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The development of two types of internet use among college students

摘要

為瞭解大學生網路使用的發展狀況，本研究以 2003 年 8 月入學之彰化師大一年級學生為對象，共有自願樣本 282 人完成 5 次問卷調查。

本研究使用潛隱曲線模式分析資料，發現：（一）學生非學術性用途的網路使用時間至少是學術性用途的網路使用時間的兩倍以上，大學生時間管理的問題令人憂心（二） 網路使用的起始點與成長速度呈零相關的模式受到支持，顯示，網路使用的起始點與成長速度無關；（三）因為學術用途與非學術用途的起始點的相關未達顯著，且學術用途與非學術用途的成長速度也的相關未達顯著，顯示學術用途與非學術用途並非呈相同的變化，因此應區分學術用途與非學術用途兩項網路使用兩項概念；因此後續研究者應發展可以區分各項用途的網路使用量表。

Abstract

Latent curve models were applied to test individual differences in initial status and growth rates of internet use for 282 Taiwanese undergraduate students. The time spent on the internet for nonacademic purposes was more than twice that for academic purposes. The fit of the model hypothesizing zero covariance between growth rate and initial status was satisfactory, indicating that where one starts as a freshman does not affect whether the student increases or decreases the internet use. Furthermore, as the relationship of two initial assessments and that of slopes were not statistically significant in the multivariate latent growth model, academic and non-academic uses did not change together. Future research should differentiate between various internet uses to generate useful internet use data. A psychometrically sound instrument that can identify various uses is warranted.

Keywords: internet use, latent curve model, longitudinal study

The extensive use of the internet has impacted student way of living, communicating, and seeking information. As an instrumental device, the internet can offer research services that facilitate completion of academic tasks. The internet has also become a recreational tool. As most college students have free internet access, examining their internet uses is essential to elucidate campus life.

Despite substantial research on the relationship between internet use and psychological well-being, findings have been mixed. Researchers investigating the internet typically hold one of two positions. The first position argues that the internet provides a context for social interaction and interpersonal development, and therefore the internet can improve the psychological well-being of users. Morahan-Martin and Schumacher (2003) surveyed 277 undergraduate students to assess the differences in patterns of internet use between lonely and not-lonely students. They observed that lonely individuals used the internet more, and were more likely to use the internet for emotional support than non-lonely users; furthermore, their social behavior was enhanced online, and the lonely users typically made online friends and experienced an elevated level of satisfaction with their online friends. Along the same line, Kraut et al. (2002) investigated 406 new computer and television purchasers in a longitudinal survey between 1998 and 1999. They reported that participants generally experienced positive effects of internet use on communication, social involvement, and well-being. However, better outcomes were for individuals with sufficient social support; whereas worse outcomes were associated with individuals with little social support. Proponents of this position stress that time spent on the internet is away from family and friends, resulting in impairment of well-being and weakens family, neighborhood, and community ties (Kraut, Patterson, Lundmark, Kiesler, Mukopadhyay, & Scherlis, 1998). Caplan (2003) examined the relationships among online social interaction, depression, loneliness, problematic internet use, and negative outcomes resulting from internet use for 386 undergraduate students. According to their results, lonely and depressed individuals preferred online social interaction; this preference was associated with problematic internet use.

Given that previous research indicates that interne use is correlated with academic achievement, social, and psychological well-beings (Lanthier, Windham, 2003; Kraut, Lundmark, Patterson, Kiesler, Mukopadhyahy, & Sherlis, 1998; Kraut et al., 2002), longitudinal studies assessing development of internet use are needed to elucidate the college life of students.

Issues Associated with Computing of Hours Online

Summing the hours spent on various online activities may explain the inconsistency in research findings. The studies mentioned frequently utilized instruments that asked respondents to provide the number of hours spent on various activities. For example, the Internet Behavior Questionnaire (Egger & Rauterberg, 1996) queried users about the number of hours spent browsing the web, reading and posting to newsgroups, reading and writing emails, etc. The total hours online was derived by adding up the number of hours spent on various activities. Two primary problems are associated with simply summing up the hours spent on various activities. First, categorizing such activities is complex. For instance, browsing the web to gather information for class assignments can be categorized as instrumental; whereas such behavior is recreational when users surf the web for pornography. Second, summing up the hours spent on various activities is not always equal to total online hours because the internet supports multitasking. That is, if a researcher indexed the recreational use by summing up the hours spent chatting and downloading music, the total may overestimate actual use as these two activities can be performed simultaneously.

Clarifying the difference between work-related and recreational uses is essential to examining internet-related phenomenon. Young (2004), who identified criteria for pathological internet use, claimed that only nonessential internet use was of interest and that work-related use should be excluded when diagnosing internet addiction. Similarly, Kubey, Lavin, and Barrows (2001) argued that the research and recreational uses should be differentiated. In surveying 572 students at a large public university, they found that excessive recreational interne use was related to impaired academic performance, loneliness, staying up, tiredness, and missing class.

Internet Use and University students

Why college students are vulnerable to internet overuse is of concern to parents, clinicians, and policymakers. Young (2004) identified the following reasons that expose college students to risk of internet dependence: (a) free and unlimited internet access, (b) massive blocks of unstructured time, (c) new freedom from parental control, (d) no monitoring or censoring of is said or done online, (e) encouragement from faculty and administrators, (f) social intimidation and alienation, and (g) a higher legal drinking age. As such, examining internet use among college students is of considerable social value.

The consequences of internet overuse are detrimental. Kandell (1998) found that internet overuse leads to dismissal or poor academic performance. Ott examined why students with high SAT scores (1200-1300) were dismissed from university. He found that 43% of these students failed school due to excessive internet use (Young, 2004). Anderson (2001), who surveyed 1300 college students to examine how internet use affected their social and academic lives, showed that a small group of students used the internet excessively and that it had deleteriously affected their lives. Most of these students were male and hard science majors.

Internet dependency is a particularly acute problem as students may deny that compulsive use is a problem as the internet was viewed as a good technology (Young & Rogers, 1998). This belief was supported by Scherer (1997), who examined internet use among a sample of volunteer students from a southwestern university in the United States. Scherer found that most college students perceived internet use as positive. Only 2% of students felt that the internet had a negative effect on their lives. Overall, this positive perspective on internet use may make it difficult for students with internet dependence to identify their problem.

The percentage of college students who are internet dependent is difficult to estimate as research is frequently based on volunteer sample using different criteria (Nichols, & Nicki, 2004). For example, Kubey et al. (2001) utilized a single item to identify internet independence: ‘I think I might have become a little psychologically dependent on the internet.’ They showed that 9.26%

of the students surveyed agreed or strongly agreed the statement. In study by Anderson (2001), students were considered internet dependent when they endorsed more than 2 of 7 statements. Anderson reported that 9.8% students were internet dependent. Scherer (1997) indicated that 9% of college students felt that their internet use was excessive and considerably impaired the personal lives, including declining grades, failure to fulfill academic, professional, or social responsibilities, health problems, and legal or financial problems. In Wang (2001) study, pathological use was considered when students endorsed 4 or more than 4 out of 10 items. He identified that 4% of Australian students are pathological internet users. Niemz, Griffiths, and Banyard (2005) considered users internet dependent if they met 3 of the 13 criteria. They found that 18.3% of British college students were internet dependent. To examine whether internet dependency is a widespread phenomenon, a well-developed instrument and commonly accepted criteria are needed.

The relationship between individual variables and internet usage seems to be modest at best. Swickert, et al. (2002) examined the relationship between internet use and personality among 206 students from a college in the southeastern United States. Only moderate associations existed between internet use and personality were found. Wang (2001) investigated the relationship among internet dependency, psychosocial maturity, and general self-efficacy, for a sample of 217 Australian college students. Wang showed that internet dependency is independent of psychosocial maturity and self-efficacy.

Researchers have recognized the importance of the studying internet use among college students (Anderson, 2001; Jackson, Ervin, & Gardner, & Schmitt, 2001; Kandell, 1998; Lanthier, & Windham, 2004; Scherer, 1997), however few broke internet use into various types. As a communication tool with wide-ranging functions, the internet allows users to gather information, communicate, pass time, etc. To determine the significance of the internet, categorizing uses is crucial.

Types of Internet Use

As mentioned, most research index internet use by summing up the total time respondents spent performing various activities - email, chat rooms, games, instant messaging, etc. These online activities can have multiple purposes. For instance, reading/writing emails may be as task for maintaining personal relationships or acquiring academic-based information. The total hours spent reading/writing emails are therefore not necessarily a good indication of social use. Identifying the purposes in various internet activities is a worthy research topic. Swickert et al. (2002) utilized principal component analysis to examine various internet uses and found the activities can be assigned to technical, information exchange, and leisure categories.

Few studies have distinguished between interne uses based on task purpose. Kubey et al. (2001) used research and recreational purposes in examining internet use. Recreational use is operationalized as 'spare time or personal use of the internet and is not concerned with measuring whether use that is school- or work-related.' Lanthier and Windham (2004) distinguished between concepts of social use and hours online. Social use was measured based on the number of people users communicate with regularly online and the number of friends they made that were solely online friends.

Purposes of this study

Although researchers have suggested that hours of internet use increase with years of use (e.g., Nie, 2001), no existing studies have examined growth of internet use among undergraduate students. The existing evidence is mainly based on cross-sectional data, e.g., Kraut, Patterson, Lundmark, Kiesler, Mukopadhyay, and Scherlis (1998). Jackson, et al. (2003), a notable exception, utilized a longitudinal study to examine the antecedents and consequences of internet use in low-income families. They found that mean online time decreased at the second assessment 6 months after the first assessment and then increased 1 year later. Furthermore, numerous studies (Armstrong, Philips, & Saling, 2000; Caplan, 2002, 2003; Egger & Rauterberg, Griffiths, 1996; Kandell, 1998; Nichols & Nicki, 2004; Wang, 2001; Young, 2004) investigating internet use have focused on addicted users. The purpose of this study is to examine the development of internet uses –academic and nonacademic-for a sample of typical undergraduate students in Taiwan. Identifying a developmental trend would facilitate determining which students are vulnerable to becoming internet dependent. Additionally, the aim of this study is to examine similarities/dissimilarities between the development trends for the two uses. As researchers have identified the need to differentiate between research and recreational uses, it is hypothesized that changes in academic use are not necessarily be related to nonacademic use. Moreover, this study examined whether students with varying initial status in internet use develop different use patterns over time. Do students with a higher initial status for internet use increase their use more than students with light use? Conversely, do students with low initial status increase or decrease their use? Growth curve models are suitable for testing developmental trends for various internet uses.

Growth curve analyses of internet use

Although internet overuse is clearly a predominant problem on college campuses, few studies have examined the growth of internet use. Little is known about the trends of various uses or similarity or dissimilarity of trends among uses. To address these issues, growth curve models were tested in two stages. To adequately represent individual differences in growth, a variety of univariate latent curve (LC) models were tested during the first stage. Then the univariate models sufficiently described the growth curves for the two uses were incorporated into a multivariate latent curve model. Two hypotheses were tested using a multivariate approach. The first question investigated was the correlation of two initial assessment points. The second hypothesis examined was the correlation of two growth rates, indicating a parallel change for the two uses over time for any user.

Latent curve models to the analysis of longitudinal data

The LC models proposed by Meredith and Tisak (1990) is an approach to model repeated measures using linear structural models. This approach subsumes conventional models, including repeated measures analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA), for longitudinal data analysis. LC models consist of two analysis stages. In the first stage, the growth model representing individual change is fit to the repeated measures for each individual in the sample. Then the individual difference in change is the focus (Willett & Sayer, 1994). The application of LC models to examine growth curves is documented in Bast and Reitsma (1997); Duncan and Duncan (1994; 1996), Duncan, Duncan, and Hops (1993; 1996), Duncan, Duncan, Strycker, Li, and Alpert (1999); MacCallum, Kim, Malarkey, and Kiecolt-Glaser (1997), Raykov (1996; 1997a; 1997b), and Stoolmiller (1994). A detailed description of LC models is beyond the scope of this study.

Assume that each individual $\underline{i}$ has been repeatedly assessed on $\underline{t}$ occasions. The response scores are denoted by $\underline{y}_{it}$. Let vector $\mathbf{y_i} = [\underline{y}_1, \underline{y}_2, \ldots, \underline{y}_t]$. For example, data in this study were obtained from 257 participants assessed on $\underline{t} = 5$ occasions. The general LC model can be considered a common factor model.

$$\mathbf{y_i} = \Lambda F_i + E \qquad (1)$$

where Λ is a factor loading matrix, representing specific aspects of change in y across t occasions, and called <u>basis function</u>. $\underline{F}_i$ is a vector containing factor scores on basis functions for each individual. The repeated measures y can therefore be represented via a linear combination of basis functions. A high value for factor score $\underline{F}_i$ indicates that individual $\underline{i}$'s developmental trajectory is strongly characterized by the basis function. Vector $\underline{E}$ is a vector of residual terms with mean score of zero and has no correlation with $\underline{F}_i$.

A simple and common LC model can be obtained by specifying the basis function and fixing entries in the Λ matrix. For example, Equation 2 presents a simple LC model in which observed variables are assessed at five different occasions represented by two latent factors, intercept and slope ($\underline{F}_i$ and $\underline{F}_s$). The factor of the intercept is a constant for any individual over time that captures the information for the mean and standard deviation of the collection of each individual intercept in the sample. The slope factor reflects the shape/form for growth trajectory. The means of intercept and slope factors characterize group curve parameters, whereas the standard deviation of intercept and slope factors represent the individual deviation from group means. The factors of intercept and slope are allowed to covary.

$$
\begin{array}{cc}
 & \begin{array}{cc} \text{Intercept} & \text{Slope} \\ F_i & F_s \end{array} \\
\begin{array}{c} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{array} &
\begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & * \\ 1 & * \\ 1 & * \end{bmatrix}
\end{array}
\qquad (2)
$$

Some of factor loadings in Equation 2 are unknown and can be freely estimated from the data. To identify the model with unknown Λ entries, at minimum two loadings for the slope factor must be fixed to known values (Stoolmiller, 1994). Since the basis function is common to all sample individuals, Λ must be the focus when the aspects of change for an entire group are of concern. In this case, basis functions values are not completely known. Models with unknown factor loadings can yield a curvilinear growth curve with linear spline (a curve with linear segments, piecewise). Conversely, the latent factors should be of concern when individual change is of interest. As mentioned previously, the repeated response scores for **y** are a linear combination of basis function. The factor score on F_s reflects individual difference for the effect of basis function in representing developmental profile. Means, variance, and covariance must be the focus when basis function is completely known (Raykov, 1997a).

Notably, the factor loading is arbitrary. Changing the fixed values in the Λ matrix does not affect the interpretation of $\underline{F}_s$. Conversely, the intercept factor is bound to a time scale. Changing factor loadings will therefore change the variance and covariance of F_i.

Multivariate latent curve models

For the multivariate case, each of the k response variables is measured on multiple occasions. Let y_{itk} represent a score for individual i at time t on response variable k. The multivariate model can be expressed as the common factor model.

$$y_{itk} = \sum_{k} \delta_k (\Lambda_k F_{ik} + E_k) \tag{3}$$

where $\delta_k = 1$ when a given measure is on y_k and $\delta_k = 0$ otherwise. As a subscript k is added to the basis function Λ, different response variables can have different change characteristics. Consequently, response variables can be assessed at different occasions or can have a different number of time points. The score in F_{ik} is the influence of the basis function for each individual i on k response variables. The covariance between F_{ik} and $F_{ik'}$ captures the relationship between different response variables. When the basis functions of Λ_k and $\Lambda_{k'}$ is not correlated, the correlation between variables k and k' is zero across occasions.

Method

Participants

Students in this investigation were undergraduate freshmen attending Changhua University of Education, Taiwan, during the fall semester of 2003. The first assessment was conducted in the December of 2003 and the four follow-up assessments with all participants were conducted 6, 12, 18, and 24 months following the first assessment. After deletion of missing data, the final sample consists of 282 students. Males comprised 50.4% (142 of 282) of the sample and females accounted for 49.6% (140/282).

Models

The models proposed by Stoolmiller (1994) were tested by Mplus (Mǘthen & Mǘthen , 1998) for the hours of academic and nonacademic uses of the internet per week. Particularly, Model 1 is the general model represented by Equation 2. The remaining models are nested in Model 1.

Model 2 assumes that time-specific error variance is constant. That is, $Var(E_1) = Var(E_2) = \ldots = Var(E_m)$. Model 3 proposes a zero correlation between intercept and slope. Support of this model suggests that the growth rate is unrelated to initial status. A strict stability model is tested in Model 4. In this model, the mean and variance of slope are set at zero. Acceptance of Model 4 demonstrates no growth in the interest attribute. Model 5 posits no individual difference in growth (parallel stability). In this model, the variance of slope is fixed at 0. Model 6 proposes straight-line growth. This model is obtained by fixing factor loadings to a linear metric. In the no-mean growth model, the slope mean is set at zero. Then the univariate model that sufficiently represents growth curves of various uses was incorporated into a multivariate LC model. A multivariate LC model comprising academic and nonacademic uses was tested to determine whether individual differences in growth parameters for both uses are correlated. The research question is whether change in academic use relates to nonacademic use over the same period.

Internet use

The hours online consists of two items that tapped the total number of hours of internet use for academic and nonacademic purposes in 1 week during the past 6 months. To overcome the problem of summing the hours spent on various activities, these two items were open-ended and respondents were asked to enter the number of hours online during an average week. Table 1 presents descriptive statistics for academic and nonacademic internet use. Due to the possibility of multi-tasking, the total hours of weekly internet use can not be estimated in this study. Mean hours for academic use were from 5.58 to 8.35 hours per week and 15.99 to 19.12 for nonacademic use. The total hours for nonacademic use per week was higher than that obtained by Kubey, Lavin, and Barrows (2001), which engenders a concern of that this nonacademic use can potentially decrease academic performance.

Goodness of Fit

Although many goodness of fit indices are available, their relative performance leaves room for debate. The multiple indices recommended by Hoyle and Panter (1995) are reported in this investigation.

1.χ^2

The χ^2 index reflects the discrepancy between an a priori model and data. A significant value of the χ^2 index indicates that the proposed model deviates from the data and the hypothesized model should be rejected. On the other hand, a nonsignificant value of χ^2 suggests that a model is a good representation of the data. One limitation associated with the χ^2 value is its dependency on the sample size. In other words, a large sample size typically leads to model rejection even when the discrepancy between the model and data is trivial, whereas a small sample size commonly results in an acceptance of a model despite of the a substantial disagreement between model and data. Hence, practical measures of fit as well as statistical fit were used in this study.

When a relatively restrictive model is obtained by imposing constraints on another model, the restrictive model is nested within the latter. As the χ^2 difference, $\Delta\chi^2$, between two nested models is χ^2 distributed with degrees of freedom equal to the difference in degrees of freedom for the two models; and therefore, the relative performance for hierarchically nested models can be compared by testing the significance of $\Delta\chi^2$. A significant $\Delta\chi^2$ value indicates a better fit for the less restrictive model, whereas a non-significant $\Delta\chi^2$ value argues for superior fit for more restrictive model due to parsimony.

2.Comparative Fit Index (CFI, Bentler, 1990)

Indicators 2 and 3 are incremental fit indexes that capture the proportionate improvement of fit as compared to that for the baseline model. As values for the Fit Index can fall outside the range of 0 to 1, Bentler (1990) developed the Comparative Fit Index (CFI), which ranges between 0 and 1. A value of .90 or larger indicates what many researchers considere a satisfactory degree of fit of the model to data. The formula is as follows:

$$CFI = 1 - \max [(\chi^2_T - df_T), 0] / \max[(\chi^2_T - df_T), (\chi^2_B - df_B), 0] \qquad (4)$$

where B denotes a baseline model and T stands for a target model. The independence model, in which all observed variables are hypothesized as uncorrelated, was used to provide a baseline in this study. The CFI indicates the extent to which the target model is superior in reproducing the observed covariances among scores to that of an alternative model, typically the baseline model.

3.*Tucker-Lewis index (Tucker & Lewis, 1973)*

Tucker-Lewis Index (TLI) is a widely used practical measure of fit; the formula for TLI given by Marsh (1995) is:

$$TLI = [(\chi^2_B / df_B) - (\chi^2_T / df_T)] / [(\chi^2_B / df_B) - 1] \qquad (5)$$

The TLI reflects the improvement of fit per degree of freedom of the target model. As the number of degrees of freedom is associated with the number of estimated parameters, TLI accounts for the inclusion of estimated parameters. A value of .90 or greater for TLI indicates a psychometrically satisfactory fit.

Insert Table 1 here.

Results

Table 1 presents descriptive statistics for academic and nonacademic internet use over five assessments. For nonacademic purposes, mean scores showed an inverse U-shaped development in which the hours of use increased through to the third assessment and then declined at the forth assessment. Table 2 shows the correlations among uses measured at 5 time points. Twenty-two out of 45 correlation coefficients were significant at the .01 level for a two-tailed test. The correlation matrix was computed based on pairwise deletion. The minimum pairwise N was 255.

Insert Table 2 here.

Tables 3 and 4 present the fit indices for general and alternative models for academic and nonacademic internet use, respectively. All alternative models are nested within the general model. The general model, an unspecified two-factor model, for academic and nonacademic uses was rejected, χ^2 = 23.607 and 9.692, with 3 degrees of freedom. The values of CFI and TLI were .930, .900 for academic purpose and .987 and .982 for nonacademic purposes, thereby supporting initial status during the freshman year and growth rates from freshman to junior years from a practical standpoint. The first two a priori models tested two different sets of restrictions, (a) the equality of variance of time-specific errors and (b) zero covariance between initial status and growth rate. The equality of variance of time-specific error was tenable with CFI = .970 and TLI = .973 for nonacademic purposes. The second constraint was reasonable for the two uses, indicating that at which level a user starts at first assessment does not affect whether one's internet use increases or decreases.

The strict-stability model (Model 4) proposing no growth at all, the most restrictive model, was rejected for both academic and nonacademic uses. The fit of the parallel stability model (Model 5) positing no individual differences in growth was good based on practical fit indexes. This finding indicates that internet use for every student grew by the same amount.

The fit of the straight line growth model for academic use was satisfactory with CFI = .962 and TLI = .926 and CFI and TLI = .903 for nonacademic use. The hypothesis of no mean growth was either not supported or did not converge to a proper solution.

Table 5 presents growth curve parameters for supported models. For model identification, growth curve parameters for the first and second assessment were fixed at 0 and 1, respectively. The supported models revealed an upward trend for academic use over the 2.5-year period for academic use, whereas a reverse U-shaped trend was found for nonacademic use.

Insert Table 5 here.

Means of intercept and slope factors (Tables 6 and 7) represent group growth parameters. According to a micro-level examination, all intercept means were significant, revealing significant mean use levels. For supported models for academic use, 3 of 4 mean slopes were statistically significant. In contrast, all mean slopes were not statistically significant for nonacademic use, suggesting no significant mean growth for nonacademic use.

Insert Tables 6 and 7 here.

Tables 8 and 9 present the intercept and slope variances for each construct. These variances reflect the variation for each student from the group mean. All intercept variances were significant, indicating individual difference for initial status of internet uses. Consistent with a macro-level analysis of the parallel stability model, most slope variances were not statistically significant. This supports that no significant individual variation existed in growth for the two uses.

Insert Tables 8 and 9 here.

A multivariate latent curve model for academic and nonacademic uses were tested to assess the relationship between two development trajectories. The primary focus is the correlation of two slopes and intercepts. The univariate general model for the two uses was incorporated into the multivariate model. The fit of the multivariate model was marginal with CFI = .892 and TLI = .861. The correlation between two growth rates factors is weak (.35), indicating that both uses did not change together. The individual differences in developmental trends for the two uses were considered dissimilar. The correlation of two intercepts was small (.18) and not statistically significant. That is, where a student starts academic use as a freshman is not associated with where s/he starts nonacademic use.

Conclusions and Discussion

The research investigating growth in internet use is mainly based on cross-sectional data. The purpose of this study was to examine the growth of internet use using longitudinal data. Particularly, data were for Taiwanese undergraduate students. The number of hours of nonacademic use was much larger than the corresponding hours for internet-dependent and academically impaired students obtained by Kubey, Lavin, and Barrows (2001). The time spent on the internet for nonacademic purposes was more than twice that for academic purposes. These findings raise a concern regarding college student time management. The time for real social interaction, exercise, or sleeping were traded for interne use. A related concern is the well-being of heavy internet users. Notably, internet use has been associated with loneliness (Kubey, Lavin, & Barrows) and, furthermore, meaningful interaction or friendship can not be developed via the internet (Numes, 1995; Turkle, 1995).

The application of LC methodology to growth of internet use has been not existent. This omission was impetus for this study. Research utilizing a panel study consisting of more than 2 waves of data is scarce and the comparisons between previous findings are difficult. For both academic and nonacademic uses, a two-factor unspecified model was supported, indicating that initial status at the freshman year grew through to junior year. From a practical perspective, the fit of model hypothesizing zero covariance between growth rate and initial status was the most satisfactory among all alternative models. These findings indicate that usage as a freshman does not affect whether a student will increase or decrease their internet use. Furthermore, the constraint of parallel stability was tenable for both uses, suggesting that each student increased their usage by the same amount. This finding is consistent with a micro-level examination indicating that most slope variances were not statistically significant. Therefore, this study concludes that no individual differences exist in growth of internet use for either purpose. In other words, heavy and light users increased their usage time by the same amount throughout the assessment period. Early detection of heavy users is crucial. Effective intervention programs may prevent these students from becoming excessive users. Additionally, the no-mean-growth model was not a good representation of data, demonstrating that overall, students increased their internet use over the 2.5-year period. Future research should investigate what factors can prevent student overuse. A study of these factors will likely facilitate the establishment of effective intervention programs for internet overuse.

The multivariate LC model, an extension of the univariate model, provides for investigation of the relationships among individual differences parameters for the two uses. As the relationship of two initial assessments of and that for two slopes were not statistically significant, the two uses did not change together. This finding supports the dissimilarity in developmental trajectories for both uses and, therefore, viewing internet use as a unitary construct is inappropriate. Future research needs to differentiate between various uses to yield useful data. A psychometrically sound instrument that can identify various uses is required. A well-designed measure is a prerequisite for examining internet-related issues.

Because of internet's ability to support multitasking, summing up the hours spent on various activities will typically not equal to the total hours spent online. Future research should examine which factors affect the magnitude of this discrepancy. Such a study may aid the establishment of a good indicator for total online hours.

Despite its strengths, this investigation has important limitations. Convergence problems were found in a model and interpretation of the model should be cautious. As in most studies, a convenience sample limits the generalizablity of results. In future research, models employed in this study should be tested with a new sample to cross-validate growth of internet use.

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Table 1: Descriptive statistics for Academic and Nonacademic Internet use

	Mean	SD
Academic1	5.58	5.60
Academic2	6.50	7.03
Academic3	6.17	5.92
Academic4	7.09	6.96
Academic5	8.35	7.66
Nonacademic1	15.99	16.48
Nonacademic2	17.67	16.57
Nonacademic3	19.12	16.41
Nonacadmic4	18.51	15.75
Nonacadmic5	18.10	16.25

Table 2: Correlation Matrix for Academic and Nonacademic Internet Use

	A1	A2	A3	A4	A5	N1	N2	N3	N4
A2	.341**								
A3	.329**	.260**							
A4	.235**	.249**	.474**						
A5	.302**	.299**	.485**	.318**					
N1	.062	.148*	-.069	-.132*	.031				
N2	-.021	.127*	.035	.060	-.018	.354**			
N3	-.019	.095	-.012	-.041	-.017	.221**	.375**		
N4	.129*	.175**	.048	.152*	.052	.246**	.232**	.451**	
N5	.188**	.166**	.157**	.095	.089	.264**	.264**	.375**	.283**

* significant at .05 level

** significant at .01 level

Table 3: Fit indices for Academic Internet use

	χ^2	df	CFI	TLI
Model 1	26.607	7	.930	.900
Model 2	57.541	11	.805	.822
Model 3	24.337	8	.931	.914
Model 4	60.245	9	.785	.761
Model 5	24.706	8	.930	.912
Model 6	26.479	10	.931	.931
Model 7	46.070	8	.840	.840

Table 4: Fit indices for Nonacademic Internet use

	χ^2	df	CFI	TLI
Model 1	9.692	7	.987	.982
Model 2	17.279	11	.970	.973
Model 3	12.047	8	.981	.976
Model 4	30.169	9	.899	.888
Model 5	23.274	8	.927	.909
Model 6	30.444	10	.903	.903
Model 7	No convergence.			

Table 5: Growth curve parameters for each construct

	Academic Use	t	Nonacademic Ust	
Model 1	1.456	2.206	2.744	2.267
	1.961	2.144	2.037	2.539
	3.793	2.116	1.403	2.565
Model 2	This model was not supported.		3.632	1.399
			3.286	1.410
			2.184	1.444
Model 3	1.603	2.379	4.123	1.491
	1.967	2.307	2.702	1.591
	3.817.	2.248	1.805	1.553
Model 4	This model was not supported.		This model was not supported.	
Model 5	.935	2.274	2.052	1.877
	1.692	2.426	1.242	1.807
	3.040	2.429	1.147	1.735
Model 6	Fixed to2, 3 and 4, respectively.	Fixed to2, 3 and 4, respectively.	Fixed to2, 3 and 4, respectively.	Fixed to2, 3 and 4, respectively.
Model 7	This model was not supported.		No convergence.	

Table 6: Intercept means for Academic and Nonacademic Internet Use

	Academic	t	Nonacademic	T
Model 1	5.472	16.922	16.145	17.541
Model 2	This model was not supported.		16.193	17.598
Model 3	5.465	16.865	17.395	24.055
Model 4	This model was not supported.		This model was not supported.	
Model 5	5.466	16.513	16.149	17.124
Model 6	5.442	18.281	16.875	19.965
Model 7	This model was not supported.		No convergence.	

Table 7: Slope means for Academic and Nonacademic Internet Use

	Academic	t	Nonacademic	t
Model 1	.736	1.929	1.276	1.741
Model 2	This model was not supported.		.981	1.567
Model 3	.721	2.037	.129	.374
Model 4	This model was not supported.		This model was not supported.	
Model 5	.936	2.212	1.572	1.500
Model 6	.607	5.498	.509	1.901
Model 7	This model was not supported.		No convergence.	

Table 8: Intercept variances for Academic and Nonacademic Internet Use

	Academic	t	Nonacademic	t
Model 1	10.041	4.326	111.475	3.683
Model 2	This model was not supported.		111.075	5.248
Model 3	11.519	6.818	70.325	6.087
Model 4	This model was not supported.		This model was not supported.	
Model 5	8.818	3.945	54.299	2.947
Model 6	10.440	4.107	88.464	4.636
Model 7	This model was not supported.		No convergence.	

Table 9: Slope variances for Academic and Nonacademic Internet Use

	Academic	t	Nonacademic	t
Model 1	.823	.872	25.367	1.063
Model 2	This model was not supported.		11.301	.936
Model 3	1.212	1.138	3.112	.375
Model 4	This model was not supported.		This model was not supported.	
Model 5	Fixed to 0.		Fixed to 0.	
Model 6	.679	1.836	2.106	.964
Model 7	This model was not supported.		No convergence.	