Will Fit Work Here? Using Multiple Data Sources to Adapt a Student–Institution Fit Instrument to a New Institutional Context

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About the Author

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Abstract

Several authors (Bowman & Denson, 2014; Gilbreath et al., 2011) have claimed that measures of fit between a student and the institution they are attending should be useful for institutional decision-making. These student–institution fit instruments were originally developed for research with specific student populations in one institution, but have not been assessed at other institutions. Institutional research offices rarely assess surveys or other instruments that are developed at one institution to determine whether those same instruments would provide results that are reliable and valid in different institutional contexts. The purpose of this study was to determine if the factor structure of a measure of student–institution fit would be appropriate to use at another institution. A survey that included a student–institution fit instrument developed by Gilbreath et al. (2011) was administered to a random sample of first-year students and new external transfers at a large, public university in the Midwest. Confirmatory factor analysis was used to determine if the underlying factor structure in the original instrument provides an appropriate fit for data obtained from a new sample. In addition, open-ended comments were collected to gain insight into students' interpretation of each item. The results suggested changes from the original scale to create a more robust measure. Specifically, Great Support Services was moved from the Social Environment fit to the Academic Environment fit, and covariances between multiple items were integrated. Similar methods could be used by institutional researchers at other institutions to gather data on students' interpretation of survey items, to evaluate the underlying factor structure of external instruments, and to create appropriate modifications to account for their own institutional contexts.

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INTRODUCTION

Student–institution fit might be one data point in a broad array that could be used to determine a student's propensity to enroll at a university, to remain enrolled, and, eventually, to graduate. Care needs to be taken, however, when using instruments developed for basic, scholarly research at one institution before using those instruments to inform decision-making at another. The Association for Institutional Research's (AIR) Statement of Aspirational Practice for Institutional Research (AIR, 2016) advises institutional research (IR) professionals to ground their initiatives within a student-focused paradigm (Swing & Ross, 2016). If IR professionals are to adopt a new, validated instrument for the student population at their institution, it is important for them to understand whether that instrument will yield the data intended; if not, it is important for them to make appropriate adjustments to the instrument.

The purpose of this study was to determine if the factor structure of a measure of student–institution fit would be appropriate to use at another institution. In framing this analysis, however, the author hopes to outline procedures that IR professionals can use to assess the validity of an instrument for use with their students, and to make changes and adapt an instrument to their own institutional context. The procedure included confirmatory factor analysis (CFA) to assess if the factor structure discovered by previous researchers matched the data collected, the use of modification indices to identify potential changes, and the qualitative data collected directly from students to determine if changes suggested by quantitative data analysis could be triangulated using students' perspectives.

The article begins with a literature review highlighting institutional research and retention studies, and fit as a psychological construct. Next, the article describes the methods used, including data and data sources; survey procedures, sample, and respondents; and analytical techniques. The article continues with a description of the results and how results were used. Finally, the article concludes with a discussion of how institutional researchers can use similar procedures at their institutions.

LITERATURE REVIEW

Institutional Research and Retention Studies

Identifying which student behaviors, attitudes, or characteristics are associated with retention and degree completion has long been an area of interest for higher education researchers, dating back to at least the 1920s (Summerskill, 1962). Today, federal and state governments, as well as numerous nonprofit organizations, have endorsed a wide variety of initiatives designed to encourage institutions to improve retention and graduation rates. Bold college completion goals cannot be attained, however, if students leave higher education before earning their degree. According to Gardner (2022), about 66% of students who began college in the Fall of 2020 were still enrolled in their original institution in the Fall of 2021, and 75% were enrolled in any institution.

Increasingly, institutional researchers have begun to use predictive analytics to address challenges in student retention. Zheng and Zhou (2020) described a project in which East Carolina University partnered with IBM to integrate demographic information; high school academic performance;

and information from student applications, financial aid data, and first semester performance to identify students who were at risk of leaving the institution. Likewise, Renick (2020) discussed a program at Georgia State University in which registration behaviors, attendance, early course grades, grades in prerequisite courses, and other factors were used to flag students in need of additional interventions from academic advising. Such approaches have been criticized, most often for the ways in which predictive algorithms can unintentionally reinforce existing structural inequities (O'Neil, 2016; Zheng and Zhou, 2020). Also, Howard and Borland (2007) suggested that using data from a variety of different sources could help institutional researchers not only illuminate trends, but also better understand why those trends are occurring. For example, Borden et al. (2021) described a process they call the Insight Engine, in which results from machine learning research are triangulated using both qualitative and quantitative data from surveys and administrative records. Drawing data from university surveys could still be used to supplement or validate findings from predictive analytics and to identify students who might benefit from potential intervention.

While drafting original surveys to examine problems unique to a campus might be preferable, finding a survey that has already been validated can lend credibility to a research project. Suskie (1996) suggested that using surveys developed at another university could save IR professionals time by asking others for permission to use their instruments or adapting other professionals' instruments to a new context.

Fit as a Psychological Construct

Existing research on factors impacting retention and success suggests that psychological factors, including student–institution fit, could enhance the performance of models designed to predict Fall-to-Fall retention. Bean and Eaton (2000, 2001) particularly advocated for the integration of psychological constructs into retention models. Specifically, academic and social integration would lead the student to feel as if there were a fit between them and the institution. This sense of fit, along with a sense of organizational commitment, could foster an intent to persist, which would guide subsequent persistence behaviors.

Person–environment fit refers to the degree of match between an individual and the environment within an organization (Ostroff & Schulte, 2007). One conceptualization of person–environment fit, referred to as needs–supplies fit, explores the extent to which the environment provides something that an individual is lacking (Edwards & Ship, 2007): "needs" refers to personal strains caused by certain internal conditions or external situations, and "supplies" refers to the extent to which an environment supplies or meets someone's self-described needs (Gilbreath et al., 2011). For the purposes of this study, "fit" will be defined as the difference between students' self-reported needs and students' perceptions of the degree to which an organization meets those needs (i.e., supplies). Student–institution fit would therefore be defined as the fit between the student and their current higher education institution.

Conyne (1975, 1978) approached lack of student–institution fit as a source of stress to be addressed in college counseling centers. He advocated for students' needs to be examined in relation to how well the institution provides for those needs (Conyne, 1978). Conyne further advocated that counselors work with faculty and administrators to identify and address areas where students' needs are not being met.

Gilbreath et al. (2011) revived Coyne's conceptualization of fit when they proposed a student–institution fit instrument that could be used to identify, target, and recruit students who display high levels of fit with an institution. That instrument (i.e., questionnaire) was designed to assess the extent to which students' needs are met by the environment of their institution (supplies) (Edwards & Ship, 2007). A series of focus groups with students, academic advisors, and counselors in campus mental health centers provided the information needed to develop a 16-item instrument that measured the extent to which the supplies of an institution's social, academic, and physical environment met students' needs.

The social environment encompassed a wide variety of experiences, including social life, academic reputation, and diversity. The Academic Environment scale included the intellectual climate of the campus, availability of academic resources, and size of the university. The broadest scale in this instrument was the Physical Environment scale, which included items on campus location, aesthetics, and affordability. The Gilbreath et al. (2011) instrument asked students to rate the importance of various aspects of the social, academic, and physical environment and the degree to which their current institution satisfied their needs within these aspects, thus yielding a measure of both student's self-reported needs and their perceptions of the extent to which the supplies of the institution fulfill these needs. The final instrument produced six scales, which included Academic Environment needs and supplies scale, Social Environment needs and supplies scale, and Physical Environment needs and supplies scale.

Using polynomial regression analysis, Gilbreath et al. (2011) found that satisfaction with the university increased as students' perceptions of supplies provided by the university rose toward students' reported needs. In other words, as the degree to which the university met students' needs increased, student satisfaction also increased. Satisfaction increased at a lower rate as supplies along the academic and physical environment exceeded students' needs. All coefficients were statistically significant at $p < 0.01$. However, psychological well-being increased at a much greater rate as supplies along the physical environment exceeded students' needs.

According to Gilbreath et al. (2011), student–institutional fit instruments could be used to identify, target, and recruit students who are likely to find high levels of fit at an institution. Identifying students who are likely to have high levels of fit will increase retention rates, because students with high levels of fit would be more likely to persist and ultimately earn a degree. Similarly, Bowman and Denson (2014) advocate that student–institution fit instruments could be used as part of an early warning system: students demonstrating low levels of fit could be directed to appropriate interventions, thus decreasing the risk of departure. Before these instruments are used by institutions for these purposes, however, it is important to first consider whether the instruments can be used in ways other than how they have been originally developed.

One reason for further investigation of the Gilbreath et al. (2011) instrument is because of the relatively low levels of reliability obtained from the scales described in their original research. Cortina (1993) advised that an acceptable level for alpha (α) be based on the intended use of the scale. Both the Physical Environment needs ($\alpha = 0.54$) and Physical Environment supplies ($\alpha = 0.62$) scales had particularly low reliability estimates, which would suggest the need for additional evidence of fit. In addition, the proposed Physical Environment fit scale included a diverse set of items covering campus aesthetics, safety, and affordability that might not be appropriate to combine in a different institutional context. While Gilbreath et al. may have deemed these to be acceptable levels of internal consistency for research purposes, a more reliable instrument would be preferred if these scales are to be used for institutional decision-making.

Second, even if sufficient evidence of internal consistency were demonstrated, evidence should be provided that the instrument is usable for its intended purpose. Messick (1995) suggested that, if an instrument is to claim construct validity, then the researcher must provide evidence that the instrument is valid for its intended use. Gilbreath et al. (2011) derived their scales almost entirely using data from the campus at which their study was originally conducted. While the survey is likely appropriate for that institution, further evidence would be needed to determine whether these same scales are valid at another university.

Finally, bringing qualitative data to supplement the findings of quantitative studies can provide additional insight into the validity of data. For example, Borden and Jin (2022) highlighted how the Insight Engine at one university combined advanced analytics, expert panels, and qualitative data to investigate strategies for closing achievement gaps in high-value courses. Triangulation of data from a variety of sources enabled faculty and staff to redesign existing training programs, develop support for students in Promise Scholarship programs, and assess the effectiveness of K–12 initiatives at the program level. A similar process involving triangulation of data from quantitative and qualitative sources could also be used to refine a survey for a new student population.

Faculty and staff at one large, public, urban university in the Midwest believed that the Gilbreath et al. (2011) instrument could be useful for identifying students who might be at risk of leaving the institution. Nonetheless, concerns about the appropriateness of this instrument suggested a need for further exploration. IR offices rarely assess survey instruments developed at other institutions to determine whether those same instruments are appropriate for their institutional context.

The purpose of this study was to determine if the student–institution fit measure developed by Gilbreath et al. (2011) fit the data obtained from students at this target university. Traditional methods, including CFA, were used to determine whether the original underlying factor structure was appropriate for different data that were obtained in a new administration of the survey. Results from the CFA were supplemented with qualitative data in the form of comments from students' interpretations of items from the student–institution fit instrument. This study could be used as an exemplar of the types of analyses that institutional researchers could use at their own institution to determine the appropriateness of a survey instrument for the student population at a different institution.

METHODS

These analyses used data obtained from a survey conducted as part of an exploratory study to identify the characteristics of students who felt a lack of fit with their university. Bowman and Denson (2014) advised that universities could use student–institution fit instruments to identify students in need of specific interventions, or to determine the characteristics of prospective students who could experience better fit with a university to inform admissions decisions. Institutional researchers and student affairs professionals had planned to use these data to inform subsequent interventions designed to better meet students' needs.

Data and Data Sources

STUDENT–INSTITUTION FIT INSTRUMENT

The survey was adapted from the instrument used in Gilbreath et al.'s (2011) initial investigation of student–institution fit. The Gilbreath et al. instrument was conceptualized using the needs–supplies perspective first advocated by Conyne (1978) as an appropriate lens to conceptualize student–institution fit. This survey was selected because it was originally developed at an institution where undergraduate students primarily do not live on campus, similar to the population at the institution used in this analysis. First, the respondents were presented with 16 items and asked to rate the university on a seven-point scale (1 = Not at all, 7 = Very much) by answering the question, "How important are the following to you?" Respondents were then presented with the same 16 items and asked to rate the university on a similar seven-point scale (1 = Not at all, 7 = Very much) by answering the question, "To what degree does [your institution] do the following?" For these analyses, fit was calculated as the absolute value of the respondents' needs rating minus the respondents' supplies rating. Fit was evaluated along three dimensions: (1) Academic Environment fit, (2) Social Environment fit, and (3) Physical Environment fit. The proposed Academic Environment fit scale consisted of items that corresponded broadly with students' perceptions of the formal educational structures within the institution. Items ranged from abstract aspects of the academic environment, such as academic climate and reputation, to more-concrete features such as state-of-the-art classrooms and size of the institution. Conversely, the proposed Social Environment fit was concerned with aspects of the institution that were less overtly academic, such as social life, athletics, and student support services. Finally, the Physical Environment fit dimension consisted of items related to the material space of the institution, such as location and campus layout. In the Gilbreath et al. study, this factor also included an item called "Great affordability."

Exploratory factor analysis (EFA) conducted by Gilbreath et al. (2011) found that these 16 items (four Academic Environment items, seven Social Environment items, and five Physical Environment items) aligned with the three proposed factors of fit with the academic environment, social environment, and physical environment. A complete list of the items, as well as the factors with which each item was aligned in the initial study, is available in Appendix A.

ADDITIONAL SURVEY QUESTIONS

A series of open-ended items that asked respondents to provide their interpretation of each item were added to the end of this survey. The open-ended items were originally included for the purposes of internal survey development. Specifically, students were prompted, "In order to improve this survey for future administrations, we would like to know a little bit more about what you thought of the items. Please describe how you would define each of the following." The students' responses to this item were especially useful in understanding modification indices in the analysis. The full survey is available from the author upon request.

Survey Procedures, Sample, and Respondents

The initial survey was sent to 3,000 new bachelor's degree–seeking students three weeks after the beginning of classes. This period was selected because evidence from Woosley & Miller (2009) suggested that early experiences could influence Fall-to-Fall retention. Reminder emails were sent one, two, and three weeks following the initial survey distribution.

The random sample for this survey was drawn from students who were starting at a large, urban, public university in the Midwest at the beginning of the Fall semester. There were 3,622 first-year students and 1,296 new external transfers who were beginning at that institution (Institutional Research and Decision Support, 2015). From that group, a random sample of 3,000 new bachelor's degree–seeking first-year students and new transfers were selected to participate in this survey. Per Institutional Review Board guidelines, only students who were 18 years of age or older were selected. Of the students in the original random sample, emails to 14 students were returned as undeliverable, bringing the adjusted sample size to 2,986. A total of 414 students completed the survey for an overall response rate of 13.9%. Of those 414 students, 351 had completed all fit items and the responses were therefore deemed useable for this study. The sample was then halved, with 176 responses used for CFA, and the remaining 175 responses used to assess the factors derived. Tanaka (1987) advocates that a ratio of five observations per parameter to be estimated would be appropriate for structural equation models using maximum likelihood estimation. Given that 32 parameters are to be freely estimated in the CFA model to answer, the total of 175 survey respondents per analysis should be sufficient.

A comparison between the full survey population and respondents using data points retrieved from the Student Information System can be found in Tables 1 and 2. A slightly larger percentage of full-time students responded to the survey compared to the percentage of full-time students in the initial sample: 95% of respondents were full-time students compared to 91% of students in the survey sample. A t-test of fit scores revealed only one statistically significant difference in response patterns between full-time and part-time students. Specifically, part-time students were significantly more likely to experience a greater degree of misfit when asked whether their current or their ideal university had a "great student body" ($t = 3.87$, $p = 0.049$). Given the small number of part-time students who responded to this item ($n = 15$ part-time students) and the relatively small effect size ($\varphi = 0.041$), it is possible that this result is not a true effect (Button et al., 2013). No adjustments based on enrollment status were deemed necessary.

Respondents also had a significantly higher mean high school GPA and earned a higher mean GPA in their first Fall semester than nonrespondents. However, a similar difference was not noted with regard to transfer GPA. Respondents did have a significantly higher GPA in their first Fall semester than all students in the initial sample, however.

Analytical Techniques

CFA is the most appropriate method for determining model fit. CFA is a data reduction technique in which the relationships between the underlying latent constructs and the observed variables are specified in advance (Bollen, 1989). This technique differs from the EFA procedure in that EFA models determine the nature of the underlying structure of the data. To put the difference more succinctly, in

Table 1. Differences in academic characteristics between full sample and survey respondents

	Full Sample	Respondents
Admit Type		
First-year students	74.8%	73.2%
External transfer	25.2%	26.8%
Enrollment status [a] *		
Full time (12 hours or more)	91.3%	95.4%
Part time (less than 12 hours)	8.7%	4.6%
Received Pell Grant	40.6%	39.3%
Did not file a FAFSA	12.4%	10.0%

Source: All data were obtained from Indiana University Student Information System student enrollment and financial aid records.

Note: [a] As of August 31, 2015.
* Chi-square test revealed statistically significant difference between respondents and total population at $\alpha < 0.05$.
FAFSA is the Free Application for Federal Student Aid.

Table 2. Differences in means between full sample and survey respondents*

	Full Sample		Respondents	
	N	Mean	N	Mean
Age [a]	4,845	19.7	351	20.0
High School GPA [b] *	4,235	3.36	306	3.45
Transfer GPA [c]	1,109	2.93	83	3.01
Fall Semester GPA*	4,748	2.80	350	3.03

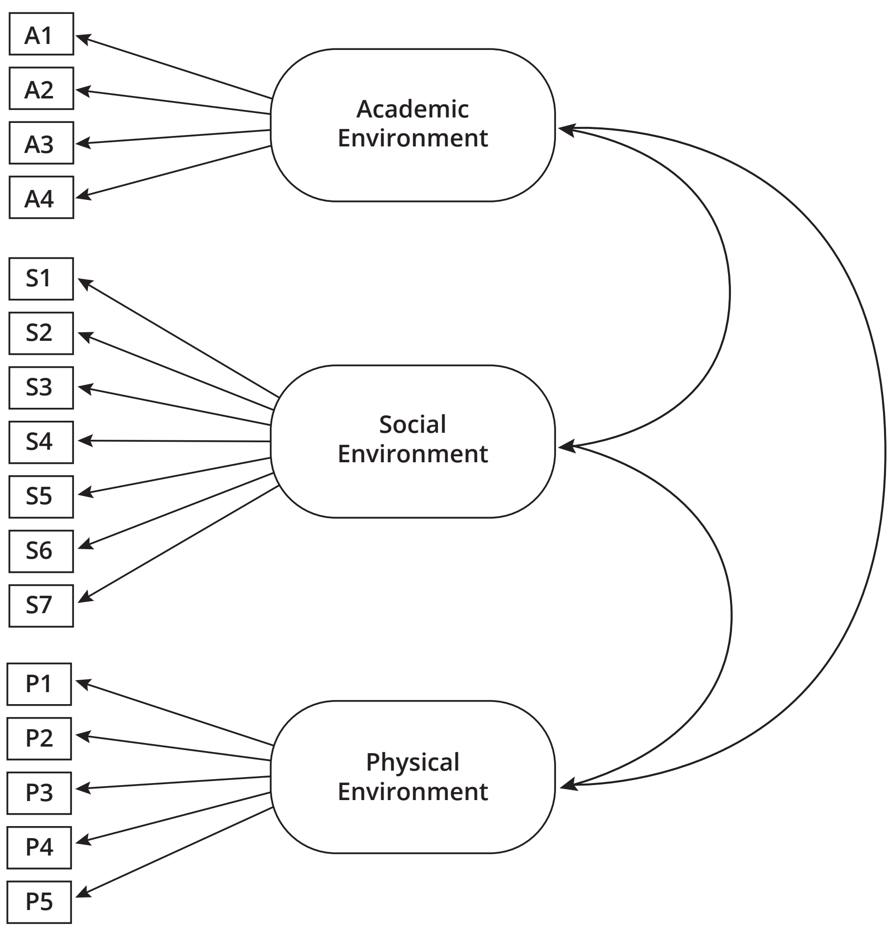
Source: All data were obtained from Indiana University Student Information System student enrollment and financial aid records.

Note: [a] As of August 31, 2015.
[b] Of students for whom high school GPA is available. External transfer students are not required to submit high school GPA for admission to Indiana University–Purdue University Indianapolis (IUPUI).
[c] Transfer students only, based on courses from previous institutions that had been reviewed and processed as of March 1, 2017. Additional transfer credits may have been processed since.
* Independent samples t-test revealed statistically significant difference between respondents and total population at $\alpha < 0.05$.

CFA you start with an underlying structure and see if it fits, whereas in EFA you begin with no underlying structure and try to find one. Gilbreath et al. (2011) used principal axis factor analysis, an EFA procedure that uses shared variance along the correlation matrix, to specify a three-factor model for their data. Gilbreath et al. do not provide much detail on their exploratory model, however. For example, they fail to specify which, if any, rotational method was used to determine appropriate factor loadings for each of the three factors. Examining the underlying three-factor structure proposed by Gilbreath et al. first would be crucial to determine if this structure provides an appropriate fit for data obtained from another institution.

Figure 1 displays the relationships between variables on the student–institution fit instrument as they were initially proposed by Gilbreath et al. (2011). This model formed the basis for the CFA procedure. The three-factor structure consists of a four-item Academic Environment factor, a seven-item Social Environment factor, and a five-item Physical Environment factor. Correspondence between

Figure 1. Proposed Model of Institutional Fit for Question 1



Source: Adapted from Gilbreath et al., 2011.

specific items from the student–institution fit instrument and labels can be found in Appendix A. One factor loading in each model was set to 1.0 so that the model would be appropriately scaled. The proposed model has 16 observed variables and 32 freely estimated parameters. The model therefore is identified as it meets both the t-rule (32 < (16)(16 + 1)) and the three-factor rule for identification (Bollen, 1989).

Three fit indices were used to determine if the proposed model is appropriate for the data. The chi-square test for model fit examines the extent to which the observed sample covariance matrix differs from the restricted covariance matrix (Byrne, 2012). A small value for the chi-square statistic indicates a more perfect match between the two matrices. Therefore, a low value for the chi-square statistic means both that we will accept the null hypothesis and that the model fits the data. Although it is an appropriate statistical test, the chi-square statistic may be easily influenced by sample size and may be overly sensitive to misspecification in the model (Bollen, 1989). The sensitivity of the chi-square statistic is not the only issue. Specifically, the American Statistical Association issued a series of principles regarding the use of p-values, such as those produced by the chi-square goodness-of-fit test (Wasserstein & Lazar, 2016). Among the principles is that conclusions should not be based solely on p-values, and that p-values alone may not be sufficient evidence to reject or accept a null hypothesis. The Mplus statistical package offers additional fit indices to supplement the chi-square test, thus making it an appropriate software to use for these analyses (Byrne, 2012). The standardized root mean squared residual (SRMR) and root mean square error of approximation (RMSEA) were also considered. Different cutoff criteria are recommended for different fit indices based on sample size or estimation methods (Hu & Bentler, 1995). Per the recommendations of Hu and Bentler (1999), a cutoff value of less than 0.08 for SRMR and less than 0.06 for RMSEA would suggest good model fit.

When results from the CFA did not meet the cutoff criteria, modification indices were used to determine if changes in model specification could lead to a better-fitting model. The modification indices, also referred to as the univariate Lagrangian Multiplier test, assesses which specific changes to the specification of the model will lead to the largest decrease in the chi-square statistic (Bollen, 1989). This study generally used the technique described as most common by Bollen, in which the researcher selects the changes that will lead to the greatest reduction in the chi-square statistic. This process is repeated until the model meets the predefined fit criteria.

In addition, the definitions provided by respondents through open-ended survey items yielded additional contextual information that was helpful in justifying modifications. Specifically, students were asked to describe how they would define each item. Each individual comment was collected from the survey instrument and coded for specific emergent themes, using the procedure for examining qualitative data described by Creswell (2014, chap. 9). When results from modification indices suggested potential changes, individual comments were used to determine if suggested modifications were consistent with students' definitions of the items. No further modifications were made after the model demonstrated an adequate level of fit, which reduced the chances of over-specification resulting from nuances in sample data (MacCallum et al., 1992). Cronbach's alpha was also calculated for reconfigured scales in the path analysis model sample to provide further evidence that changes in the structure of the model were not overly influenced by chance from the limited sample size (MacCallum et al., 1992).

RESULTS

To conduct the following analyses, fit scores were calculated based on the absolute value of the difference between needs and supplies. Means therefore represent the difference between respondents' ideal university and their perceptions of their current university. A total of 175 responses were used to conduct a CFA to assess whether the factor structure described by Gilbreath et al. (2011) matches the survey data obtained from the collected sample. The model assessed in the first analysis is detailed in Figure 1. Table 3 provides all fit statistics used in this analysis. The chi-square test was statistically significant ($\chi2 = 212.70$, $df = 101$, $p < 0.01$), suggesting that the data did not fit the specified model. The RMSEA estimate of 0.079 was above the advised cut point of 0.06, which also hinted at a low level of model fit. The SRMR result (0.070), however, was below the advised cut point of 0.08.

The comprehensive results did not provide sufficient evidence that the factor structure proposed by Gilbreath et al. (2011) is an appropriate fit for the data obtained. Modification indices suggest four changes that would be consistent with theoretical assumptions: The largest assumption would be to move Great Support Services fit from the Gilbreath et al. suggested loading with Social Environment fit to Academic Environment fit. Illustrative responses to the open-ended item asking students to indicate their personal meaning of Great Support Services can be found in Table 4. Several respondents

Table 3. Fit statistics for models using the survey

		Value
Gilbreath et al. (2011) model	Chi-square test of model fit	212.70 Df = 101
	RMSEA	0.079 90% CI: 0.065 – 0.094
	SRMR	0.070
Revised Model	Chi-square test of model fit	156.56 Df = 98
	RMSEA	0.058 90% CI: 0.041 – 0.075
	SRMR	0.064

Table 4. Selected comments illustrating students' definitions of Great Support Services

"Knowledgeable staff, and a good Tutor–Student ratio."

"Staff members who are always there when a student is in need."

"You have someone to turn to for help"

"Having resources if you need help with college or personal life"

"Easy access to help over any topic a student is struggling with that can help the student efficiently"

"MAC, programs"

"any type of mentors available"

"Talking with my advisor"

"available and well knowledge tutors"

"I thought of things specific to the transfer process"

"Accessible tutoring, counselling, etc."

"Effective counseling for students struggling in classes or coping with mental illnesses"

"academic counseling"

"Disability Services"

"Multiple free support services that are helpful to any and all students."

"helpful counseling, tutoring, health care, social services"

"advising sessions"

"the fact that i wasn't even assigned a specific counselor nor do i ever hear from any of the advisors about my major and/or classes really irritates me because i have no idea who to email when i have questions"

"There are plenty of opportunities to get help with your studies or classes"

"MAC, consolers [*sic*], etc."

"there is a good writing center to help international students or even local students with english writing"

"Great. Many resources (tutors, learning center, etc.) however needs more for engineering programming classes."

"Helpful study centers/tutors"

[a] Question worded as follows: "Please indicate how you would define the following: Great Support Services."

defined Great Support Services by referring to tutoring services, such as the Math Assistance Center (MAC), and the University Writing Center. Other comments mentioned academic advisors, tutoring, mentoring, or other services that provided academic support. These comments provided additional justification for moving Great Support Services to the Academic Environment fit scale.

Two additional modification indices suggest that correlated error terms between items within two scales would produce noteworthy reduction in the chi-square statistic. These would include specifying a cross-loading between Great Support Services and "A scholarly/intellectual campus climate" (both within Academic Environment fit) and a cross-loading between "Sport and recreational opportunities" and "A diverse student body" (both within Social Environment fit). The largest reduction from correlated error terms would arise from an assumed cross loading between "State-of-the-art classrooms, labs, library" (Academic Environment fit) and "Great geographic location" (Physical Environment fit). This modification seems appropriate, given that

Table 5. Factor loadings and standardized coefficients for revised model

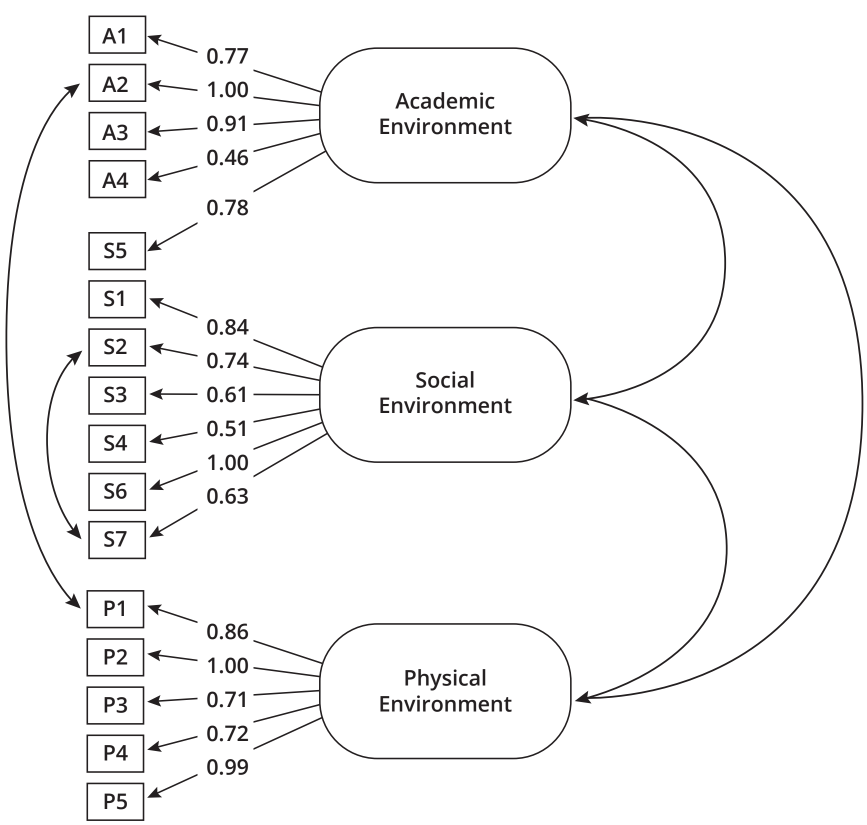
Item		Factor loadings in second CFA	Standardized coefficients
Academic Environment fit			
A3	A highly regarded academic reputation	0.91	0.76
A1	A scholarly/intellectual campus climate	0.77	0.69
S5	Great Support Services (e.g., academic counseling, health care, and placement center)	0.78	0.59
A2	State-of-the-art classrooms, labs, library	1.00	0.56
A4	Great school size	0.46	0.34
Social Environment fit			
S6	Great nonacademic facilities (e.g., gyms, dining room, and game room)	1.00	0.69
S1	Enjoyable social life	0.84	0.61
S3	Great student body	0.61	0.59
S2	Sports and recreational opportunities	0.74	0.53
S7	A diverse student body	0.63	0.41
S4	A highly regarded athletic reputation	0.51	0.31
Physical Environment fit			
P2	A safe environment	1.00	0.59
P5	Great affordability	0.99	0.52
P1	Great geographic location	0.86	0.51
P4	Convenient campus layout	0.72	0.50
P3	A pleasing physical environment (aesthetics)	0.71	0.42

"Great geographic location" had a moderate factor loading with Academic Environment fit in the original Gilbreath et al. (2011) study (0.25), while "State-of-the-art classrooms, labs, library" had a similarly moderate factor loading with the Physical Environment fit scale (0.26).

Fit statistics for the revised model can be found in Table 3. The chi-square test was statistically significant ($\chi 2 = 156.56$, df = 98, $p < 0.01$), suggesting lack of model fit. However, RMSEA (0.058) was below the predetermined cut point of 0.06 and SRMR (0.064) was below the predetermined cut point of 0.08. These measures seem to recommend that model fit was appropriate. Analysis conducted by Hu and Bentler (1999) suggests that a combination of RMSEA below 0.06 and SRMR below 0.08 yielded the lowest combination of Type I and Type II error rates when N was less than or equal to 250 cases. Using these criteria, the respecified model was determined to be adequate for subsequent analyses.

The results described in Table 3 suggest mixed evidence of model fit. The overall weight of the evidence suggests that the proposed model does explain the relationship between the observed and latent variables, however. Because of the correlated

Figure 2. Final Model of Institutional Fit with Factor Loadings



Source: Original model adapted from Gilbreath et al., 2011.

errors between "state-of-the-art classrooms, labs, library" and "great geographic location," the interfactor correlation between Academic Environment fit and Physical Environment fit would likely be somewhat inflated (Asparouhov & Muthén, 2009).

The final factor structure model to be used in all subsequent analyses, including coefficients, can be seen in Table 5 and Figure 2. Factor loadings were sufficiently high to assert convergent validity with each factor (Huck, 2012). Table 5 also includes standardized coefficients to assist in the interpretation of each factor. For CFA, standardized coefficients can be interpreted in the same way as standardized coefficients in ordinary least squares (OLS) regression, in that a one-standard-deviation increase in the variable would yield a one-standard-deviation increase in the latent variable. These standardized coefficients can be discussed broadly with colleagues and other users to understand the impact of each item on each fit factor. However, it should be noted that, because these are latent factors, using standardized coefficients to calculate factor scores will include a greater degree of measurement error than a calculation of a predicted value using an OLS regression formula (Bollen, 1989). For subsequent research, fit on each factor was calculated as the absolute difference between needs and supplies summed for each factor (Graunke, 2018).

Interfactor correlations for both split samples can be viewed in Table 6. The correlation between Academic Environment fit and Physical Environment fit was the largest correlation using both the sample for the CFA and the validation sample, as was expected given the shared variance between "great geographic location" on the Physical Environment fit factor and "state-of-the-art classrooms, labs, library" on the Academic Environment factor. In both samples, all correlations between factors were statistically significant and positive at the $\alpha < 0.05$ level. These results suggest that factors may not be independent, or that a second-order factor may be present. Gilbreath et al. (2011) did not propose a second-order overall fit. Future researchers attempting to replicate these results may collect

Table 6. Interfactor correlations using CFA and path model samples

		Academic Environment fit	Social Environment fit	Physical Environment fit
CFA Sample	Academic Environment fit	–		
	Social Environment fit	0.57*	–	
	Physical Environment fit	0.58*	0.56*	–
Validation Sample	Academic Environment fit	–		
	Social Environment fit	0.46*	–	
	Physical Environment fit	0.59*	0.50*	–

Note: * Statistically significant correlation at $\alpha \leq 0.05$.

additional data to determine if a second-order fit factor is appropriate, however.

Cronbach's alpha calculations for each scale can be found in Table 7. Analysis of Cronbach's alpha using the CFA sample proposes that reliability would be improved on the Academic Environment fit scale if "great school size" were deleted. Cronbach's alpha was therefore calculated for Academic Environment fit with "great school size" both included and excluded. The only fit factor that demonstrated acceptable reliability using both the CFA sample and the path model sample was Social Environment fit (α = 0.71 in CFA sample, α = 0.72 in path model sample). Academic Environment fit demonstrated adequate fit after dropping "great school size" when using the CFA sample. These results were not replicated using the validation sample, however, either with or without "great school size" included. Physical Environment fit did not demonstrate adequate levels of reliability with either sample.

DISCUSSION

The results from these analyses provide evidence that some modifications to the original model proposed by Gilbreath et al. (2011) were necessary before using data from this survey. The most noteworthy change would be to move Great Support Services from Social Environment fit to Academic Environment fit. However, that modification is not consistent with the original principal axis factor analysis results obtained in Gilbreath et al.'s initial study, on which Great Support Services loaded alongside other items pertaining to nonacademic aspects of the institution on the Social Environment fit scale. Unlike other items on this scale, however, students at the target institution believed Great Support Services referred directly to services provided by the university that might be related to the academic experience, while the remaining Social Environment fit items are explicitly nonacademic in nature. Other measures of student–institution fit, such and Bowman and Denson's (2014) student–institution fit model and Anthoney's (2011) factors of Academic Environment press, generally do not explore the role of support services in facilitating student–institution fit. Nonetheless, it is clear that some academic support services play some role in facilitating student retention and other positive outcomes. Tinto (2012) mentions that support services can help not only by enhancing students' academic skills, but also by enhancing connections to their institutions' academic and social context. Likewise, Strayhorn (2012) advocated for the importance of "mattering," which is defined as a

Table 7. Cronbach's alpha for factors in CFA and path model samples

	CFA sample	Validation sample
Academic Environment fit: With great school size fit	0.70	0.60
Academic Environment fit: Without great school size fit	0.73	0.55
Social Environment fit	0.71	0.72
Physical Environment fit	0.62	0.65

sense that an individual is appreciated by someone at their institution. This feeling of mattering could come from a variety of sources, including faculty or academic support staff. Neither Tinto nor Strayhorn was explicitly speaking of student–institution fit, though the types of support each mentioned would typically come from an academic rather than from an explicitly social context. The results from the present study do seem to indicate that the support received from support services is part of the academic environment rather than being part of the more explicitly social environment.

Though the model obtained through these analyses presented an acceptable match for the data obtained, it is noteworthy that only the Social Environment fit scale demonstrated adequate reliability using both the sample for the CFA analysis and the sample for the path models. The findings of low reliability for the Physical Environment fit factor are ultimately not surprising. In the original Gilbreath et al. (2011) study, neither Physical Environment need nor Physical Environment supply reached an acceptable level of reliability ($\alpha = 0.54$ for Physical Environment need and 0.59 for Physical Environment supply). Gilbreath et al. continued to use this scale in subsequent analyses because high scores obtained from students completing the Physical Environment need scale suggest that the physical environment was extremely important to students. Similarly, Denson and Bowman (2015) found that the reliability of their Physical Environment fit scale was inadequate for future analysis and removed it from their final instrument in the Australian study. When using an American sample, Bowman and Denson (2014) obtained a Cronbach's alpha estimate of 0.65 for their Physical Environment fit scale. This estimate is lower than might be deemed acceptable in most research, but it was deemed acceptable by Bowman and Denson because the items used in the fit scale included measurement error from two survey items rather than from only one item. The weight of the evidence suggests that an adequate scale measuring higher education students' perceptions of fit with their physical environment has not yet been developed. This scale was not used at subsequent studies at this institution, and it is recommended that other institutions hoping to explore fit develop their own measure of Physical Environment fit.

Of more pragmatic value to institutional researchers are the techniques used to validate the instrument for an individual institutional context. The final fit measure developed from the analyses described were used in a comprehensive study of the effect of fit on Fall-to-Fall retention net the effect of external commitments and socioeconomic status (SES) (Graunke, 2018). Graunke found that fit with the social environment had a significant and positive effect on retention, but this effect disappeared when SES variables were entered into the model. While this model was particularly effective for one institution, IR professionals should consider conducting CFA analysis and assessing qualitative information when bringing external instruments to their institution.

Supplementing CFA results with qualitative data proved especially useful in this study. Student comments on the Great Support Services item highlighted that this item was viewed as referring to academic resources. Taken together with the modification indices, these qualitative data provided triangulation that supported the change of this item to the Academic Environment subscale. Qualitative data analysis is designed to illuminate participants' personal meaning about a specific question (Creswell, 2014, chap. 9). Adding students' definitions to quantitative data provides a holistic view of students' experiences. Incorporating this kind of student feedback with CFA results will enable researchers to modify a survey in ways to make it more valid for the student population at different institutions.

As institutional researchers continue to incorporate predictive modeling into their work, the collection of reliable and valid data from students becomes even more critical. It is therefore important that institutional researchers use all the appropriate quantitative and qualitative research tools to make sure surveys developed at one institution are appropriate for another. Conducting CFA analysis along with the collection and analysis of qualitative feedback could help institutional researchers refine instruments to collect better data and improve student success.

APPENDIX A. STUDENT–INSTITUTION FIT SCALE

Item		Need Reliability[1]	Supply Reliability[1]
Academic Environment fit		**0.59**	**0.72**
A1	A scholarly/intellectual campus climate		
A2	State-of-the-art classrooms, labs, library		
A3	A highly regarded academic reputation		
A4	Great school size		
Social Environment fit		**0.80**	**0.79**
S1	Enjoyable social life		
S2	Sports and recreational opportunities		
S3	Great student body		
S4	A highly regarded athletic reputation		
S5	Great Support Services (e.g., academic counseling, health care, and placement center)		
S6	Great nonacademic facilities (e.g., gyms, dining, and game room)		
S7	A diverse student body		
Physical Environment fit		**0.54**	**0.62**
P1	Great geographic location		
P2	A safe environment		
P3	A pleasing physical environment (aesthetics)		
P4	Convenient campus layout		
P5	Great affordability		

Source: Adapted from Gilbreath et al. 2011.

Note: **1** Cronbach alpha estimates obtained from Gilbreath et al. 2011.

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