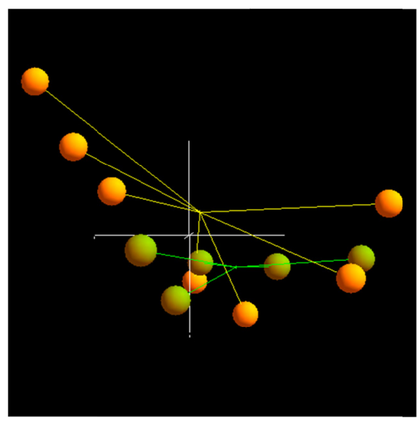
Front View of Four Groups
Red – High Females, Green – Low Females,
Yellow – High Males, Blue Low Males



Side View of Four Groups (Z-axis to the Left)



Front View of Gender Groups
(Red – Females, Blue Males)



Top View of Academic Groups (Z-axis to the Left)
(Yellow – High Performers, Green – Low Performers)

Figure 38. Cluster star plots of all four groups, gender groups, and academic groups, in the three factor space shown in Figure 8.

Utilizing the ordered profiles derived from the path in the time-spent vector plot of Figure 8, a set of line plots is created (see Figure 39). Simple line plots are an efficient way to visually interpret the MANOVA results from Table 20. The greatest separation in the academic group plot is for class hours; high performers clearly spend more time in class than low performers

($p=0.0347$, $R^2=0.252$). The two activity categories that were univariately significant for the main effect of gender are class hours ($p=0.0131$, $R^2=0.395$) and study hours ($p=0.0382$, $R^2=0.393$), with females spending more time doing both, which is evident in Figure 39. Although time spent watching television was not statistically significant in the MANOVA, you can also see a large difference on the line plot, with males watching more than females.

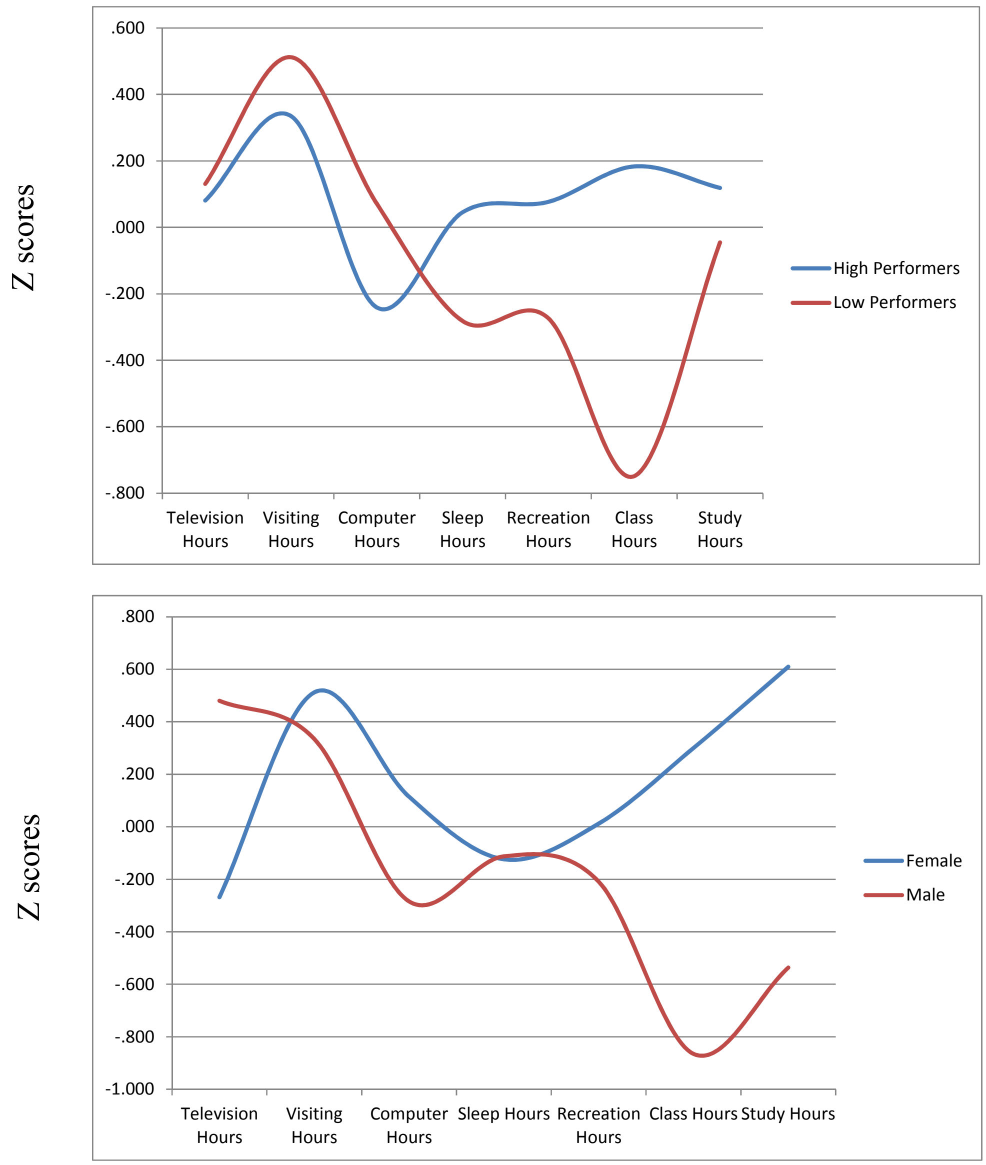


Figure 39. Line plots of the average number of hours spent on the seven activities by gender and academic group. Academic group is shown in the top graph, and gender is shown in the bottom graph.

Variable Set B – Activity Evaluations[14]

Hypothesis.

4. The time evaluation data from the time logs will produce substantially greater effect sizes in predicting GPA than those reported from the studies from either of the two subcategories (IC and EM) from the Robbins et al. (2004) meta-analysis.

Results. As was the case with variable set A, only 12 had the complete data needed for variable set B, activity evaluations. Four of the participants are high performing males, three are high performing females, three are low performing males, and two are low performing females.

A two-way MANOVA is run on the activity evaluation data with gender group and academic performance group as main effects, and a test of their two-way interaction. The small number of observations for the data in this section results in insufficient degrees of freedom. Therefore, no multivariate tests can be calculated. Hypothesis four is not strongly supported by the time evaluation data. Factor 2 (wasted) of sleep and Factor 3 (alert) of study are both statistically significant for the entire model ($p=0.0495$ and $p=0.0252$ respectively), and Factor 2 (wasted) of sleep has an R-squared value of 0.455. This Factor 2 for the evaluation of sleep, feeling that time spent sleeping is unproductive and wasted, is the only variable with an effect size greater than the effect sizes reported in Robbins et al. (0.238), or either of the subcategories from the meta-analysis (0.260 and 0.343). The low performing group evaluated their time spent sleeping as more wasted than the high performing group, with means of 1.258 and 0.514, respectively. There are no significant differences for the main effect of gender.

Factor 3 (alert) for study is significant for the two-way interaction between gender and academic group ($p=0.0067$, $R^2=0.543$). The group means from highest to lowest are as follows:

[14] Originally there was a hypothesis for this section regarding low performers placing value on trivial activities. I am currently unable to test it because of a loss of data due to the campus R drive crash.

high performing females ($\bar{X}$=0.907), low performing males ($\bar{X}$=0.693), high performing males ($\bar{X}$=0.404), low performing females ($\bar{X}$= -0.345).

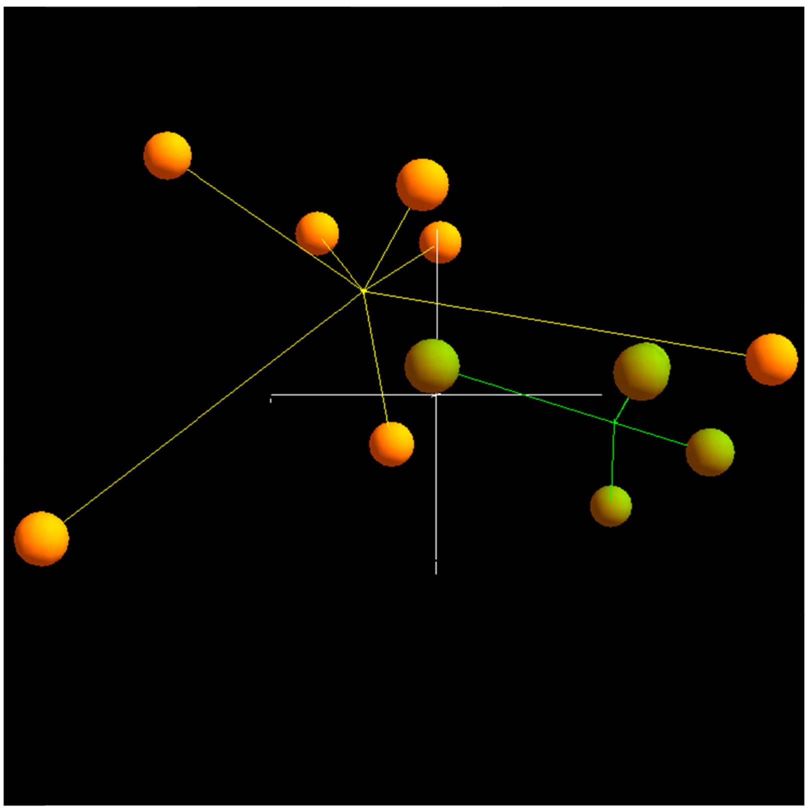
Table 21

Two-Way Multivariate Analysis of Variance of the Time Evaluation Variables, with Main Effects for Gender and for Academic Group, and Also the Two-Way Interaction, Showing Multivariate Results at the Bottom of the Table and Univariate Results for the Nine Time Evaluation Variables at the Top

Univariate Statistics	Entire Model			Gender			Academic Group			Gender X Academic Group		
	F (3,8)	*p*	R^2	F(1,8)	*p*	R^2	F(1,8)	*p*	*R2*	F(1,8)	*p*	R^2
Nine Time Evaluation Variables												
Factor 1 ("good") Eval of Class	1.41	.3099	.345	1.88	.2076	.154	0.25	.6323	.020	1.25	.2962	.102
Factor 2 ("wasted") Eval of Class	1.02	.4326	.277	0.05	.8231	.005	2.79	.1333	.252	0.02	.8815	.002
Factor 3 ("alert") Eval of Class	1.40	.3128	.344	2.48	.1541	.203	1.47	.2600	.121	0.01	.9158	.001
Factor 1 ("good") Eval of Sleep	0.21	.8866	.073	0.11	.7435	.013	0.49	.5048	.056	0.16	.7005	.018
Factor 2 ("wasted") Eval of Sleep	4.08	.0495	.605	1.72	.2265	.085	9.22	.0161	.455	1.35	.2796	.066
Factor 3 ("alert") Eval of Sleep	1.11	.3989	.295	0.40	.5448	.035	0.80	.3968	.071	1.41	.2698	.124
Factor 1 ("good") Eval of Study	1.13	.3938	.297	0.37	.5604	.032	1.61	.2399	.142	2.24	.1729	.197
Factor 2 ("wasted") Eval of Study	1.29	.3438	.325	3.23	.1098	.273	0.16	.7013	.013	0.68	.4350	.057
Factor 3 ("alert") Eval of Study	5.40	.0252	.669	1.58	.2444	.065	5.13	.0533	.212	13.14	.0067	.543

Note. Because of the small number of observations and the resultant insufficient degrees of freedom in the error term, no multivariate tests can be calculated.

In Figure 40, the individual factor scores for each of the 12 participants are used to plot them within the space defined by the vector plot of Figure 14. Individuals are connected with lines to their respective academic group means. The low performing group is lower on the Z-axis signifying that they view their hours spent sleeping as wasted, whereas the high performing group, who are positive on the Z-axis, evaluate their sleep as good, and also reported being alert during their class time.



Top View of Academic Groups (Z-axis to the Left)
(Yellow – High Performers, Green – Low Performers)

Figure 40. Cluster star plot of the two academic groups, low and high performing participants, in the three factor space shown in Figure 14.

Utilizing the ordered profile derived from the path in vector plot of Figure 14, a line plot of the adjective evaluations visually confirms the results of the MANOVA. The low performers evaluate their sleep as being wasted much more than the high performing group ($p=0.0161$, $R^2=0.455$). And, not surprisingly, the high performing group reported being more alert during their study time than the low performers ($p=0.0533$, $R^2=0.212$).

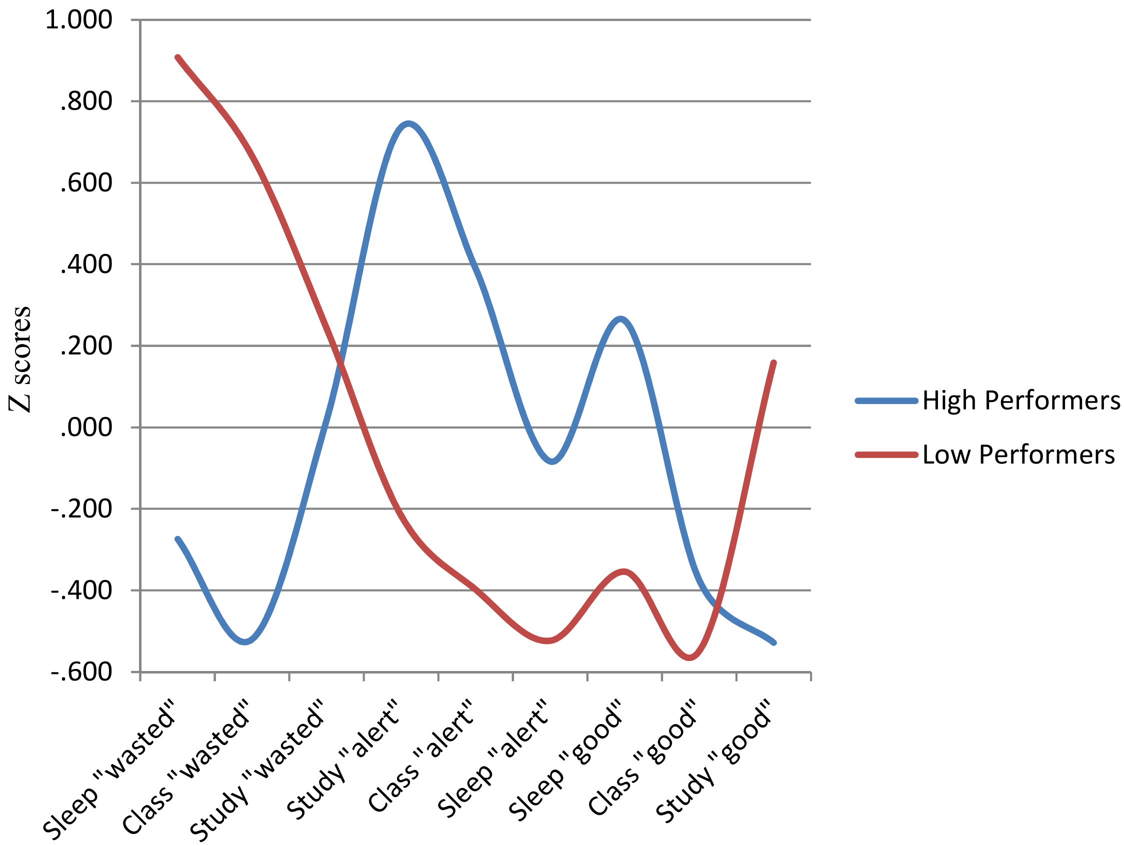


Figure 41. Line plot of the adjective evaluations for sleep, class, and study by academic group.

Variable Set C – Six Question Survey

Hypothesis.

5. Students who report being organized and concerned with time management skills have higher GPAs than students who report being spontaneous, and successful without time management.

Results. All 18 participants recruited specifically for the hypothesis testing study are utilized for the analysis of variable set C, six question survey. Six of the participants are high performing males, five are high performing females, four are low performing males, and three are low performing females.

A two-way MANOVA is run on the six question survey data. Roy's Greatest Root is significant for the entire model ($p=0.0066$), and the Wilk's Lambda for academic group is also significant ($p=0.0213$).

Univariately, the entire model shows statistical significance on questions two (IMorg, $p=0.0245$, $R^2=0.478$), three (Iplan, $p=0.0115$, $R^2=0.534$), and four (Spont, $p=0.0191$, $R^2=0.497$). Those same three variables have univariate significance for the main effect of academic group, with p-values of 0.0035, 0.0013, and 0.0032, respectively. The high performing group report being more organized ($\bar{X}=3.917$) than the low performing group ($\bar{X}=2.583$). Similarly, the high performing group reports that they organize their study time more carefully than the low performing group, with means of 3.550 and 2.125, respectively. The low performing group have a higher average on the self-descriptor "I am Spontaneous" ($\bar{X}=3.708$) than the high performing group ($\bar{X}=2.200$). All three of these variables account for approximately half of the variance in the statistical model, with R-squared values near 0.50. All of these findings support the hypothesis for this variable set.

None of the variables were even close to significance for the main effect of gender, with p-values ranging from 0.3947 (Using time wisely is important) to 0.8360 (I organize carefully). Naturally, the R-squared values are very small, ranging from 0.001 to 0.042.

Table 22

Two-Way Multivariate Analysis of Variance of the Six Time Management Attitude Question Variables, with Main Effects for Gender and for Academic Group, and Also the Two-Way Interaction, Showing Multivariate Results at the Bottom of the Table and Univariate Results for the Six Question Variables at the Top

Univariate Statistics	Entire Model			Gender			Academic Group			Gender X Academic Group		
	$F\,(3,14)$	p	R^2	$F\,(1,14)$	p	R^2	$F\,(1,14)$	p	R^2	$F\,(1,14)$	p	R^2
Seven Time-Spent Variables												
TM skill is important.	1.06	.3987	.185	0.11	.7437	.006	1.78	.2035	.104	1.78	.2035	.104
I am organized.	4.27	.0245	.478	0.19	.6674	.007	12.33	.0035	.460	0.00	1.0000	.000
I organize carefully.	5.36	.0115	.534	0.04	.8360	.001	16.07	.0013	.534	0.24	.6302	.008
I am spontaneous.	4.61	.0191	.497	0.14	.7147	.005	12.63	.0032	.454	0.32	.5781	.012
I am successful without TM.	0.53	.6700	.102	0.17	.6879	.011	0.00	.9831	.000	1.12	.3080	.072
Using time wisely is important.	1.41	.2812	.232	0.77	.3947	.042	0.77	.3947	.042	2.75	.1194	.151

Multivariate Statistics	Entire Model			Gender		Academic Group		Gender X Academic Group	
	Value	p	$\eta 2$	Value	p	Value	p	Value	p
Wilks' Lambda	.16704	.2816	.833	.88956	.9732	.24753	.0213	.74959	.7935
Roy's Greatest Root	3.10	.0066							

Note. Only Wilks' Lambda is reported here in the multivariate section for the main effects and interaction, since with one degree of freedom in the numerator the other three multivariate significance tests yield the same p value. The multivariate η2 is calculated as 1-Λ from a one-way MANOVA analysis (Wilks, 1963) of the four categorized groups (gender x hi/lo academics).

A Metrika scatterplot of the 18 participants in the three-dimensional six question space, shown in Figure 27, shows a fairly clear split between the high performing and low performing students at the Y-axis. The high performing students are higher on the factors that define the positive X-axis, which are the three statistically significant factors (IMorg, Iplan, and Not Spont), whereas the participants in the low performing group are lower on the X-axis.

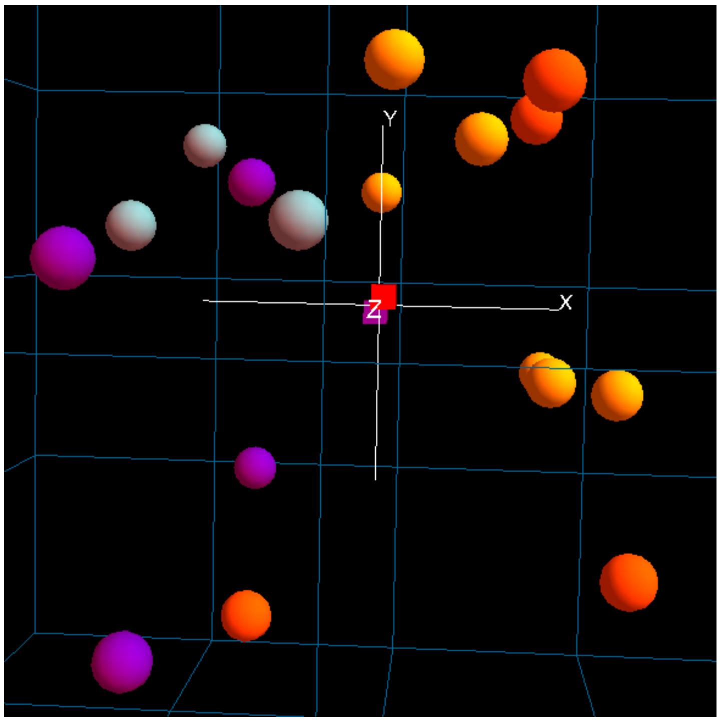


Figure 42. Metrika scatterplot of the 18 participants in the three-dimensional six question space shown in Figure 27.

Utilizing the ordered profile derived from the path in the six question survey vector plot of Figure 27, the ordered profiles line plot of Figure 43 is created. This clearly shows the separation between the high and low performing groups on questions two, three and four. It also shows that gender essentially has no effect on the six-question survey results.

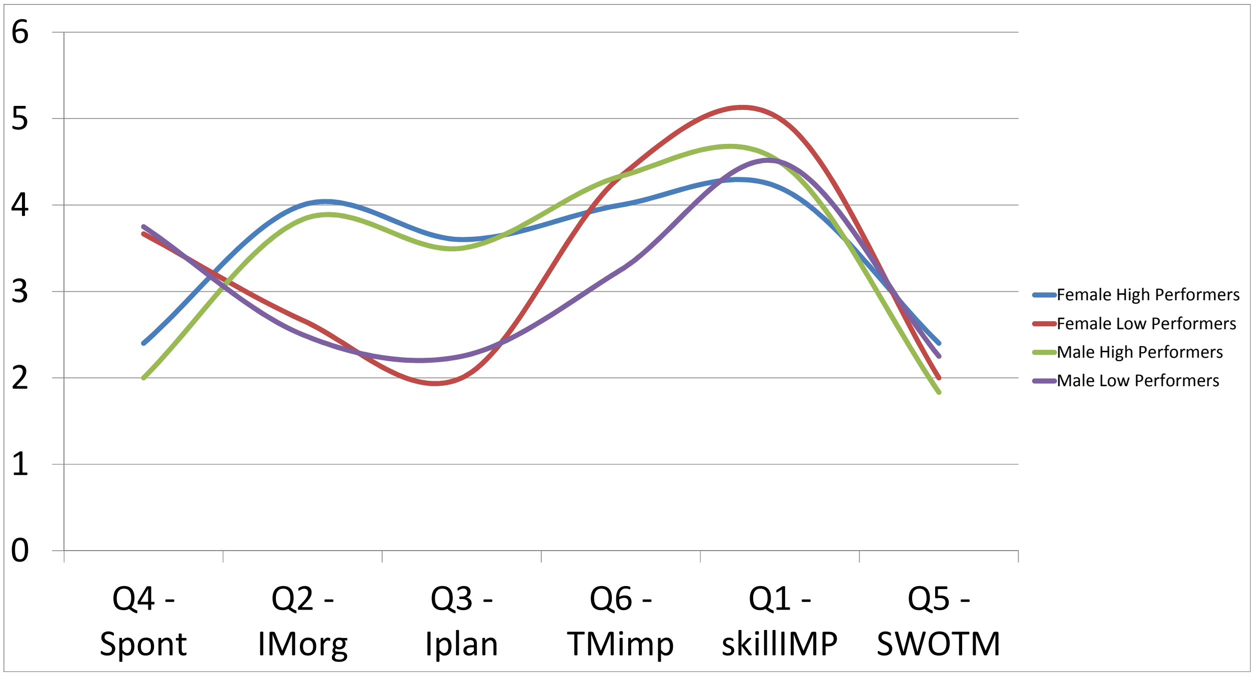


Figure 43. A profile plot showing the average scores from the four groups on the six question survey.

Variable Set D – Adult Self Expression Scale (ASES)

Hypothesis.

6. The students in the high performing group will score higher on the ASES, showing a propensity to act and be more assertive.

Behavioral results. Just like variable set C, all 18 participants recruited specifically for the hypothesis testing study are utilized for the analysis of variable sets D and E, the behavioral and situational subscales of the ASES. Six of the participants are high performing males, five are high performing females, four are low performing males, and three are low performing females.

Multivariate results from the MANOVA show academic group to be the only significant variable (p=.0410). Roy's Greatest Root is also significant for the entire model (p=0.0090).

Despite the multivariate significance of academic group, none of the univariate statistics for that main effect, or for gender are significant. The only significant univariate statistic is the two-way interaction for positive feelings (p=0.0300, R^2=0.284). It may be, once again, that the small sample size prevented the multivariate statistic for the interaction from being significant.

Table 23

Two-Way Multivariate Analysis of Variance of the ASES Behavioral Variables, with Main Effects for Gender and for Academic Group, and Also the Two-Way Interaction, Showing Multivariate Results at the Bottom of the Table and Univariate Results for the Eight ASES Variables at the Top

Univariate Statistics	Entire Model			Gender			Academic Group			Gender X Academic Group		
	F (3,14)	p	R^2	F (1,14)	p	R^2	F (1,14)	p	R^2	F (1,14)	p	R^2
Seven Time-Spent Variables												
Behavioral-Favors	0.18	.9083	.037	0.20	.6607	.014	0.31	.5891	.021	0.00	.9754	.000
Behavioral-Initiative	0.82	.5024	.150	1.57	.2310	.095	0.57	.4620	.035	0.99	.3378	.060
Behavioral-Negative Feelings	0.85	.4898	.154	0.41	.5332	.025	2.04	.1755	.123	0.00	.9870	.000
Behavioral-Opinions	1.79	.1945	.278	1.08	.3158	.056	4.04	.0642	.208	0.03	.8679	.001
Behavioral-Positive Feelings	2.19	.1346	.319	0.83	.3790	.040	0.22	.6489	.011	5.83	.0300	.284
Behavioral-Requests	1.11	.3765	.193	2.12	.1676	.122	1.40	.2571	.080	0.21	.6565	.012
Behavioral-Rights	0.25	.8611	.051	0.73	.4067	.050	0.00	.9545	.000	0.09	.7631	.006
ASES Total	0.83	.4981	.151	1.17	.2983	.071	1.12	.3080	.068	0.16	.6932	.010

Multivariate Statistics	Entire Model			Gender		Academic Group		Gender X Academic Group	
	Value	p	$\eta2$	Value	p	Value	p	Value	p
Wilks' Lambda	.06795	.2566	.932	.74931	.9468	.17808	.0410	.38165	.3293
Roy's Greatest Root	5.01	.0090							

Note. Only Wilks' Lambda is reported here in the multivariate section for the main effects and interaction, since with one degree of freedom in the numerator the other three multivariate significance tests yield the same p value. The multivariate $\eta2$ is calculated as 1-Λ from a one-way MANOVA analysis (Wilks, 1963) of the four categorized groups (gender x hi/lo academics).

Because the original principal component analysis, and subsequent vector plot, for the ASES variables combined the behavioral and situational variables, a new principal component analysis is run for only the seven behavioral subscale variables plus total ASES score. The principal component summary table is given in Table 24. The principal component analysis accounts for more than three-quarters of the variance in the eight variables within a three-factor space. The first of the three varimax-rotated factors accounts for almost 40% of the variance, whereas the other two factors account for about 18% each. Expressing positive feeling and standing up for rights are the variables least accounted for within this XYZ space (0.4074 and 0.4167 uniqueness, respectively). The vector plot for this three-factor space of the eight behavioral variables of the ASES are given in Figure 44, with the path through the eight variables shown, for the creation of ordered profile line plots.

Table 24

Principal Component Analysis Summary Table of the Seven Behavioral Subscale Variables of the ASES and Total ASES, Varimax Rotated

	Loadings			Communalities				Uniqueness
	factor 1	factor 2	factor 3	factor 1	factor 2	factor 3	Total	U
Behavioral-Favors	.8042	-.1785	.1359	.6467	.0319	.0185	.6971	.3029
Behavioral-Initiative	.3423	-.2617	-.7692	.1172	.0685	.5917	.7773	.2227
Behavioral-Negative Feelings	.2120	.9076	.0494	.0449	.8237	.0024	.8711	.1289
Behavioral-Opinions	.8480	.2199	-.1262	.7191	.0484	.0159	.7834	.2166
Behavioral-Positive Feelings	.7066	.2994	-.0605	.4993	.0896	.0037	.5926	.4074
Behavioral-Requests	.3111	-.0706	.8507	.0968	.0050	.7237	.8255	.1745
Behavioral-Rights	.5364	.4745	.2654	.2877	.2252	.0704	.5833	.4167
ASES Total	.8793	.4396	.1312	.7732	.1932	.0172	.9836	.0164
Sums of squares by columns:				3.1849	1.4855	1.4435	6.1139	1.8861
Percents of sums of squares:				39.81%	18.57%	18.04%	76.42%	23.58%

Another vector plot is created, utilizing only the seven behavioral variables and total ASES.

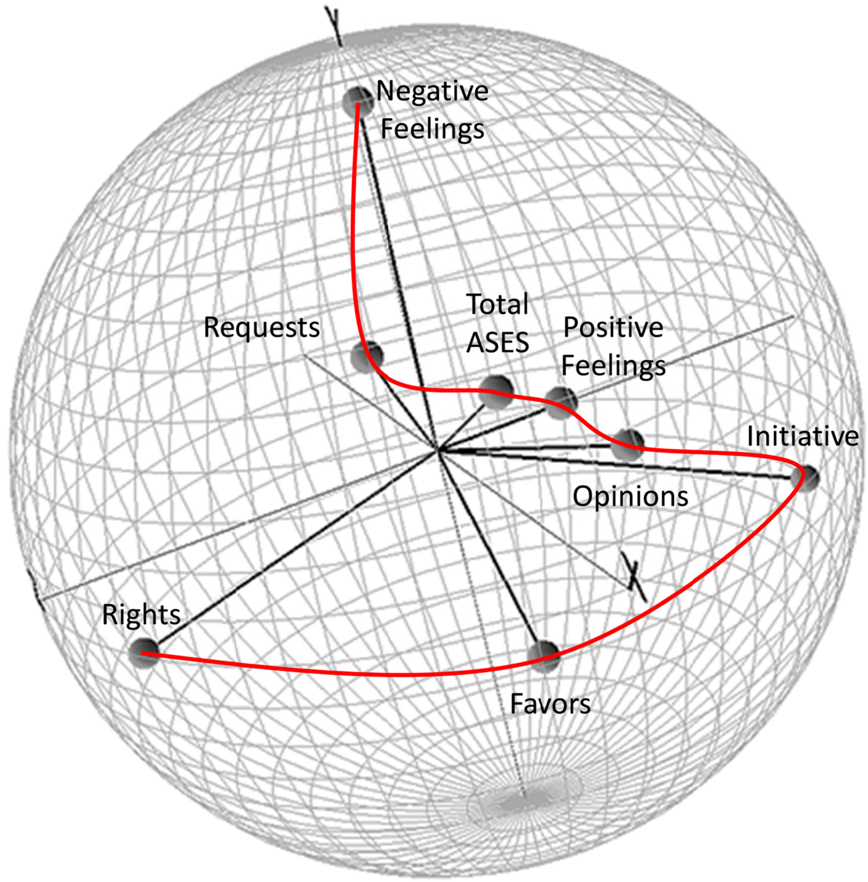


Figure 44. Vector plot of the three-factor space of the behavioral variables of the ASES.

In Figure 45, the individual factor scores for each of the 18 participants are used to plot them within the space defined by the vector plot of Figure 44. Individuals are connected with lines to their respective academic group means, represented by cubes. The low performing group is lower on the Z-axis signifying that they take more initiative than the high performing group. The high performing group mean is positive on the Z-axis indicating that they tend to make more requests than the low performing group. The low performing group is also higher on the Y-axis indicating that they have more of a tendency to express negative feelings than the high performing group.

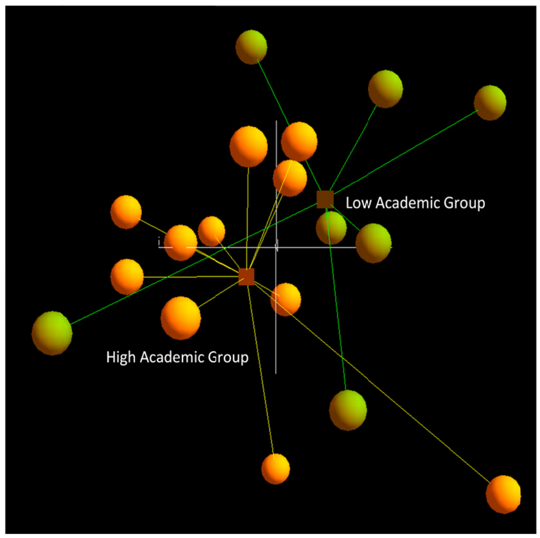


Figure 45. Star plots of the low and high academic groups, within the three-factor ASES space shown in Figure 44. This is a side view with the positive Z-axis extending to the left.

Utilizing the ordered profile derived from the path in the ASES behavioral vector plot of Figure 44, two line plots are created (see Figure 46), one comparing the high and low performing groups, and the other comparing men and women. The first line plot clearly shows the separation between the high and low performing groups on most of the ASES behaviors. Contradicting the hypothesis for this variable set, the low performing group has higher scores on every ASES behavior except for making requests. The largest separation is for expressing opinions with the low group being much higher than the high performing group, almost to the point of significance ($p=0.0642$, $R^2=0.208$).

The behavior with the greatest discrepancy on the main effect of gender is making requests. The difference, however, is not great enough to be significant ($p=0.1676$, $R^2=0.122$). Men report higher scores on every behavior except for taking initiative. These results are quite interesting, and seem to support the common stereotype that women are usually the driving force behind getting things done. While men are able to express their feelings (positive and negative), make requests of others, share opinions, and ask for favors, it takes a woman to take the initiative, and get the ball rolling.

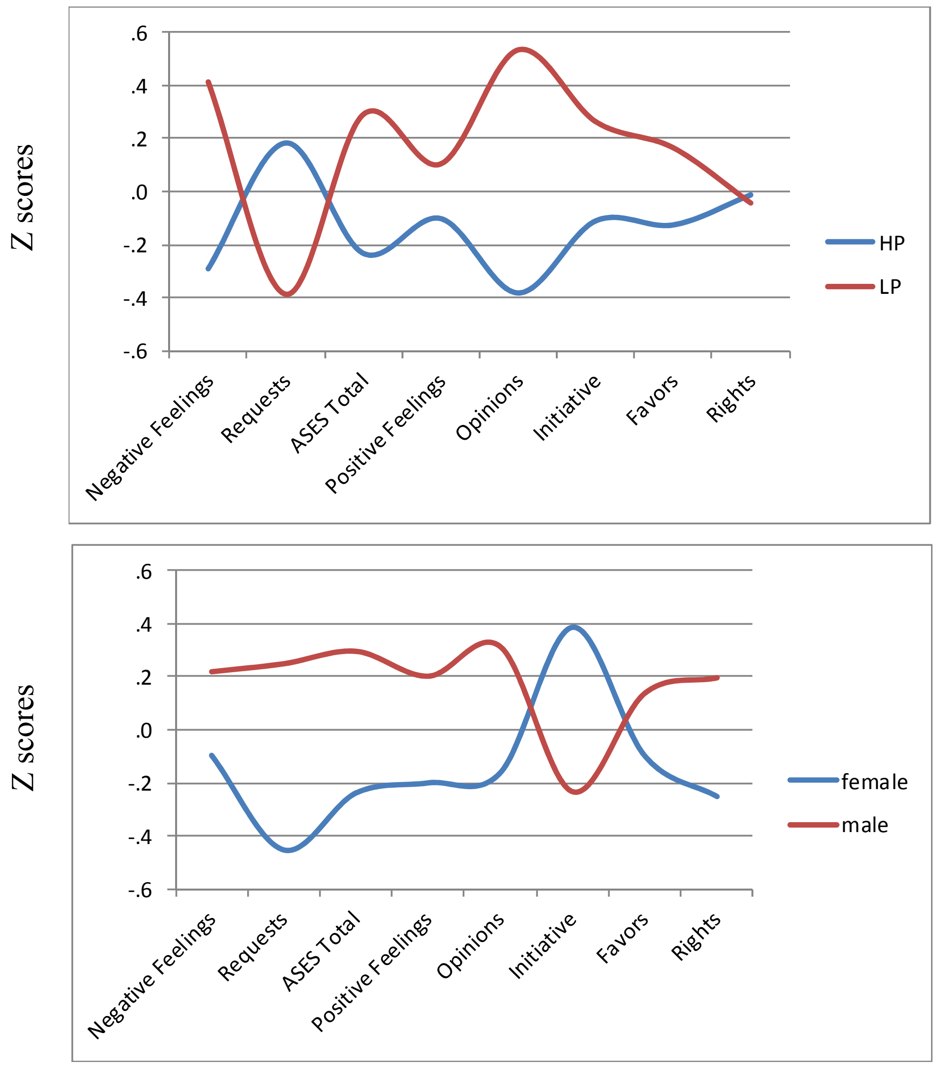


Figure 46. Line plots of the average scores on the Behavioral subscale of the ASES for academic group and gender. Academic group is shown in the top graph, and gender is shown in the bottom graph.

Situational results. Multivariate results from the MANOVA show academic group to be the only significant variable (p=0.0143). Roy's Greatest Root is also significant for the entire model (p=0.0025).

Just like the ASES Behavioral results, despite having multivariate significance, none of the univariate statistics for academic group are significant. The only significant univariate statistic is the gender main effect for parents (p=0.0320, R^2=0.252). Once again, the study must be replicated with a larger sample size before the validity of this result can be confirmed.

Table 25

Two-Way MANOVA of the ASES Situational Variables with Main Effects for Gender and for Academic Group, and Also the Two-Way Interaction, Showing Multivariate Results at the Bottom of the Table and Univariate Results for the Seven ASES Variables at the Top

Univariate Statistics	Entire Model			Gender			Academic Group			Gender X Academic Group		
	$F(3,14)$	p	R^2	$F(1,14)$	p	R^2	$F(1,14)$	p	R^2	$F(1,14)$	p	R^2
Seven Time-Spent Variables												
Situational-Authorities	1.81	.1918	.279	3.57	.0797	.184	1.47	.2459	.076	0.41	.5337	.021
Situational-Friends	0.27	.8448	.055	0.56	.4686	.037	0.27	.6127	.018	0.15	.7014	.010
Situational-Global	1.67	.2189	.264	0.88	.3651	.046	2.45	.1401	.129	1.34	.2657	.071
Situational-Intimate/Close	0.99	.4257	.175	0.01	.9140	.001	2.09	.1703	.123	0.57	.4632	.034
Situational-Parents	2.82	.0770	.377	5.67	.0320	.252	0.60	.4521	.027	0.85	.3721	.038
Situational-Public	1.57	.2417	.251	3.94	.0671	.211	0.57	.4633	.030	0.05	.8286	.003
ASES Total	0.83	.4981	.151	1.17	.2983	.071	1.12	.3080	.068	0.16	.6932	.010

Multivariate Statistics	Entire Model			Gender		Academic Group		Gender X Academic Group	
	Value	p	$\eta2$	Value	p	Value	p	Value	p
Wilks' Lambda	.05512	.0591	.945	.47360	.3695	.17246	.0143	.62926	.6923
Roy's Greatest Root	5.28	.0025							

Note. Only Wilks' Lambda is reported here in the multivariate section for the main effects and interaction, since with one degree of freedom in the numerator the other three multivariate significance tests yield the same p value. The multivariate η2 is calculated as 1-Λ from a one-way MANOVA analysis (Wilks, 1963) of the four categorized groups (gender x hi/lo academics).

Like the ASES behavioral subscale, a new principal component analysis is run for only the six situational subscale variables plus total ASES score. The principal component analysis accounts for 86.34% of the variance of the seven variables within a three-factor space. The first two varimax-rotated factors account for about one third of the variance each, whereas the third factor accounts for only about 19%. All of the variables are accounted for relatively well within this XYZ space, with the highest uniqueness value being only 0.2322. Figure 47 gives the vector plot space for the seven ASES situational variables, with a path for ordering the variables.

Table 26

Principal Component Analysis Summary Table of the Six Situational Subscale Variables of the ASES and Total ASES, Varimax Rotated

	Loadings			Communalities				Uniqueness
	factor 1	factor 2	factor 3	factor 1	factor 2	factor 3	Total	U
Situational-Authorities	.7147	.4957	.1684	.5108	.2457	.0284	.7849	.2151
Situational-Friends	.5009	.7686	-.0683	.2509	.5907	.0047	.8463	.1537
Situational-Global	.0170	.8694	.3380	.0003	.7559	.1142	.8704	.1296
Situational-Intimate/Close	.9146	.0281	.0829	.8365	.0008	.0069	.8442	.1558
Situational-Parents	-.0797	-.1118	-.9570	.0064	.0125	.9158	.9347	.0653
Situational-Public	.5562	.4503	.5056	.3094	.2028	.2556	.7678	.2322
ASES Total	.7318	.6715	.0970	.5355	.4509	.0094	.9959	.0041
			Sums of squares by columns:	2.4497	2.2593	1.3350	6.0440	.9560
			Percents of sums of squares:	35.00%	32.28%	19.07%	86.34%	13.66%

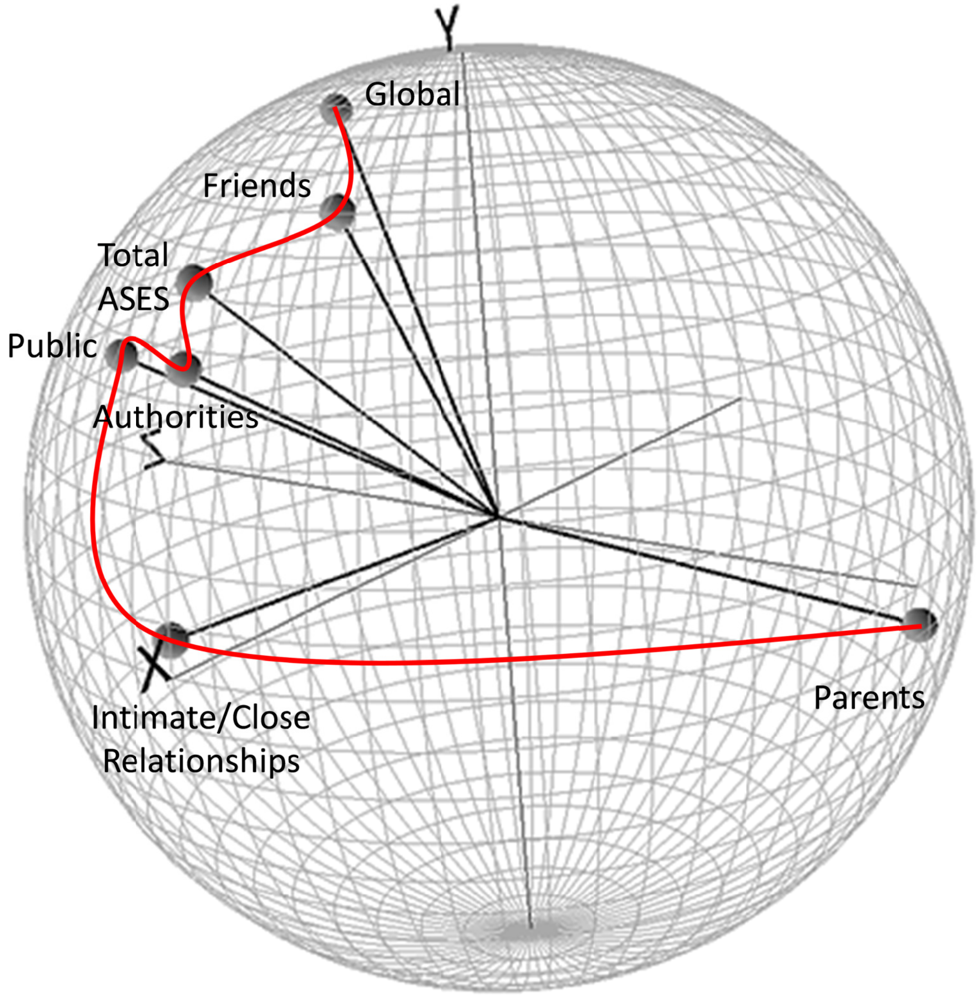


Figure 47. Vector plot of the three-factor space of the situational variables of the ASES.

In Figure 48, the individual factor scores for each of the 18 participants are used to plot them within the space defined by the vector plot of Figure 47. Individuals are connected with lines to their respective academic group means. The high performing females cluster tightly at the negative end of the Z-axis, meaning that they show more of a propensity to act assertively with their parents than all three of the other groups.

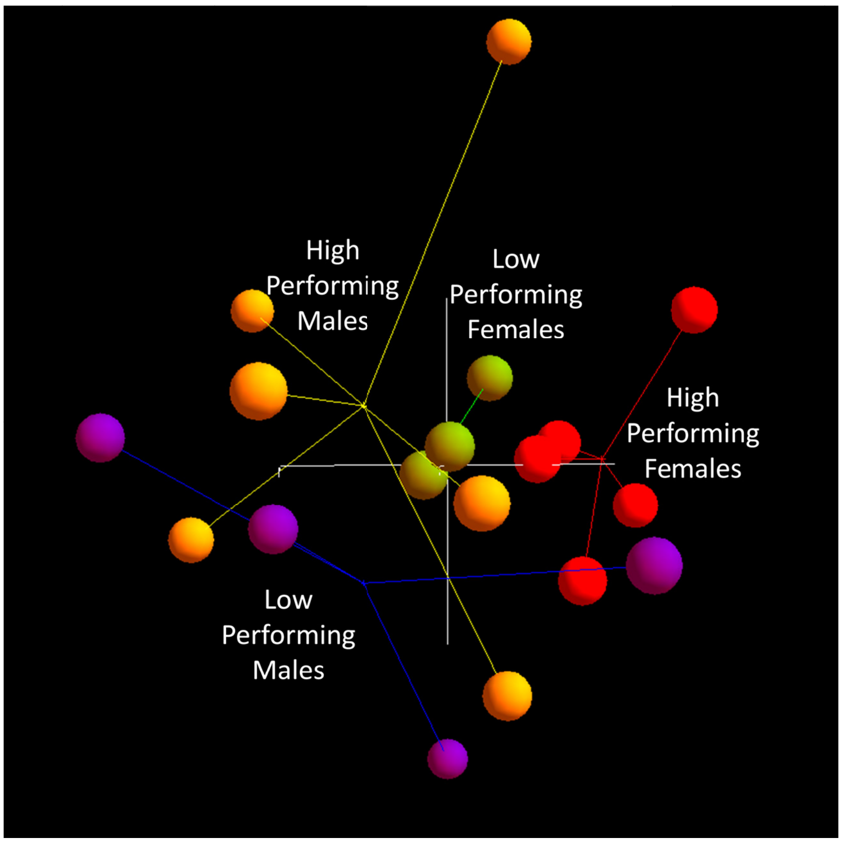


Figure 48. Star plots of the four groups defined by high and low academic performance, and gender, within the three-factor ASES space shown in Figure 47. This is a top view with the positive Z-axis extending to the left.

Utilizing the ordered profile derived from the path in the ASES behavioral vector plot of Figure 47, two line plots are created (see Figure 49), one comparing the high and low performing groups, and the other comparing men and women. The first line plot clearly shows the separation between the high and low performing groups on most of the ASES situations. Like the earlier

ASES behavioral subscale, the low performing group, again has higher scores on every situation except for interactions with parents and friends. This, once again, contradicts the hypothesis for this variable set. The largest separation is for interactions globally, however it is not great enough to be significant ($p=0.1401$, $R^2=0.129$).

Men, once again, report higher scores in every situation except for interactions with parents, where females are higher, and interactions with intimate or close relationships, where the two groups score about equally. The only significant difference between the genders is interactions with parents ($p=0.0320$, $R^2=0.252$). However, it is clear that there are large, almost significant, differences for interactions in public ($p=0.0671$, $R^2=0.211$), and interactions with authority figures ($p=0.0797$, $R^2=0.184$).

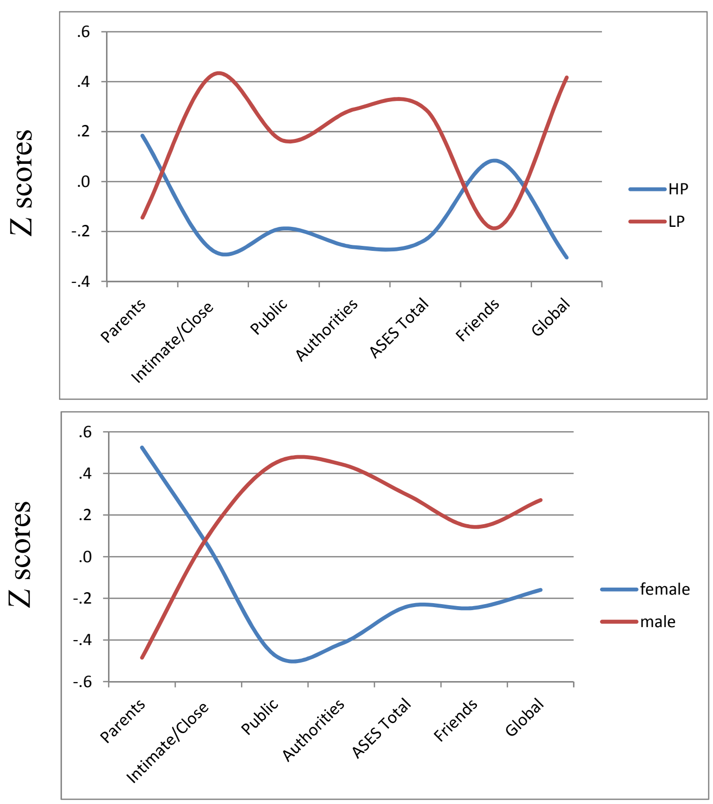


Figure 49. Line plots of the average scores on the Situational subscale of the ASES for academic group and gender. The academic group comparison is shown in the top graph, and gender is shown in the bottom graph.

Discussion

In the introduction I discussed how the current state of time management literature is relatively bleak. The variables are often ill defined, factor scores are given without also giving the factor loadings to help interpret them, studies find completely different results even when using the same scale, and sometimes so little information is given as to preclude incorporating studies into a meta-analysis. Most of these issues can only truly be solved by going through the pains-taking process of a re-analysis of every scale and study using disciplined meta-analytic methods. This approach would be tedious, but perhaps necessary if progress is to be made.

This dissertation takes another approach to solving these data-stability problems. By using groups of predictor variables and criterion variables multivariately, instead of just a single variable that combines sundry scale items, a more holistic view is made possible. When using a set of variables to predict another set of variables, one's chance of accounting for more variance and identifying stable structural relationships increases. Clearly several predictor variables have a better chance of predicting a set of criterion variables than one single variable. It also enables one to account for the overall pattern within the set of criterion variables.

The set of predictor variables with the most success in predicting GPA in this study is the six question survey. It has three perfect, statistically significant canonical correlations, allowing us to trust the percent of variance accounted for, shown as 'percents of sums of squares' in Table 16. The six question survey accounts for 60.1% of the variance in the GPA variables. And the GPA variables account for 57.3% of the variance in the six question survey variables. In other words, the two variables sets are very closely related, and do a very good job of predicting one another.

In addition to predicting GPA, the six question survey also does the best job of distinguishing the high performers from the low performers in the hypothesis testing study. Questions two, three and four are all statistically significant for the main effect of academic group, showing that high performing participants describe themselves as more organized and less spontaneous than low performing participants. While this result is not surprising, the predictive strength of the survey is.

I did not expect the simple six question survey to do a better job predicting academic performance than some of the more complex, multi-faceted sets of variables, especially the time logs. I anticipated that the time logs, specifically a combination between number of hours spent on certain activities, and the adjective evaluations of how time was spent, would be strong predictors of GPA. I was not completely wrong; the combination time log variables were stronger than the individual time-spent and evaluation variable sets alone. The combination variable set had near perfect canonical correlation coefficients, with the first one being $R=0.9878$, and accounting for almost half (47.79%) of the variance in GPA.

We must also take into account the previously discussed fact that not every possible combination of time log data was examined in this dissertation. When a larger sample size is utilized, and more complete time log data are collected, a more thorough analysis of the time logs' predictive power can be performed. While it is unconventional to place future hypotheses in the discussion section, I predict that the more comprehensive collection of time log data will produce just as strong, if not stronger, results than the six question survey.

The ASES variable set was definitely the weakest predictor of GPA. ASES results only account for 15.12% of the variance in GPA. The large number of variables in the set, and the low number of participants also made it difficult, if not impossible, to run and interpret some of the statistical analyses.

My hypothesis that the high performers would be more assertive, and have a greater propensity to act than the low performers, thus scoring higher on the ASES, was not supported in the least. With the exception of three variables (making requests, interactions with parents and interactions with friends) the low performers scored higher on each one of the other nine ASES variables. It will be interesting to see if these results are duplicated with a larger sample size.

Limitations of the Present Study & Future Research

Clearly the greatest limitation to this study is the small number of participants. Although there were significant findings in many areas, clear patterns emerging from a larger sample size will give further strength to those results.

In an effort to cover many different facets of time management, five different variable sets were used in this study. While this did indeed help to cover a wide variety of time management aspects, it also made the study a bit daunting and sometimes convoluted. Future research should focus on just one of the five sets of variables at a time, leading to thorough, but concise, smaller studies.

There are a number of studies that can be done as follow-ups to this dissertation. Of course, as mentioned in the introduction, a thorough corrective meta-analysis of the Robbins et al. study would be a great service to the time management literature, and the academic prediction literature, in general. Adding more recent studies would also help to move the literature forward, and provide more current, and accurate, results.

The time log data alone is a rich source for future research. Using this same data from the dissertation, a larger analysis of all of the time evaluation data could be performed to see if using the raw data, instead of simplified factor scores, may predict the GPA-related variables better. A further expansion would be to include all 21 of the activity categories, instead of the trimmed seven activities used in these studies.

The six question survey was the strongest predictor of academic group in this dissertation. A larger study with more participants would validate these findings. Also, a thorough examination of the large canonical correlations run between the possible combinations of time evaluation and time-spent variables (Figure A1), could yield the groundwork for successful multiple regressions for predicting GPA.

Based on the results from this study, there is a good possibility that self-expression, or assertiveness, may have no effect on GPA. However, perhaps if the questions on the ASES were more pertinent to academics specifically, instead of life in general, the results would be different. It would be useful to make a version of the ASES specifically geared towards students. Each of the variables in the behavioral subscale (taking initiative, making requests, expressing opinion, etc.) could remain the same, but the questions testing each one could be focused on an academic setting. The variables on the situational subscale could be reworded to include teachers, teaching assistants, peers, etc. I believe that an academically-focused ASES would show that high performers are more assertive in their academic interactions, even if that is not the case in their lives in general.

Conclusion

It is easy to see how it is possible that so many researchers in various fields have spent years studying time management, and its effects on GPA, and yet, there are still no concrete conclusions. The innumerable facets of time management attitudes, skills, and practices are complex and often difficult to measure and study. The approach taken in this dissertation, separating time management into several domains and comparing them in their relative predictive strength, seems to have worked. Some expectations were confirmed, and some were not. Surprisingly, actual time usage behavior was not a stronger predictor of academic performance than the six question survey focused on attitudes toward time management. The six question survey accounted for over 60% of the variance in academic performance, whereas actual time spent on each of seven selected activities accounted for only 32%, evaluation of time spent accounted for 38%, and the combination of the two accounted for only 48%. My idea that measures which assess actual time usage, (in this case time logs), will correlate strongly with GPA, was false. It seems that a person's perception of time management has more of an impact on GPA, than a person's actions. As we expected, assertiveness, as measured by the ASES, was lower in predictive strength than the other domains, with only 15% variance accounted for.

Perhaps one of the most important discoveries from this dissertation is the effectiveness of canonical correlation, and particularly canonical correlation summary tables, in creating theory that leads to specific predictions. In each of the domains, the summary table revealed which variables in the X set were responsible for the prediction of the academic performance variables, and also which of the academic performance variables were best predicted. In each case the pattern made sense and led to the creation of a statistically significant multiple regression. These will be followed up with simple, individual, multiple regression studies with replications across multiple datasets.

Some progress has been made in more clearly quantifying the effectiveness of several time management domains in accounting for academic performance, but obviously the problem with the time management literature is not entirely a measurement or quantitative problem. Perhaps the problem lies largely in the conceptual foundations of the time management literature. The contradictory nature of the findings, the abstract definitions, and the double-barreled scales, all seem to indicate that the whole field is in need of conceptual reconsideration and brutal critical analysis. Perhaps the entire literature needs to be stripped down and rebuilt on a solid foundation of clear scientific procedure, complete with universal operational definitions. This may be the only way to truly understand time management and its relationship with academic success.

References

Allen, W. R. (1992). The color of success: African-American college student outcomes at predominantly White and historically Black public colleges and universities. *Harvard Educational Review, 62*(1), 26–44.

Ancis, J. R., & Sedlacek, W. E. (1997). Predicting the academic achievement of female students using the SAT and noncognitive variables. *College and University, 72*(3), 2–8.

Baker, R. W., & Siryk, B. (1984b). Measuring adjustment to college. *Journal of Counseling Psychology, 31*, 179–189.

Bender, D. S. (2001). Effects of study skills programs on the academic behaviors of college students. *Journal of College Reading and Learning, 31*, 209–216

Britton, B. K., & Tesser, A. (1991). Effects of time-management practices on college grades. *Journal of Educational Psychology, 83*(3), 405-410.

Brown, B. L., Hendrix, S. B., Hedges, D. W. & Smith, T. B. (2012). *Multivariate analysis for the biobehavioral and social sciences: A graphical approach*. Hoboken, NJ: John Wiley & Sons.

Booth-Butterfield, S. (1988). Inhibition and student recall of instructional messages. *Communication Education, 37*, 312-324.

Dreher, M. J., & Singer, H. (1985). Predicting college success: Learning from text, background knowledge, attitude toward school, and SAT as predictors. *National Reading Conference Yearbook, 34,* 362–368.

Eiche, K., Sedlacek, W., & Adams-Gaston, J. (1997*). Using noncognitivevariables with freshmen athletes.* College Park: University of Maryland. (ERIC Document Reproduction Service No. ED416737).

Entwistle, N.J., & Ramsden, P. (1983). *Understanding student learning.* London: Crom Helm.

Friedman, M. (1996). *Type A behavior: Its diagnosis and treatment.* New York: Plenum Press.

Fuertes, J. N., & Sedlacek, W. E. (1995). Using noncognitive variables to predict the grades and retention of Hispanic students. *College Student Affairs Journal, 14*(2), 30–36.

Fuertes, J. N., Sedlacek, W. E., & Liu, W. M. (1994). Using the SAT and noncognitive variables to predict the grades and retention of Asian American university students. *Measurement and Evaluation in Counseling and Development, 27,* 74–84.

Gabriel, K.R. (1971). The biplot graphic display of matrices with application to principal component analysis. *Biometrick*, *58*(3), 453-467.

Gadzella, B. M., Ginther, D. W., & Williamson, J. D. (1987). Study skills, learning processes and academic achievement. *Psychological Reports, 61,* 167–172.

Gadzella, B. M., & Williamson, J. D. (1984). Study skills, self-concepts, and academic achievement. *Psychological Reports, 54,* 923–929.

Garavalia, L. S., & Gredler, M. E. (2002). An exploratory study of academic goal setting, achievement calibration and self-regulated learning. *Journal of Instructional Psychology, 29,* 221–230.

Gay, M. L., Hollandsworth, J. G., & Galassi, J. P. (1975). An assertiveness inventory for adults. *Journal of Counseling Psychology*, *22*(4), 340-344. doi:10.1037/h0076706

Gold, J., Burrell, S., Haynes, C., & Nardecchia, D. (1990). *Student adaptation to college as a predictor of academic success: An exploratory study of Black undergraduate education students.* Kent, OH: Kent State University. (ERIC Document Reproduction Service No. ED331946)

Gong, Y. (2007). Correlation between a-type personality and time management disposition of normal college students. *Chinese Journal of Clinical Psychology, 15*(6), 617-618. Retrieved from EBSCOhost.

Gredler, M., & Schwartz, L. (1997). Factorial structure of the Self-efficacy for Self-regulated Learning Scale. *Psychological Reports, 81,* 51-57.

Hackett, G., Betz, N. E., Casas, J. M., & Rocha-Singh, I. A. (1992). Gender, ethnicity, and social cognitive factors predicting the academic achievement of students in engineering. *Journal of Counseling Psychology, 39,* 527–538.

Haines, M. E., Norris, M. P., & Kashy, D. A. (1996). The effects of depressed mood on academic performance in college students. *Journal of College Student Development, 37,* 519–526.

Hawken, L., Duran, R. L., & Kelly, L. (1991). The relationship of interpersonal communication variables to academic success and persistence in college. *Communication Quarterly, 39,* 297–308.

Hedges, L. & Olkin, I. (1985). *Statistical methods for meta-analysis.* Orlando, Florida: Academic Press.

Hendrix, S. B., & Brown, B. L. (1990). *The surface of ordered profiles: A multivariate graphical data analysis method.* American Statistical Association 1990 Proceedings of the Section on Statistical Graphics (54-59). Alexandria, Virginia: American Statistical Association.

Huang, X. T. & Zhang, Z. (2001) The compiling of adolescence time management disposition inventory. *Acta Psychological Sinica*, *33*,338–343.

Kern, C. W., Fagley, N. S., & Miller, P. M. (1998). Correlates of college retention and GPA: Learning and study strategies, testwiseness, attitudes, and ACT. *Journal of College Counseling, 1*(1), 26–34.

Larose, S., Robertson, D. U., Roy, R., & Legault, F. (1998). Nonintellectual learning factors as determinants for success in college. *Research in Higher Education, 39,* 275–297.

Long, J. D., Gaynor, P., Erwin, A., & Williams, R. L. (1994). The relationship of self-management to academic motivation, study efficiency, academic satisfaction, and grade point average among prospective education majors. *Psychology – A Quarterly Journal of Human Behavior, 31*(1), 22-30.

Macan, T. H., Shahani, C., Dipboye, R. L., & Phillips, A. P. (1990). College students' time management: Correlations with academic performance and stress. *Journal of Educational Psychology, 82*(4), 760-768.

McCroskey, J.C., Booth-Butterfield, S., & Payne, S.K. (1989). The impact of communication apprehension on college student retention and success. *Communication Quarterly, 37*(2), 100-107.

McCroskey, J. C., & Sheahan, M. E. (1978). Communication apprehension and social behavior in a college environment. *Communication Quarterly, 26*, 41 -50.

Nixon, C. T., & Frost, A. G. (1990). The study habits and attitudes inventory and its implications for students' success. *Psychological Reports, 66*, 1075-1085.

Nonis, S. A., & Hudson, G. I. (2006). Academic performance of college students: Influence of time spent studying and working. *Journal of Education for Business, 81*(3), 151-159.

Nonis, S. A., Hudson, G. I., Logan, L. B., & Ford, C. W. (1998). Influence of perceived control over time on college students' stress and stress related outcomes. *Research in Higher Education, 39,* 587–605.

Polanyi, M. (1962). *Personal knowledge: Towards a post-critical philosophy.* Chicago: University of Chicago Press.

Pychyl, T. A., Morin, R. W., & Salmon, B. R. (2000). Procrastination and the planning fallacy: An examination of the study habits of university students. *Journal of Social Behavior & Personality, 15*(5), 135-150.

Rencher, A.C., & Scott, D. T. (1990). Assessing the contribution of individual variables following rejection of a multivariate hypothesis. *Communications in Statistics: Simulation and Computation, 19*(2), 535-553.

Robbins, S. B., Lauver, K., Le, H., Davis, D., Langley, R., & Carlstrom, A. (2004). Do psychosocial and study skill factors predict college outcomes? A meta-analysis. *Psychological Bulletin*, *130*(2), 261-288. doi:10.1037/0033-2909.130.2.261

Rubin, R. B., Graham, E. E., & Mignerey, J. T. (1990). A longitudinal study of college students' communication competence. *Communication Education, 39*(1), 1–14.

Rugsaken, K. T., Robertson, J. A., & Jones, J. A. (1998). Using the learning and study strategies inventory scores as additional predictors of student academic performance. *NACADA Journal, 18*(1), 20–26.

Scott, J. (2011). *The time management practices of Brigham Young University students* (Unpublished master's thesis). Brigham Young University, Utah.

Scott, K., & Robbins, K. (1985). Goal instability: Implications for academic performance among students in learning skills courses. *Journal of College Student Personnel, 26,* 129–134.

Sedlacek, W. E., & Adams-Gaston, J. (1992). Predicting the academic success of student-athletes using SAT and noncognitive variables. *Journal of Counseling and Development, 70,* 724–727.

Simons, H. D., & Van Rheenen, D. (2000). Noncognitive predictors of student athletes' academic performance. *Journal of College Reading and Learning, 30,* 167–181.

Stoynoff, S. (1997). Factors associated with international students' academic achievement. *Journal of Instructional Psychology, 24,* 56–68.

Ting, S. R., & Robinson, R. L. (1998). First-year academic success: A prediction combining cognitive and psychosocial variables for Caucasian and African American students. *Journal of College Student Development, 39,* 599–610.

Trockel, M. T., Barnes, M. D., & Egget, D. L. (2000). Health-related variables and academic performance among first-year college students: Implications for sleep and other behaviors. *Journal of American College Health, 49*(3), 125–131.

Trueman, M., & Hartley, J. (1996). A comparison between the time-management and academic performance of mature and traditional-entry university students. *Higher Education, 32*(2), 199-215.

Wilks, S.S. (1963). Multivariate statistical outliers. *Sankhya: Series A*, *25,* 407-426.

Wrench, J. S., Brogan, S. M., McCroskey, J. C., & Jowi, D. (2008). Social communication apprehension: The intersection of communication apprehension and social phobia. *Human Communication, 11*(4), 409-429.

Young, B. C., & Sowa, C. J. (1992). Predictors of academic success for Black student athletes. *Journal of College Student Development, 33,* 318–324.

Appendix A

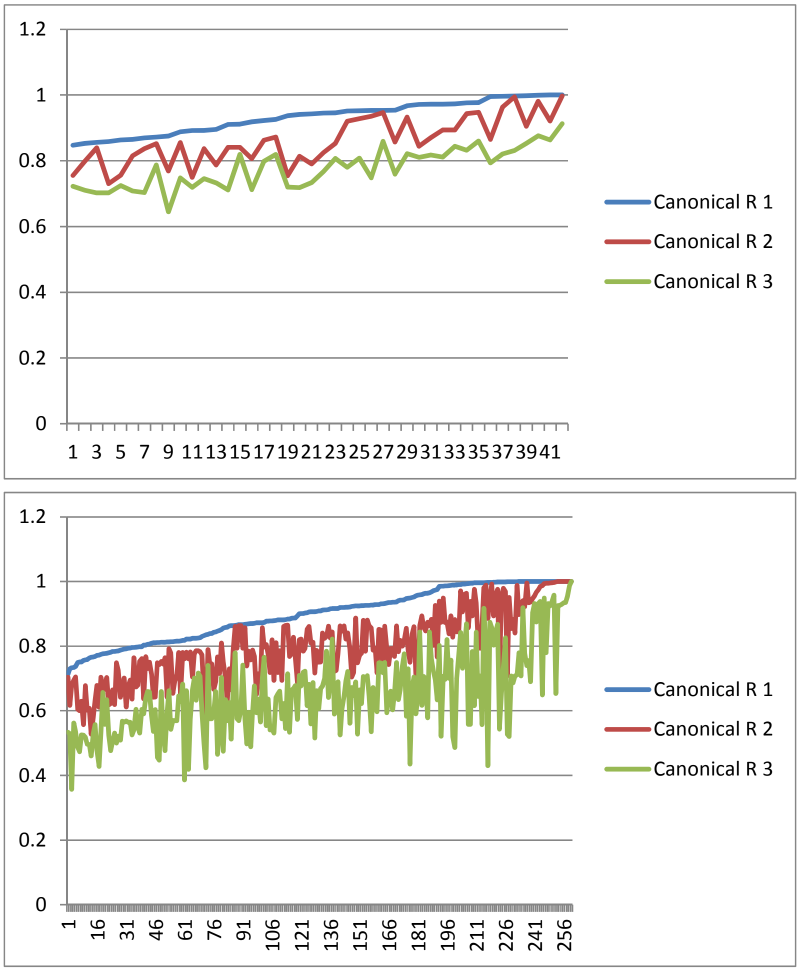


Figure A1. The top figure shows the line plot for the first canonical correlation coefficient, the second canonical correlation coefficient, and the third canonical coefficient ordered from lowest to highest for predictions of the GPA-related variables from 42 combinations of the seven time-spent variables with various groupings of the nine time evaluation variables used in this dissertation. The bottom figure shows a similar line plot but for predictions of the GPA-related variables from 260 combinations of various combinations of the nine time evaluation variables with varying numbers of predictor variables.