Coping Strategies and Emotional Intelligence: New Perspectives on Computing Students

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ABSTRACT

Recruiting and retaining students into computing curricula, computer science, information systems, and information technology, is becoming more of a challenge. In the last four years, enrollments have declined substantially. Even after enrolling into computing disciplines, evidence suggests students increasingly are migrating out of these programs. This paper reports results from the first phase of a longitudinal study that seeks to enhance the retention of students in the IT workplace and professorate. One of the study’s premises is that, beyond academic preparation, different individuals may be disproportionately attracted to different curricula delivery methods. To test this assumption, we measured the coping strategies and emotional intelligence of IT students and tested whether they predicted academic success. Only emotional intelligence was related to academic success. Second, we compared IT and non-IT majors on those dimensions. There were no significant differences. We discuss implications for research and practice.

Keywords

Coping strategies, emotional intelligence, IT students

INTRODUCTION

Recruiting and retaining students into computing curricula has become a challenge. In the last four years, computer science enrollments have declined by more than 30% (Chabrow 2004). Enrollment of students into other computing disciplines (IT and IS) have leveled off and started to decline (UCLA 2003). Reasons to explain the lack of student interest in IT usually focus on economic factors such as the dot com bust and job outsourcing, together with the perceptions that IT is for “geeks” (ITAA 1998, 2000). In the nineties students selected IT for a promise of high paying jobs, but after the dot com bust students realized that even in IT they had to work hard for jobs, especially a high paying one (Chabrow 2004).

While enrollments are declining, recent statistics suggest the need for IT workers is expected to increase. For example, the U.S. Bureau of Labor statistics estimates that within the next few years there will be a need for 307,000 more computer-software engineers, 184,000 more systems analysts, and 106,000 more network and data communication analysts (Chabrow 2004). Moreover, attracting, developing, and retaining these computing professionals remains a top priority, despite the dot bomb, outsourcing, and other industry troubles (Luftman and McLean 2004).

Adding to declining enrollments, evidence suggests that students are increasingly migrating out of computing majors (Cohoon and Chen 2002). It is this migration that we address in this research. Specifically, we focus on better understanding how to retain students in computing programs to increase graduation rates for given levels of
enrollment. Several external factors have been identified as affecting student persistence in educational programs, including financial pressures and cultural and family issues (Anonymous 2005). Researchers have also looked at skills needed to be a successful IS professional, but most of these studies focus on cognitive skills (Eierman and Schultz 1995; Lee et al. 1995; Li et al. 2004). There have been few, if any, studies focusing on intrapersonal factors as potential determinants of success for computing students and professionals. What, if any, are the unique characteristics of students attracted to computing? How do personality-based attitudes and behaviors influence persistence and success in the computing major? To explore these questions we examine the impact of rarely studied intrapersonal factors (i.e., coping styles and emotional intelligence) on computing students’ performance, and hopefully on their ultimate retention in computing programs.

BACKGROUND
Student Attraction and Retention
Beyond computing’s student attrition, issues of student retention in general are not new, and several models of student attraction and retention have been developed. Perhaps the most widely used model of student retention is Tinto’s (1993) theory of university departure. Tinto’s interactionalist theory suggests two classifications of factors – academic integration and social integration – are important in the retention of college students. Academic integration includes grade point average, perceived intellectual development, and perceived faculty concern for teaching and students. Social integration includes interpersonal variables (e.g., quality of interactions with peers and faculty) as well as intrapersonal variables (e.g. students’ goals, commitments to the university, and background variables).

Retention and Success
Reviewing the literature on university departure shows that the majority of these studies examine first year undergraduates’ decisions/intentions to reenroll, but ignore decisions of upperclassmen to remain in previously declared majors. In this research, we focus on upper level students who have declared computing as their major. The ultimate goal is to look at retention of students within computing programs. In the context of our study, success is ultimately graduation and employment in a computing position. At a given point in time, however, success can be measured by the students’ in-major grade point average (GPA). Consequently, we will use this measure, as done in previous research (Schutte et al. 1998).

The present study posits that beyond academic preparation some key intrapersonal characteristics result in different individuals being disproportionately attracted to different curricula delivery methods, which affect their success. We focus on two such rarely studied intrapersonal characteristics: coping strategies and emotional intelligence.

Coping Strategies
Coping strategies are “thoughts or actions that people sometimes engage in when under stress” (Carver et al. 1989, 267). Some coping strategies are considered positive, such as actively trying to fix the problem, while others are considered dysfunctional, for example denying the problem even exists. While other coping strategies have been identified (Carver et al. 1989; Lazarus and Folkman 1984), we selected only five of the most relevant for this study: change the situation, accommodation, devaluation, avoidance, and symptom reduction (Guppy et al. 2004).

Change the Situation
Change the situation involves taking active steps to alter the circumstances or address the problem. Other names for this coping strategy include active coping (Carver et al. 1989) and problem-focused coping (Lazarus and Folkman 1984). Individuals using active coping strategies tend to be more optimistic and are more likely to succeed (Carver et al. 1989). Therefore, we can expect students who tend to change the situation when they are faced with stressful events to have higher GPAs.

H1: Students using higher levels of the “change the situation” coping strategy will have higher in-major GPAs.

Accommodation
Another coping strategy students employ when confronted with stress is to accept the fact that the stressful situation exists, typically by revising their expectations. This strategy is called accommodation, but has also been termed acceptance (Carver et al. 1989). The idea is that once a student accepts the situation and begins working to accommodate to the situation, he or she is making an effort to effectively respond. Students that are actively engaged in accommodating stress are in fact dealing with the situations and should, over time, be more successful than students who refuse to address stress.
H2: Students using higher levels of the “accommodation” coping strategy will have higher in-major GPAs.

Devaluation

Devaluation is a coping strategy whereby people diminish the importance of the situation. It involves persuading oneself that the problem is not as important as it really is. Diminishing the importance of a stressful situation is a poor way to cope. While diminishing the magnitude of a situation may help avoid stress early on, it often leads to diminished, delayed, or no action. Therefore, students that devalue the importance of stressful situations should be less successful over time.

H3: Students using higher levels of the “devaluation” coping strategy will have lower in-major GPAs.

Avoidance

Also called denial (Carver et al. 1989), avoidance occurs when a person tries to ignore a stressful situation by not thinking about it. It can be positive in that it may reduce stress (Breznitz 1983; Cohen and Lazarus 1973), but, unlike devaluation, where the magnitude of the problem is diminished, avoidance involves completely ignoring the problem. Avoiding the reality of a stressful situation can allow the situation to worsen, thereby increasing stress in the long run (Matthews et al. 1983). Others argue that avoidance might be useful when a problem first occurs but becomes an counterproductive later on (Mullen and Suls 1982). Students employing avoidance should be less successful that those that do not.

H4: Students using higher levels of “avoidance” coping strategy will have lower in-major GPAs.

Symptom Reduction

Students can also cope with stress by venting the emotions that lead to it. This strategy, also called focusing on and venting of emotions (Carver et al. 1989), involves redirecting the emotions related to the stressful situation. While the strategy can help reduce stress, it can also be dysfunctional if students focus too much on the situation that created the stress when venting (Carver et al. 1989; Scheff 1979). As a result, students using more symptom reduction coping strategies will tend to be less successful.

H5: Students using higher levels of “symptom reduction” coping strategy will have lower in-major GPAs.

Emotional Intelligence

One potentially important but not explored predictor of student persistence in IT programs may be emotional intelligence (Goleman 1995), which is derived from the concepts of interpersonal and intrapersonal intelligences (Gardner 1993a). Emotional intelligence is defined as a combination of three types of adaptive abilities: “appraisal and expression of emotion, regulation of emotion, and utilization of emotions in solving problems” (Schutte et al. 1998, p. 168). In other words, individuals high on emotional intelligence ratings should be able to better understand, control, and use their emotions.

Some attempts have been made to develop an emotional intelligence scale that captures the concepts proposed by Goleman (Bar-On 1996a, b; Bernet 1996; Schutte et al. 1998). In a series of studies to validate their emotional intelligence scale, Schutte et al. (1998) found that emotional intelligence is a significant predictor of first-year college grades. Consequently, we use the Schutte et al. 33-item scale in this study.

Goleman suggests that emotional intelligence is a better predictor of success for individuals once they have entered a particular setting (e.g., having already embarked in a major), while cognitive intelligence plays a more prominent role in trying to enter a setting (e.g., selecting a major). For college students in computing, this suggests that while cognitive intelligence may be a predictor of entering into a computing major, emotional intelligence should be a better predictor of student retention within the major.

H6: Students with high levels of emotional intelligence will have higher in-major GPAs.

Are computing students different?

This study is particularly interested in evaluating the coping strategies used by computing students in dealing with the stresses resulting from their student lives, in particular within their computing academic programs, as well as measure the effects of their emotional intelligence on their academic success. Although most studies of coping strategies have been conducted in the medical field, not in academic settings, emotional intelligence studies have occurred in several fields, including studies of student emotional intelligence. In their study, Schutte et al. (1998) found that students who had higher levels of emotional intelligence at the beginning of their academic program had...
higher overall GPAs at the end of their first academic year. They did not measure emotional intelligence in upper level classes, nor within a specific major. Do students in computing have different emotional intelligence or use different coping strategies from students in non-computing majors? There is no theoretical support for this idea, nor has it been studied.

Covariates

Previous research has identified other predictors of student retention in computing programs: comfort level in the computing-related course work, previous computer experience (McClelland 2001; Sandy and Burger 2001), and self-efficacy (Clark 2003; Karsten and Roth 1998; Lent et al. 1984; Lent et al. 1996). Self-efficacy has been found to influence choice and persistence in computing careers as well (Hackett and Betz 1981). Although many researchers, some in IS, argue that self-efficacy is domain specific (e.g., Compeau and Higgins 1995), a general measure of self-efficacy, a “global confidence in one’s ability across a wide range of demanding or novel situations,” has been found significant in studies of academic success (Schwarzer and Scholz 2000).

METHODOLOGY

This project involves a longitudinal study where students are followed through junior, senior and graduate levels. The research reported here, however, presents the results from the cross-sectional first phase of data collection. The analysis is conducted in two stages. First, we measure coping strategies and emotional intelligence of computing students and determine if they are predictors of academic success in the computing major. Second, we compare computing and non-computing majors on those dimensions.

Survey Instrument

The survey instrument was implemented using WebSurveyor and was administered online. It included multiple observed indicators to measure the variables of interest (Harris and Schaubroeck 1990). The Cybernetic Coping Scales from Guppy et al. (2004) measured students’ coping strategies, while the 33-item Emotional Intelligence scale was taken from Schutte et al. (1998). These items used 5-point Likert type scales ranging from “strongly disagree” to “strongly agree”. The Self-Efficacy items were taken from Schwarzer and Scholz (2000), with 4-point Likert type scales ranging from “not at all true” to “exactly true.” In-major GPA was measured on a 12-point Likert type scale to group students into categories. It started at “Below 2.00” with 0.20 increments to “Above 4.00” including a “don’t know” category.

Instructions reminded students there were no right or wrong answers, that every item should be considered separately, and that responses should reflect what the students actually do, not what they think other people should do. Questions and sections were randomized to avoid fatigue effects. The instrument was pre-tested several times to ensure completeness and readability. We refined the instrument so it would take a maximum of 30 minutes to complete. It was then pilot tested with computing and non-computing students.

Sample

We surveyed undergraduate juniors and seniors with declared majors in computing (one information systems and one computer science class) and non-computing business disciplines (one management and one accounting class) in three large Southeastern USA universities. Participation was voluntary and students received extra course credit for participation. Table 1 presents the general demographics of the students in the four classes surveyed.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Non-Computing</th>
<th>Computing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Males</td>
<td>70</td>
<td>39</td>
</tr>
<tr>
<td>Females</td>
<td>61</td>
<td>14</td>
</tr>
<tr>
<td>Age ** (years)</td>
<td>21.0</td>
<td>23.4</td>
</tr>
<tr>
<td>Hours per day using computers (for non-academic purposes) *</td>
<td>2.7</td>
<td>3.7</td>
</tr>
<tr>
<td>Hours per day watching TV</td>
<td>2.6</td>
<td>2.1</td>
</tr>
<tr>
<td>Hours per week working at paying job **</td>
<td>10.2</td>
<td>15.9</td>
</tr>
<tr>
<td>Hours per day studying outside of class *</td>
<td>2.6</td>
<td>3.4</td>
</tr>
<tr>
<td>Hours per week participating in student organizations **</td>
<td>3.7</td>
<td>1.3</td>
</tr>
</tbody>
</table>

Statistically significant difference at p< 0.005 ** or * p< 0.05

Table 1. Demographics
Reliability and Validity Analyses

To test the reliability of the scales, we used Cronbach’s alpha. Table 2 shows that all scales achieved the required 0.70 cutoff (Nunnally 1978).

<table>
<thead>
<tr>
<th>Scale Description</th>
<th># Items</th>
<th>Alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCS_CS (change the situation)</td>
<td>4</td>
<td>.778</td>
</tr>
<tr>
<td>CCS_AC (accommodation) * An item was removed (reliability was 0.69).</td>
<td>3</td>
<td>.728</td>
</tr>
<tr>
<td>CCS_DV (devaluation)</td>
<td>4</td>
<td>.859</td>
</tr>
<tr>
<td>CCS_AV (avoidance)</td>
<td>4</td>
<td>.851</td>
</tr>
<tr>
<td>CCS_SR (symptom reduction)</td>
<td>4</td>
<td>.706</td>
</tr>
<tr>
<td>Emotional intelligence</td>
<td>33</td>
<td>.900</td>
</tr>
<tr>
<td>Self-efficacy</td>
<td>10</td>
<td>.892</td>
</tr>
</tbody>
</table>

Table 2. Reliabilities

To assess statistical validity, we ran two separate factor analyses given the large number of items for Emotional Intelligence. First, we tested the validity of the Cybernetic Coping Strategies (CCS) and Self-Efficacy (SE) scales with confirmatory factor analysis. The resulting factor pattern showed proper loadings for all items except one, which was removed for the remaining analyses. For the Emotional Intelligence scale, we ran a factor analysis to obtain the single-factor solution Schutte et al. (1998) produced. Six of the thirty-three SE items did not load properly on the solution. They were removed from further analyses. The resulting variables for hypothesis testing are summarized in Table 3.

<table>
<thead>
<tr>
<th>Variables (5-point scales)</th>
<th># Items</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change the situation</td>
<td>3</td>
<td>3.54</td>
<td>0.81</td>
</tr>
<tr>
<td>Accommodation</td>
<td>3</td>
<td>3.17</td>
<td>0.79</td>
</tr>
<tr>
<td>Devaluation</td>
<td>4</td>
<td>2.57</td>
<td>0.91</td>
</tr>
<tr>
<td>Avoidance</td>
<td>4</td>
<td>2.48</td>
<td>0.96</td>
</tr>
<tr>
<td>Symptom reduction</td>
<td>4</td>
<td>3.82</td>
<td>0.55</td>
</tr>
<tr>
<td>Emotional intelligence</td>
<td>27</td>
<td>3.90</td>
<td>0.46</td>
</tr>
<tr>
<td>In-major GPA (12 point scale)</td>
<td>n/a</td>
<td>6.42</td>
<td>3.03</td>
</tr>
<tr>
<td>Self-efficacy (4 point scale)</td>
<td>10</td>
<td>3.22</td>
<td>0.47</td>
</tr>
<tr>
<td>Non-school computer use per day (hrs)</td>
<td>n/a</td>
<td>2.69</td>
<td>2.23</td>
</tr>
</tbody>
</table>

Table 3. Variables Summary – IT Majors (n=53)

Hypothesis Testing

To test our hypotheses, we ran a multiple regression on the computing student sample where the likert-scaled, self-reported in-major GPA was the dependent variable and the coping strategies and emotional intelligence scales were independent variables. Self-efficacy and computer use were used as covariates. Prior to conducting these analyses, assumptions of multivariate normal distribution, independence of errors, and equality of variance were tested. There were no violations of the assumptions except that some of the distributions were slightly skewed. We also ran a main effects model with Variance Inflation Factors, which revealed no problems of multicollinearity (values between 1 and 3). Outlier influential observations were identified with studentized residuals and Cook’s D-statistic. We identified one outlier, which was removed from subsequent analyses. The overall model’s adjusted r-square was 25.2%, and the model was statistically significant at p< 0.012 with an F value of 2.938. We then examined individual coefficients. These results are presented in Table 4.
Only emotional intelligence and the devaluation coping strategy are significant at the p<0.05 level in predicting self-reported in-major GPA. However, the coefficient for emotional intelligence is in the reverse direction as that predicted by our hypothesis, H6, while the devaluation coefficient supports our hypothesis H3.

To test for differences between computing and non-computing students on the intrapersonal variables we compared the means of the two samples using independent sample T-tests. Results are presented in Table 5.

Given there were no differences in the intrapersonal variables between computing and non-computing students, it should be expected that emotional intelligence is also a good predictor of in-major GPA for non-computing students. We ran the identical multiple regression analysis on the non-computing sample. We found no outliers. The resulting model had an r-square of 36.9% and a p value of <0.006. The coefficients are presented in Table 6.
DISCUSSION

In the first part of this research, we measured computing students’ coping strategies and emotional intelligence and explored whether these intrapersonal factors had effects on academic success. Emotional intelligence (EI) was significantly, but negatively, related to likert-scaled, self-reported in-major GPAs. Students with higher emotional intelligence seem to be the less successful computing students, having lower in-major GPAs. This is contrary to results obtained by Schutte et al. (1998) when they measured EI at the beginning of students’ first academic year and then correlated this to GPA of students at year’s end. One potential explanation is that IT students are in a discipline that demands more mathematical and logical thinking than control of emotions. In other words, computing is less of a good fit for students with high emotional awareness, control, and use. This needs to be studied further as emotional intelligence might be a good predictor for students to know whether they will succeed in computing careers before declaring a major. Another potential explanation is the difference between the measures of freshman year overall GPA and in-major GPA for juniors and seniors. In their test of the EI measure, Schutte et al. (1998) found that while EI was related to freshman year GPA, it was not significantly related to SAT scores although that correlation was negative, which is what we found in our data. This may indicate specific measures of academic success may have different relationships to the EI measure. Future studies should replicate tests of EI on GPA.

For coping strategies, only the devaluation strategy was negatively related to academic success. This suggests that students who minimize a stressful situation seem to be less successful over time, as predicted. However, it is surprising that four of the strategies were not significant. Most of the studies that have used coping strategies have focused on people in medical situations, predicting success from operations based on patients coping strategies. Other research has found that men and women differ in their coping strategies, with women taking more emotion oriented strategies (Carver et al. 1989). It may be that all students use similar coping strategies, independent of whether they are good or struggling students, and that the differences are more along gender or racial groups. We hope to test this in the longitudinal study this research is part of.

Are Computing Students Different?

Interestingly, there was a lot of valuable information on how computing students are different from the demographics data. Computing students tend to be somewhat older than non-computing students, spend more time using a computer for non-academic activities, work more hours per week at paying jobs, study more outside of class, and spend fewer hours participating in student organizations. This may suggest the computing student is a less social person, doing more individual activities (work, study, and use computers) than the non-computing student (spend more time in student organizations).

When testing for differences between computing and non-computing students on coping styles and emotional intelligence ratings we found that the students did not differ significantly. Perhaps students are students, with similar emotional intelligence and coping strategies whether in computing or not. Alternatively, our populations of computing and non-computing majors are similar to those studied in the literature. Previous studies of emotional intelligence found that differences exist across major groups rather than within groups. Schutte et al. (1998) found that psychotherapists scored higher than prisoners and substance abuse clients on EI measures. These are dramatically different from the groups we compared.

We tested the effects of emotional intelligence and coping styles on in-major GPA for non-computing majors. The model is highly significant, although none of the coping strategies had effects on success. Emotional intelligence, again, showed a significant impact on in-major GPA. As for computing students, emotional intelligence is negatively related to academic success. Interestingly, the self-efficacy and computer use covariates were significant in predicting success for non-majors while they were not for majors. Self-efficacy is positively related to success, as previous research suggests, while hours of computer use for non-class activities is negatively related to academic success. We must recall that we used a general self-efficacy measure which has been found to affect success, as in this analysis. For hours of computer use, it makes sense that students using the computer for non-academic activities are actually “playing” on the computer rather than working on their academic tasks, and hence the negative relationship to academic success. Further, since they are not in computer-related majors, this extra activity does not add to their understanding of their academic subject matter.

There are limitations inherent in the design of this study. First, the data collected represent the first phase in a longitudinal study. Actual measures of retention can only be obtained over time. Using in-major GPA to measure success is no guarantee that the student will not leave the major, although it seems likely that successful students at that stage of their program will graduate in their major. Also, we focused on only five types of coping strategies for sake of survey brevity. Carver et al. (1989) identified 14 categories of coping strategies. Because of enrollments, our sample included fewer computing students than non-computing students. Balanced samples would be preferred.
Finally, it must be noted that quantitative methods represent only one point of view and that interviews could provide more insights.

Many other intrapersonal characteristics may be important determinants of academic success and should be explored. We captured only some of the concepts with the EI scale. For example, one of the intelligences identified by Gardner (1993b), logical-mathematical type intelligence, is said to be important for students in technology and sciences. However, visual-spatial intelligence, the ability to manipulate and create mental images in order to solve problems (Gardner 1993b), should become a significant predictor of success as computing becomes more visual (e.g., visual computing and graphical user interfaces), increasing the need for those with Visual-Spatial Intelligence abilities (Gardner 1993b; Schneiderman 1992).

CONCLUSION

The study focuses on rarely measured intrapersonal variables and their effects on academic success in computing majors. Emotional intelligence is a key predictor of academic success in computing, as is one of the coping strategies: devaluation. An understanding of these unique characteristics of computing students might enable educators to target the special needs of computing students, increasing program retention and student learning.

ACKNOWLEDGMENTS

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i The IS2002 AIS/ACM/AITP/AITP curriculum defines the Information Systems field as focusing on the integration of information technology solutions and business processes to meet the information needs of businesses and other enterprises, enabling them to achieve their objectives in an effective and efficient way. The joint committee recognizes four other computing fields: Computer Engineering, Computer Science, Software Engineering, and Information Technology. All of these disciplines are included in the study.

ii Additional literature is available from the authors.

iii The NSF grant supports a longitudinal study of retention of African Americans in IT programs, but we report here on a broader cross sectional (all ethnicities) data collection.

iv Please contact the first author for a copy of the items.