Original Manuscript

Journal of College Student Retention:
Research, Theory & Practice
1–23

DOI: 10.1177/15210251221074379
journals.sagepub.com/home/csr
SAGE

Modeling University Retention and Graduation Rates Using IPEDS

Chen Zong[1] and Alan Davis[2]

Abstract

This study aimed to replicate, revise, and validate the model of Institutional Performance in Graduation Rate developed by Fung based on Tinto and Astin theories. The sample included 706 public, 4-year, Title IV postsecondary institutions in the United States. Two CFA-SEM models were conducted with the IPEDS 2011–2017 data. The relationships among student background, finance, academic and social environment, retention rate, and graduation rate were reevaluated and remodeled. The final best fitting model reflects possible changes in the factors of student finance and academic environment in higher education since 2010. The practical application of the best fitting model was discussed, including the evaluation of an institution's graduation rate performance based on four latent factors.

Keywords

higher education, retention, graduation, structural equation modeling

Introduction

Numerous studies conducted within institutions of higher education (IHEs) have identified observable variables that are predictive of graduation (e.g., Anstine and Seidman, 2017; Harrison, 2016; Price and Tovar, 2014; Youmans, 2017). In contrast, relatively few studies have been conducted across a large sample of IHEs to facilitate peer

[1]Office of Institutional Analysis, University of Wyoming, Laramie, WY, USA
[2]School of Education and Human Development, University of Colorado Denver, Denver, CO, USA

Corresponding Author:
Chen Zong, Office of Institutional Analysis, 1000 East University Avenue, Laramie, WY 82071, USA.
Email: c.zong@hotmail.com

comparisons and testing of models at the institutional level. After an extensive review of literature, we believe that only one study (Fung, 2010) has developed and tested a structural equation model (SEM) to explain retention and graduation in 4-year universities using the most comprehensive national IHE database, the Integrated Postsecondary Education Data System (IPEDS).

Fung (2010) developed a SEM of Institutional Performance in Graduation Rate (IPGR) using IPEDS data for all four-year, public and private not-for-profit, Title IV institutions in the United States. Fung's model made a significant contribution as a pioneer model to synthesize important theories and prior research in higher education institutional performance with a publicly available data source.

The IPGR model is the first and only SEM to fit Tinto's (1975) and Astin's (1991) conceptual models of 4-year university graduation to the NCES IPEDS national dataset. By searching for the keywords "IPEDS" and "structural equation model" on Google Scholar, we found only three studies related to retention or graduation including two studies focused on 4-year universities by Fung (2010) and Zong (2021), and the other one focused on 2-year community colleges (Yu, 2015). Fung's IPGR is a powerful model, accounting for 41.2% of the variance in institutional retention rates, and 61.8% of the variance in graduation rates. Its use of structural equation modeling has the advantage over other correlational methods such as multiple regression and hierarchical multiple regression, by showing the relationship among the independent (exogenous) and dependent (endogenous) variables, and the contributions of multiple observed variables to measure a more complex construct.

Nevertheless, the model fell marginally short of standard criteria for demonstrating an acceptable model fit, and the data it was based on are now more than 10 years old. Important changes in higher education have occurred during the interim, including a significant increase in enrollment in online learning (Seaman et al., 2018). Fung (2010) suggested that replication studies using different years' IPEDS datasets were needed to refine and improve the model.

The purpose of this study is to replicate, validate, revise, and improve the IPGR model. Due to the significant differences in institutional characteristics and performances between public and private not-for-profit institutions (Fung, 2010), as well as large differences in the number of public and private not-for-profit institutions in the IPEDS data, we chose to develop an updated and improved model specifically for all *public* 4-year Title IV institutions in the United States using the more recent IPEDS data. We examine the fit of the original IPGR model to more recent IPEDS data, and then propose and test modifications suggested by theory and recent research.

The model developed from this study has its practical significance for researchers, administrators, and other practitioners in higher education. The confirmatory factor analysis (CFA) models can be used to measure latent or unobserved factors (e.g., institutional academic and social environment) using the selected observed variables from the IPEDS data to better understand a complex problem or phenomenon associated with retention or graduation. The SEM can confirm or disconfirm the predictive relationships among institutional characteristics, retention, and graduation rate in theoretical models. The model can be used to evaluate institutional performance in admission, financial aids, expenditures, and campus facilities, etc. The evaluation results based on the model can facilitate decision-making and provide appropriate support or intervention at an early stage to improve retention and graduation rate. Moreover, because the IPEDS is the most comprehensive and the only publicly available national higher education database, valid models based on IPEDS data could be useful for more researchers or practitioners to do peer comparisons.

Conceptual Framework

Fung (2010) based his IPGR model on Tinto's (1975) model of college dropout, Astin's (1991) Input-Environment-Output theory, and other previous studies (e.g., Goenner and Snaith, 2004; Pike et al., 2006; Scott et al., 2006) of the relationship of institutional characteristics to graduation rates (Figure 1).

Tinto's Theoretical Model

Tinto's (1975) theoretical model of dropout from college is possibly the most frequently cited model in research studies about retention and graduation rates in higher education. Our use of Google Scholar located more than 14,400 citations of the model at the time of this writing. This theoretical model postulates that dropping out is a longitudinal process of interactions between a student and the institution's academic and social systems and the experiences of students in those systems. Those interactions and experiences continually influence students' goals and commitments in regard to persistence or dropout decisions and are associated with retention and graduation rates (Tinto, 1975).

Astin's Theoretical Model

Another theoretical model for the original IPGR model was Astin's (1991) Input-Environment-Output (I-E-O) model. The model includes three parts: student inputs, student outcomes, and the educational environment (Astin, 1993a). *Input* refers to background characteristics and experiences that students initially bring

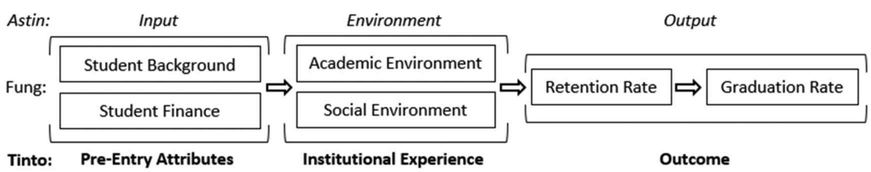

Figure 1. *Theoretical model of institutional performance in graduation rate* (Astin, 1991; Fung, 2010; Tinto, 1975).
Note. The arrows indicate time in the process, and not causal paths.

when entering college. *Output* or outcomes refers to student outcomes or performances in college. *Environment* refers to students' experiences during college. The I-E-O model can be used to understand how educational environment, policies, and practices affect student outcomes with the consideration of student inputs (Astin, 1993a).

Fung's Model of Institutional Performance in Graduation Rate (IPGR)

Fung (2010) followed the same structure of Tinto's (1975) model including student background and attributes, social and academic integrations, commitments (retention) and outcome (graduation). Fung (2010) also pointed out that the variables and constructs in the IPGR model were organized in a structure similar to Astin's I-E-O model. The *input* includes student background, attributes, and finance. The *environment* includes social and academic environment. The *output* includes retention and graduation rate. The predictor variables in the IPGR model were selected based on the findings of previous studies, but due to its originality and uniqueness, there was no reference model using the same structure with IPEDS data before Fung's IPGR model. This limitation suggests that Fung's study should best be viewed as an exploratory study, with replication studies needed to validate and improve the model.

The IPGR model includes four main latent factors to predict commitment (retention rate) and performance (graduation rate) at the institutional level: (a) student background, (b) student finance, (c) institutional academic environment, and (d) institutional social environment. The definitions of the four factors by Fung (2010, p. 228) were used in this study:

- **Student background**: This factor measures the preparedness of the student body. High scores indicate positive readiness and preparation for college education. This factor is an input factor and is affected by the institution's selectivity and admission policy.
- **Student finance**: This factor measures the financial aspects of going to college. High means that the students are financially resourceful either by their ability to afford high tuitions or their ability to access financial aid. Low means that the students are financially deprived.
- **Academic environment**: This factor measures the overall level of academic support the institution can provide to help its students succeed academically. High means supportive. Low means unsupportive.
- **Social environment**: This factor measures the overall opportunities the institution can provide to help its students establish meaningful personal and communal relationships within the institution.

Due to the model fit issues, Fung (2010) suggested that new variables should be added to improve the model, but such model modification should be supported by theories or previous research findings. We reviewed over 60 previous research studies (including, for example, Pascarella and Chapman, 1983; Seaman et al., 2018; Waller and

Tietjen-Smith, 2009; Webber and Ehrenberg, 2010; Yu, 2017) that included one or more latent variable and significant predictors that are available in the IPEDS data to guide the addition or removal of variables in the new hypothesized models (Zong, 2021). We selected 22 additional observed variables from IPEDS that logically fit the four factors, and were supported by literature, but were not included in Fung's model (see Table 1).

Methods

This study is a survey-based confirmatory correlational research design using the secondary data of IPEDS to replicate, revise, and validate a SEM developed by Fung (2010) using the recent IPEDS data (2011–2017). There were two stages of SEM modeling.

In the first stage, we tested the fit of Fung's model with more recent IPEDS data, now limited to only public 4-year Title IV institutions. The research question (RQ) guiding this stage was: How good is the fit of the IPGR model with updated IPEDS data including only public institutions (RQ1)? In the second stage, we used updated and additional variables in the IPEDS data supported by the literature to examine whether our hypothesized model was a better fit than the original IPGR model (RQ2). After we compared and identified the best fitting model from the two stages of analysis, we further tested the measurement/model invariance of both CFA and SEM models (RQ3).

Data Collection

The IPEDS final-version data for the 2017–2018 academic year were used. The IPEDS data is the core postsecondary education data collection program of the National Center for Education Statistics (NCES). The IPEDS survey is conducted annually and participation is mandatory for all postsecondary education institutions eligible to participate in Title IV federal student financial aid programs (NCES, 2017). The IPEDS is the only comprehensive and publicly available large-scale higher education dataset in the NCES collection.

Population and Data Sample

The target population for this study is all public, 4-year or above, Title IV postsecondary education institutions in the United States. The raw data included 748 institutions meeting the criteria. The data were screened and edited prior to testing CFA and SEM models. The following six key statistical issues and assumptions for SEM were checked: measurement scale of variables, missing data values, restriction in the range of data, outliers, non-normality, and linearity (Schumacker & Lomax, 2016). The data screening steps found 42 institutions with zero full-time undergraduate enrollment or with no information for the variable of full-time undergraduate enrollment. After deleting those 42 institutions, the cleaned sample included 706 institutions.

Table 1. Variables for the Model of Institutional Performance in Graduation Rate.

#	Variable	Year	Original Model	New Model
Institutional Performance				
V1	6-Year Graduation Rate (first-time, full-time, degree or certificate-seeking undergraduate students of 2011 cohort)	2017	Yes	Yes
Student Commitment				
V2	1-Year Full-time Retention Rate	2012	Yes	Yes
Student Background				
V3	Selectivity: Percent admitted = number of total admissions divided by the total applicants	2011	No	Yes
V4	Selectivity: Admissions yield = number enrolled divided by the number admitted	2011	No	Yes
V5	Selectivity: ACT/SAT 25th percentile score [a]	2011	Yes	Yes
V6	Institutional SES: non-Pell recipients as a percent = 1 - % Pell recipients	2011	Yes	Yes
V7	Age: Percent of adult age (25 +) undergraduate enrollment = adult full-time enrollment/total full-time enrollment	2011	Yes[b]	Yes
V8	Gender: Percent of women undergraduate enrollment	2011	No	Yes
V9	Race/ethnicity: Percent of undergraduate students of color enrollment = 1 - % undergraduate enrollment that are White	2011	No	Yes
Student Finance				
V10	Tuition: In-district [c]	2011	No	Yes
V11	Tuition: In-state	2011	Yes	Yes
V12	Tuition: Out-of-state	2011	No	Yes
V13	Federal Grant: Percent of undergraduates awarded federal grant aid	2011	No	Yes
V14	State Grant: Percent of undergraduates awarded state grant aid	2011	No	Yes
V15	Institutional Grant: Percent of undergraduates awarded institutional grant aid	2011	No	Yes
V16	Federal Grant: Average amount of federal grant aid	2011	Yes	Yes
V17	State Grant: Average amount of state grant aid	2011	Yes	Yes
V18	Institutional Grant: Average amount of institutional grant aid	2011	Yes	Yes

(continued)

Table 1. Continued

#	Variable	Year	Original Model	New Model
Academic Environment				
V19	Student-to-faculty ratio	2011	Yes	Yes
V20	Instruction expenses: per FTE (full-time equivalent)	2011	Yes	Yes
V21	Instruction expenses: as a percent of total core expenses	2011	No	Yes
V22	Instruction expenses: salaries and wages as a percent	2011	No	Yes
V23	Academic support expenses: per FTE	2011	Yes	Yes
V24	Academic support expenses: as a percent of total core expenses	2011	No	Yes
V25	Academic support expenses: salaries and wages as a percent	2011	No	Yes
V26	Distance education: Percent of undergraduates exclusively in distance education courses [d]	2012	No	Yes
V27	Distance education: Percent of undergraduates in some distance education courses [d]	2012	No	Yes
V28	Research expenses: per FTE	2011	No	Yes
V29	Research expenses: as a percent of total core expenses	2011	No	Yes
Social Environment				
V30	Institutional size: Full-time undergraduate enrollment	2011	Yes	Yes
V31	Institutional size: IPEDS categories	2011	No	Yes
V32	Dormitory capacity	2011	Yes	Yes
V33	Student service expenses: per FTE	2011	No	Yes
V34	Student service expenses: as a percent of total core expenses	2011	No	Yes
V35	Student services expenses: salaries and wages as a percent	2011	No	Yes
V36	Urbanization (Urban-centric locale)	2011	No	Yes
V37	Residential campus: Carnegie Classification 2010 Size and Setting	2011	No	Yes
Grouping Variables				
V38	Carnegie Classification 2000 (doctoral, master, baccalaureate)	2011	Yes	Yes
V39	Bureau of Economic Analysis (BEA) Region	2011	Yes	Yes

Note. [a]V5 ACT/SAT 25th percentile score = the average of ACT score and SAT score (converted to ACT score) (ACT, 2009).
[b]V7 Fung (2010) used average age of students.
[c]V10 was removed later due to the duplication with V11.
[d]The variables of distance education are not available in the IPEDS 2011 dataset because the information on distance education was first introduced in the IPEDS 2012 (NCES, 2017).

The Carnegie classification and geographical region of the institutions are shown in Table 2.

Variables

To replicate the method employed by Fung (2010), we used the institutional characteristics reported in 2011 to predict the 2012 retention rate (1-year) and the 2017 graduation rate (6-year). Table 1 presents the variables that were used in this study for (a) replicating the original IPGR model (RQ1) and (b) revising and improving the IPGR model with new variables (RQ2).

Table 2. Grouping Variables for the Multiple Group Analysis.

				Graduation Rate %	
Group		*n*	%	*M*	*SD*
Carnegie Classification 2000					
Doctoral ($n = 164$)	Doctoral/Research Universities—Extensive	102	14.4	69	14
	Doctoral/Research Universities—Intensive	62	8.8	50	14
Master ($n = 260$)	Masters Colleges and Universities I	238	33.7	47	14
	Masters Colleges and Universities II	22	3.1	43	15
Baccalaureate ($n = 81$)	Baccalaureate Colleges—General	45	6.4	35	12
	Baccalaureate Colleges—Liberal Arts	23	3.3	49	18
	Baccalaureate/Associates Colleges	13	1.8	40	16
Others[ab]		167	23.7	--	--
Not available[b]		34	4.8	--	--
Total		706	100.0		
Bureau of Economic Analysis (BEA) Regions[b]					
Far West AK CA HI NV OR WA		105	14.9	44	21
Great Lakes IL IN MI OH WI		95	13.5	44	19
Mid East DE DC MD NJ NY PA		111	15.7	53	18
New England CT ME MA NH RI VT		43	6.1	53	15
Plains IA KS MN MO NE ND SD		59	8.4	48	16
Rocky Mountains CO ID MT UT WY		35	5.0	41	15
Southeast AL AR FL GA KY LA MS NC SC TN VA WV		186	26.3	45	18
Southwest AZ NM OK TX		71	10.1	37	17
US Service schools[b]		1	.1	81	--
Total		706	100.0		

Note. [a]Others include associates colleges, medical schools and medical centers, other specialized institutions, schools of art, music, and design, schools of engineering and technology, teachers colleges, and tribal colleges.
[b]Multiple group analysis was not conducted on these groups.
[b]The territories of the United States are excluded for analysis.

Data Analysis

To address RQ1 and RQ2, two SEM modeling processes were conducted using the IPEDS 2011–2017 data with IBM® SPSS® Statistics software ("SPSS") Amos26 to check whether the data fit the models. The original model (Stage 1) was tested for fit to the recent IPEDS data. Then the hypothesized model using new variables (Stage 2) was tested to determine whether it provided a better fit to the data than Fung's original model. The models were examined with (a) the chi-square test, (b) the statistical significance of individual paths, and (c) the magnitude and direction of the parameter estimates (Schumacker & Lomax, 2016). In addition, the following model-fit criteria were checked:

- Root-Mean-Square Error of Approximation (RMSEA) <.10 (Browne & Cudeck, 1992; MacCallum et al., 1996);
- Comparative fit index (CFI) >.90 (Hu & Bentler, 1999);
- Normed Fit Index (NFI) >.90 (Schumacker & Lomax, 2016).

All models were modified based on the model testing results using *scale purification* methods (Churchill, 1979; Frohlich, 2002; Wieland et al., 2017): Using statistical criteria, the non-significant variables ($p \geq .05$) and the variables with the lowest factor loadings were deleted stepwise. Only one item was deleted in each step, and the revised or "purified" model was rerun until the model fit indices did not increase. Using judgmental criteria, the practical and theoretical considerations were discussed with relevant literature.

To address RQ3, multiple group analysis was conducted to examine the measurement invariance and model validity for the best fitting CFA and SEM models across groups based on (1) Carnegie Classification 2000 and (2) Bureau of Economic Analysis (BEA) Regions. The automatic multiple-group analysis function in AMOS was used with Emulisrel6 (Byrne, 2016). Both the significance of χ^2-difference ($\Delta\chi^2$) test and the cutoff value of the CFI-difference test (<.01) were used to examine the results of the multiple group analysis in this study (Byrne, 2016; Cheung & Rensvold, 2002).

Results

In this section we describe the SEM modeling processes for the original IPGR model and our hypothesized IPGR model with the new indicators. For each model, the CFA measurement model was tested first and then modified based on the statistical criteria to identify a best fitting measurement model, which was used and examined further in the SEM model to predict retention rate and graduation rate. Finally, all measurement models and structural models were compared to determine the best fitting model overall.

The Comparison of CFA Models

Stage 1: The Original Model. The first CFA measurement model tested (CFA 1.1) was the four-factor model with 12 variables (see Table 1) developed by Fung (2010). The CFA results showed that this was not a good fit to the data (Table 3). Using the statistical criteria of scale purification (Wieland et al., 2017), three variables (V16, V17, V19) were deleted. CFA Model 1.2 demonstrated acceptable fit, χ^2 (21) = 164.18, $p < .001$; CFI = .95; NFI = .94; RMSEA = .10. All variables were statistically significant in respect to the associated factors at $p < .001$, and the factor loadings were all good with values ranging from.62 to.99. The factor intercorrelations in CFA 1.2 suggested that all latent factors were highly correlated, with Pearson's r values above.50 (Figure 2).

Stage 2: The Hypothesized New Model. The hypothesized new CFA model used the same four-factor structure with the addition of 22 variables (see Table 1) to assess if this was a better model. The results showed that CFA 2.1 was not a good fit (Table 3). Using the scale purification steps (Wieland et al., 2017), the non-significant or low-loading variables were deleted. Figure 2 shows that CFA Model 2.2 had a better fit, χ^2 (48) = 493.43, $p < .001$; CFI = .91; NFI = .90, RMSEA = .12. All variables were statistically significant, and the factor loadings were all good with values from.60 to.99.

Table 3 compares the model fits of four CFA models tested for Stage 1 and 2. Among these measurement models, the revised model based on Fung's original CFA model (CFA 1.2) showed the best model fits to the data with the highest CFI and NFI values (CFI = .95, NFI = .94) and a good RMSEA value of.098. This

Table 3. CFA Model Fit Statistics Comparison.

#	CFA Model	*n*	χ^2	*df*	*p*	CFI	NFI	RMSEA	Are all factor loadings sig?
1.1	Fung's original model	706	562.715	48	.000	.853	.843	.123	YES
1.2	**Fung's model revised**	**706**	**164.177**	**21**	**.000**	**.950**	**.943**	**.098**	**YES**
2.1	Hypothesized model	706	9390.469	521	.000	.419	.408	.155	NO
2.2	Hypothesized model revised	706	493.431	48	.000	.909	.900	.115	YES

Note. Lower chi-square values indicate a better model fit. CFI values above.90 indicate good model fit (Hu & Bentler, 1999). RMSEA values less than.05 indicate good fit, values less than.08 indicate acceptable fit, values between.08 and.10 indicate mediocre fit, and values greater than.10 indicate poor fit (Browne & Cudeck, 1992; MacCallum et al., 1996). Bold font indicates the model with the best fit.

CFA Measurement Model Comparison

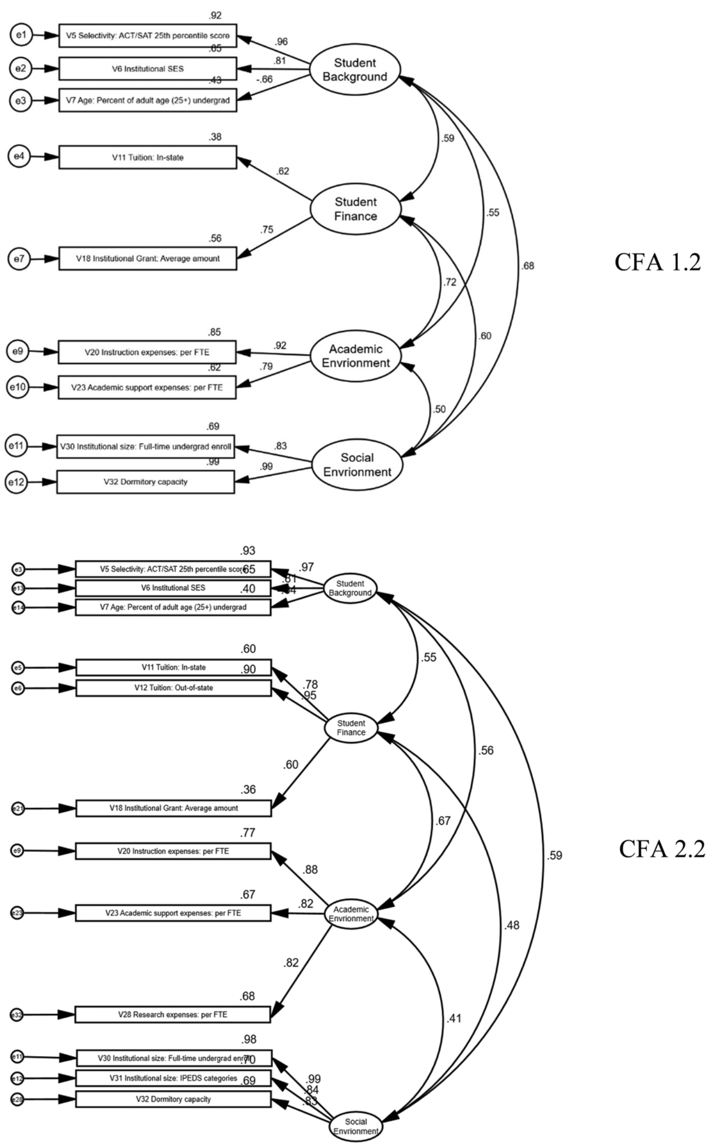

Figure 2. CFA measurement model comparison.

Note. Number on a single-headed arrow indicates the standardized factor loading of each variable. Number on a double-curved arrow indicates the intercorrelation between two latent factors (oval shape). Number on a rectangle (observed variables) indicates the squared multiple correlation of each variable, or the percent of variance in the variable explained by the factor.

model also showed the best factor loadings with all items significantly loaded on the underlying latent factor.

The Comparison of SEM Models

Stage 1: The Original Model. Using the revised measurement model structure (CFA 1.2), the original IPGR structural model (SEM 1.1a) was tested (Figure 3). The results showed that this model was not a good fit. The non-significant paths were removed for SEM 1.1b, but the results still showed that the model fit was still unacceptable (Table 4). To revise and improve the model, we added four paths (single-headed arrow) from each latent factor to graduation rate. We made this decision based on previous studies' findings that the four latent factors and associated observed variables in the model could directly or indirectly correlate with graduation rate, not only retention rate (e.g., Astin, 1993b; Goenner and Snaith, 2004; Waller et al., 2009; Yu, 2015).

The results of SEM 1.2a showed that the model fit was acceptable (Table 4), however, five structural paths were non-significant. These paths were deleted, and the model was rerun. The results of SEM 1.2b showed that it was a good fit to the data, χ^2 (37) = 268.13, $p < .001$; CFI = .95; NFI = .95; RMSEA = .09. All structural paths were statistically significant at $p < .001$. Figure 3 shows that 69% of the variance

Table 4. SEM Model Fit Comparison.

	SEM Model	*n*	χ^2	*df*	*p*	CFI	NFI	RMSEA	Are all paths sig?
1.1a	Fung's model based on CFA 1.2	706	616.443	36	.000	.879	.873	.151	NO
1.1b	Fung's model – revised	706	618.478	38	.000	.879	.873	.147	YES
1.2a	Fung's model new paths added	706	261.792	32	.000	.952	.946	.101	NO
1.2b	**Fung's model new paths added – revised**	**706**	**268.129**	**37**	**.000**	**.952**	**.945**	**.094**	**YES**
2.1	Hypothesized model based on CFA 2.2	706	984.486	69	.000	.867	.859	.137	YES
2.2a	Hypothesized model new paths added	706	622.772	65	.000	.919	.911	.110	NO
2.2b	Hypothesized model new paths added – revised	706	627.408	68	.000	.918	.910	.108	YES

Note. Lower chi-square values indicate a better model fit. CFI values above.90 indicate good model fit (Hu & Bentler, 1999). RMSEA values less than.05 indicate good fit, values less than.08 indicate acceptable fit, values between.08 and.10 indicate mediocre fit, and values greater than.10 indicate poor fit (Browne & Cudeck, 1992; MacCallum et al., 1996). Bold font indicates the model with the best fit.

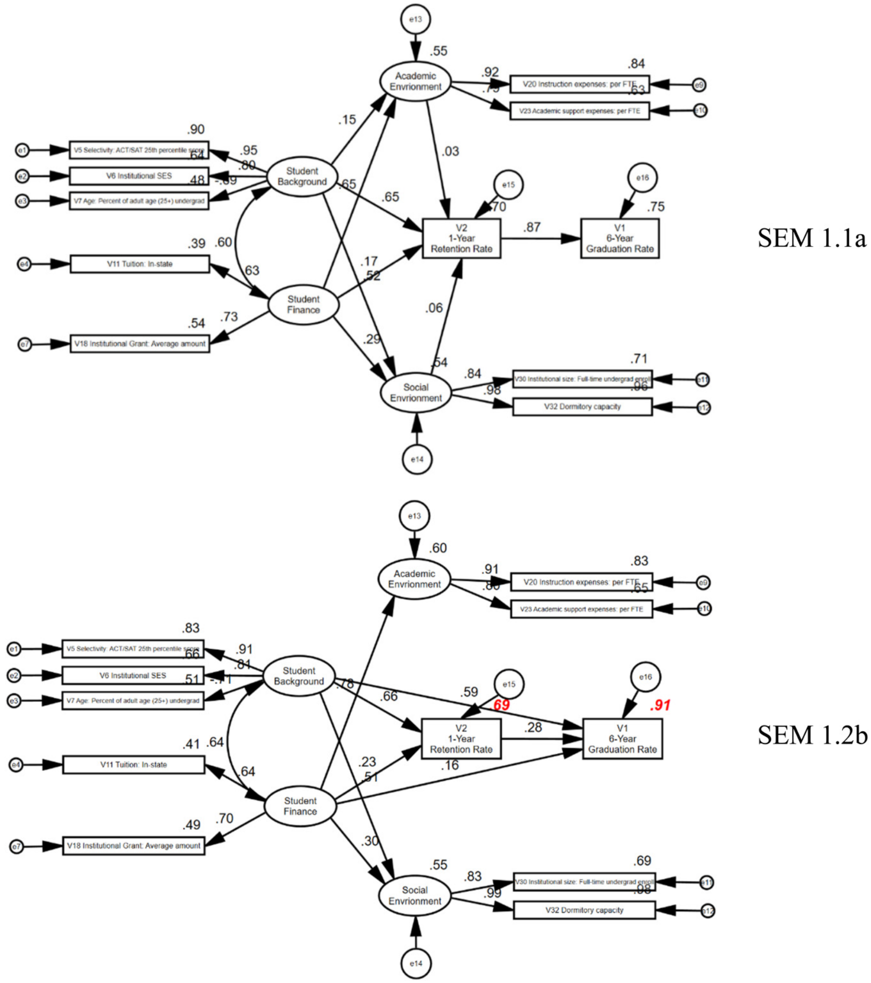

Figure 3. Stage 1 SEM models.

Note. Number on a single-headed arrow indicates the standardized factor loading of each variable. Number on a double-curved arrow indicates the intercorrelation between two latent factors (oval shape). Number on a rectangle (observed variables) indicates the squared multiple correlation of each variable, or the percent of variance in the variable explained by the factor.

in retention rate was explained by the predictors, and 91% of the variance in graduation rate was explained by the predictors.

Stage 2: The Hypothesized New Model. Based on the results of CFA 2.2, the SEM model 2.1 using Fung's same model structure was conducted (Figure 4), but the results indicated that this model was not a good fit (Table 4). Again, to revise and improve the model, four paths from each latent factor to graduation rate were added to the structural model. The results of SEM 2.2a showed that this was a better fit, but three structural paths were non-significant and then deleted. SEM 2.2b had a better model fit, χ^2 (68) = 627.41, $p < .001$; CFI = .92; NFI = .91; RMSEA = .11. All structural paths were statistically significant at $p < .001$. Figure 4 shows that 68% of the variance in retention rate was explained by the predictors, and 91% of the variance in graduation rate was explained by the predictors in SEM Model 2.2b.

Table 4 compares the model fits of the SEM models tested for Stage 1 and 2. The corresponding structural model of the best CFA model (CFA 1.2), SEM 1.2b Fung's model with added new paths to predict graduation rate, showed the best model fits to the data with the highest CFI and NFI values (CFI = .95, NFI = .94) and the RMSEA value was good at.094. The structural paths of this model were all statistically significant at $p < .01$. The best pairing of measurement model (CFA 1.2) and structural model (SEM 1.2b) further confirmed the validity and reliability of Fung's model, which was based on multiple theoretical frameworks including Tinto's (1975) model of college dropout, and Astin's (1993a) input-environment-output model.

Multiple Group Comparison Analysis

The multiple-group analysis results of CFA 1.2 indicated that the model was non-invariant across the groups of Carnegie Classification: the difference in χ^2 between the unconstrained and constrained models was statistically significant, $\Delta\chi^2$ (10) = 45.68, $p < .001$; the difference between the CFI values did not meet the recommended cutoff criterion of.01, ΔCFI = .026. Regarding the BEA Regions, the results indicated that the model was invariant across the groups of Regions: $\Delta\chi^2$ (10) = 15.03, $p = .13$; ΔCFI = .001. The multiple-group analysis results of SEM 1.2b indicated that the model was not invariant across the groups of Carnegie Classification: $\Delta\chi^2$ (48) = 464.75, $p < .001$; ΔCFI = .14. The fully constrained model could not be conducted for the BEA Regions in AMOS due to under-identification with too many groups of Region.

Discussion

The purpose of this secondary data study was to replicate, revise, and validate Fung's model of IPGR using the most recent IPEDS data. In summary, the results indicated that both the measurement model (CFA 1.2) and structural model (SEM 1.2b) revised based on Fung's original IPGR model provided the best fit to the data for all public institutions.

Conceptual Judgments Regarding Variable and Path Deletion

Both statistical and judgmental criteria of scale-purification decisions (Wieland et al., 2017) were considered to eliminate variables in the sequence of models of this study.

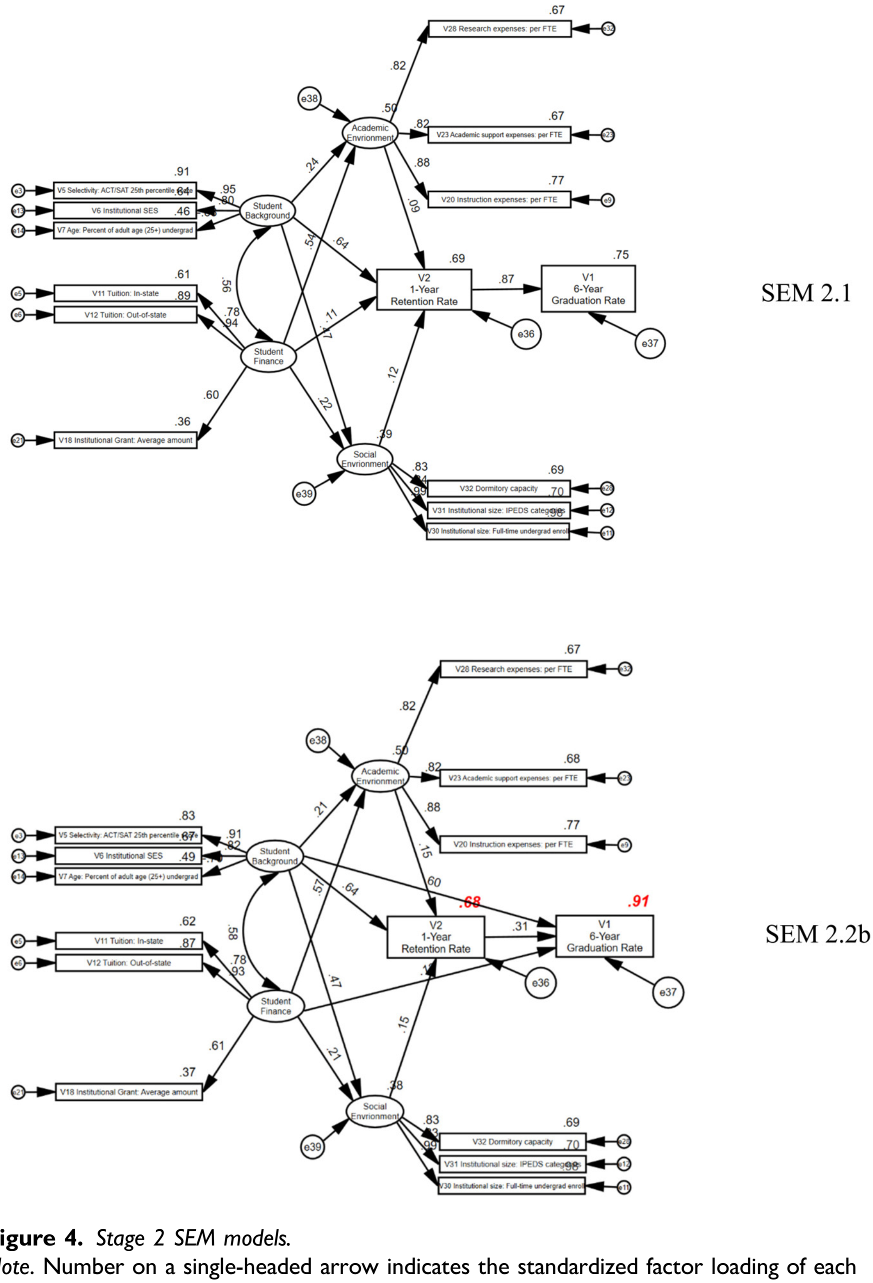

Figure 4. *Stage 2 SEM models.*
Note. Number on a single-headed arrow indicates the standardized factor loading of each variable. Number on a double-curved arrow indicates the intercorrelation between two latent factors (oval shape). Number on a rectangle (observed variables) indicates the squared multiple correlation of each variable, or the percent of variance in the variable explained by the factor.

In the Results, we discussed the statistical criteria, and in this section, we discuss the judgmental criteria.

In the measurement model CFA 1.2, *average amount of federal grant aid* (V16) was deleted because it includes both need-based and merit-based grants. Merit-based grants logically are an indication of the previous academic performance of the applicant, consistent with the definition of student *background*, whereas need-based grants are more consistent with the IPGR definition of student *finance*. *Average amount of state grant aid* (V17) was deleted because it varies widely by state due to different policies related to higher education and whether states distribute the grant aid to students directly or through the university indirectly (Kerr, 2020). After deleting these two variables, *average amount of institutional grant aid* (V18) was the only remaining variable related to financial grant aid comprising the latent variable of *student finance*. For most 4-year public institutions, more than half of institutional grant aid is merit-based, which is intended for admission yield enhancement (Baum & Payea, 2011; Hurwitz, 2012). This makes institutional grant aid unique from the other types of grant aid. Hurwitz (2012) found that there was a significant positive relationship between institutional grant aid and college choice, and the impact was greater for low-income students than high-income students. This indicates that institutional grant aid could be effectively used to attract more high-performing students from low-income families, which would positively contribute to the institution's retention rate and graduation rate as well as educational equity and diversity.

In addition, *student-to-faculty ratio* (V19) was removed from the academic environment factor in CFA 1.2 due to its low factor loading. This variable was found to be a significant indicator of academic environment in Fung's study, and other studies also found significant positive indirect effects of faculty-student ratio on graduation rate (Astin, 1993b; Goenner & Snaith, 2004; Jacoby, 2006; Shin, 2010; Walsh, 2000). The different result in our study could be related to the fast growth of technology in higher education, which makes teaching a large class more effective with asynchronous or synchronous online courses using pre-recorded videos, virtual meetings, interactive assignments, and computer-assisted grading.

In structural model SEM 1.2b, both the *Student Background* and *Finance* factors were significantly positively correlated with retention and graduation rate. Surprisingly, the factor of *Academic Environment* was not a significant predictor of retention rate and graduation rate in SEM 1.2b. According to IPEDS definitions (NCES, 2017), instruction expenses and academic support expenses are directly related to students' academic experiences (e.g., instruction, academic advising, library resources). Many previous studies found a significant positive relationship between graduation rate and instructional expenditure (Gansemer-Topf & Schuh, 2003; Scott et al., 2006; Webber & Ehrenberg, 2010), as well as academic support expenditures (Crawford, 2015; Gansemer-Topf & Schuh, 2006; Ryan, 2004). Our different results could be due to the insufficient number of observed variables that can reliably measure the factor of Academic Environment. From the conceptual perspective, the two indicators for this factor are both at the *institutional* level, which are indirectly related to students' *personal* academic experiences.

The other non-significant factor of *Social Environment*, measured by institutional size (V30) and dormitory capacity (V32), was still not a good fit to the 2011–2017 IPEDS data in the measurement model, similar to Fung's results on the 2001–2007 data. Some previous studies found that there was a negative correlation between institutional size and graduation rate because larger campus size often meant less academic and social integration (Astin, 1997; Pascarella & Terenzini, 1991; Yu, 2017). Although some studies found positive effects of student dormitory capacity on retention rate (Astin, 1997; Sheridan & Pyke, 1994), others found no evidence that dormitory residence capacity had a significant effect on student retention (Reynolds, 2020). The variable is controversial and needs more investigation in future studies.

The results of the multiple-group analysis indicated that the best fitting CFA model (CFA 1.2) was invariant across the groups of BEA Regions, indicating that the model is valid for institutions in different regions. Researchers can use the CFA model to compare institutions in different regions in the United States. However, it was non-invariant across the groups of Carnegie Classification of institutional type (doctoral, master's, baccalaureate). Doctoral institutions fit the model better than master's and baccalaureate institutions. This may reflect broad variation among universities within a geographic region, but less variation among universities with the same Carnegie Classification unit.

Practical Uses

There are several potential uses of the revised IPGR model. It provides a model for 4-year public higher education institutions to use solely IPEDS data to measure and evaluate institutional performances based on the four factors associated with graduation. The CFA model can be used to compute the latent factor scores with several observed variables to better understand their unique contributions to the construct. Moreover, the factor scores can be used for benchmark analysis to improve institutional retention and graduation rates at an early stage.

To demonstrate the possible use of the final CFA model as a tool for institutions to compare themselves to institutional peers, we selected nine institutions with similar characteristics (R1 or R2 public universities located in large or medium size cities). Table 5 presents the nine peer institutions. These institutions were compared based on their factor scores of student background, finance, academic environment, and social environment.

Figure 5 compares the four factor scores of the nine peer institutions as an example of data visualization for an evaluation study. Using Institution A as the primary institution, the bar charts show that the student background and finance factors of Institution A are at the average level, and its academic environment are more supportive among the peer institutions. However, the social environment factor is the lowest in the group.

Table 5. Selected Peer Institutions.

Institution	State	locale	Carnegie Classification	BEA Regions*
A	Colorado	City: Large	Doctoral/Research Universities--Intensive	Rocky Mountains
B	Indiana	City: Large	Doctoral/Research Universities--Intensive	Great Lakes
C	Alabama	City: Midsize	Doctoral/Research Universities--Extensive	Southeast
D	Ohio	City: Large	Doctoral/Research Universities--Extensive	Great Lakes
E	Illinois	City: Large	Doctoral/Research Universities--Extensive	Great Lakes
F	New Mexico	City: Large	Doctoral/Research Universities--Extensive	Southwest
G	Utah	City: Midsize	Doctoral/Research Universities--Extensive	Rocky Mountains
H	Virginia	City: Midsize	Doctoral/Research Universities--Extensive	Southeast
I	Michigan	City: Large	Doctoral/Research Universities--Extensive	Great Lakes

Note. *BEA Regions = Bureau of Economic Analysis Regions.

The graduation rate and retention rate of Institution A are also the lowest in the peer group. Based on the results of factor scores, the *social environment* might be the most concerning factor for Institution A. To improve the graduation and retention rates, Institution A could consider addressing the problems of its social environment or the "overall opportunities the institution can provide to help its students establish meaningful personal and communal relationship within the institution" (Fung, 2010, p. 228). It is not surprising that Institution A has the lowest *social environment* factor score due to the low full-time undergraduate enrollment and low dormitory capacity. Located in the downtown of a large city, it has a large proportion of part-time undergraduate (44%) and graduate students (54%) in its student body. Although on-campus dormitory capacity is limited and difficult to expand due to its downtown location, more off-campus dormitory facilities could be built with transportation to the campus for full-time students.

Theoretical Implications

The theories of Tinto (1975) and Astin (1991) to explain differences in retention and graduation within and across IHEs provided the conceptual basis for structuring data into the four latent variables of student background, student finance, academic environment, and social environment used in this study. Fung's original IPGR model and our updated refinement, both based entirely on institutional-level IPEDS data,

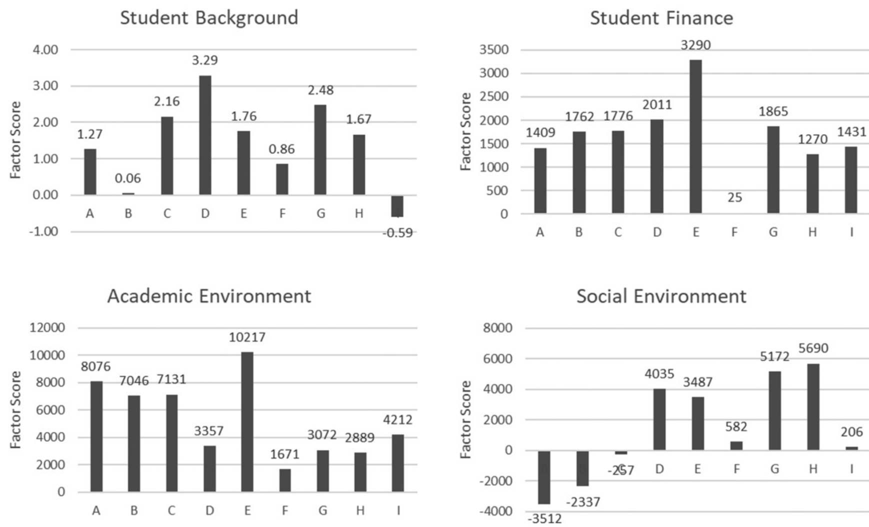

Figure 5. *Comparisons of four factor scores of institution A and peer institutions.*
Note. AMOS imputed factor scores are regression-based z-scores, a positive value of factor score indicates that this institution has a higher factor score than the population mean; and a negative factor score indicates that this institution has a lower score than the population mean ($N = 706$).

both achieved a high level of prediction using these four factors. However, the factors of student background and student finance emerged as far more predictive than academic environment or social environment. The model probably provides an exaggerated finding that what matters most is selectivity maximizing certain background characteristics of incoming students.

These findings are at odds with the common sense assumption that the quality of instruction and the quality of depth of social attachment and inclusion are related to students' decisions to persevere and complete their degrees. We argue that the "lived" or "perceived" university experience of students is logically associated with their decisions to persevere through to graduation, and these have to do with the processes that are not directly measured by IPEDS variables. Numerous studies drawing on student level data support the importance attributed to these theoretical constructs. We believe that their low salience in our results is not an indictment of the underlying conceptual model, but a reflection on the very *indirect* relationship between the amount of money an institution spends on an educational domain and the quality of the experience as perceived by students.

Limitations

There are limitations for this study. First, adding or deleting a path or a variable from a SEM model is always controversial. Although we discussed both the statistical criteria and the judgemental criteria of the scale purification methods (Churchill, 1979; Frohlich, 2002; Wieland et al., 2017) using the related studies that could support the deletion of specific variables and the addition of the new paths, the revised model still lacks an overall theoretical model/framework to confirm the whole revised model structure.

In addition, the CFA model is non-invariant for institutions of different Carnegie Classifications. This means that researchers should be cautious about using the final model for cross-group comparisons among doctoral, master's, and baccalaureate institutions.

Moreover, the selection of variables is limited to the IPEDS dataset. The main purpose of the IPEDS data is for federal grant aids and the Student Right-to-Know Act, it is not specifically designed for educational research purposes. The IPEDS data are not sufficiently direct indicators of either academic environment or social environment in the theoretical models and consequently the model likely underestimates the contribution of these conceptually important variables to both retention and graduation rates.

Recommendations for Future Research

Both the original and revised IPGR models still need to be replicated and validated with more IPEDS data. Fung's study and this study used only one cohort year's data, which could be impacted by the particular year's educational, economic, or demographic conditions. Additionally, future study is needed to further modify the variables in the measurement model and improve the overall model fit of both CFA model and SEM model. Better indicator variables are needed for the social environment and academic environment factors. Multi-level modeling based on the IPGR model is recommended if another level of data is available (e.g., student level or state level). Multi-level approach can provide a rigorous approach to comparing quality across institutions with the consideration of student level data.

Fung's (2010) IPGR model is a pioneer model and a "beginning of a new line of research" (p. 241). Given that IPEDS is the most comprehensive and the only publicly available national higher education database, valid and reliable models to measure and predict institutional performance based on it will continue to be valuable to higher education researchers and practitioners.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Chen Zong https://orcid.org/0000-0003-4743-2372

References

ACT. (2009). *ACT-SAT concordance tables*. http://www.act.org/content/dam/act/unsecured/documents/ACTCollegeBoardJointStatement.pdf

Anstine, J., & Seidman, M. (2017). Graduation rates at colleges and universities in the Midwest. *Business Education & Accreditation*, *9*(1), 43–54.

Astin, A. W. (1991). *Assessment for excellence*. Macmillan.

Astin, A. W. (1997). How "good" is your institution's retention rate? *Research in Higher Education*, *38*(6), 647–658. https://doi.org/10.1023/A:1024903702810

Astin, A. W. (1993a). *Assessment for excellence: The philosophy and practice of assessment and evaluation in higher education*. Oryx Press.

Astin, A. W. (1993b). *What matters in college? Four critical years revisited*. Jossey-Bass.

Baum, S., & Payea, K. (2011). *Trends in student aid 2011*. College Board Advocacy & Policy Center. https://files.eric.ed.gov/fulltext/ED526356.pdf

Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research*, *21*(2), 230–258. https://doi.org/10.1177/0049124192021002005

Byrne, B. M. (2016). *Structural equation modeling with Amos* (3rd ed.). Routledge.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling*, *9*(2), 233–255. https://doi.org/10.1207/S15328007SEM0902_5

Churchill, G. A.Jr (1979). A paradigm for developing better measures of marketing constructs. *Journal of Marketing Research*, *16*(1), 64–73. https://doi.org/10.1177/002224377901600110

Crawford, G. A. (2015). The academic library and student retention and graduation: An exploratory study. *Libraries and the Academy*, *15*(1), 41–57. https://doi.org/10.1353/pla.2015.0003

Frohlich, M. T. (2002). E-integration in the supply chain: Barriers and performance. *Decision Sciences*, *33*(4), 537–556. https://doi.org/10.1111/j.1540-5915.2002.tb01655.x

Fung, T. Y. H. (2010). *Analysis of graduation rates for four-year colleges: A model of institutional performance using IPEDS* [Doctoral dissertation, University of North Texas]. ProQuest Dissertations and Theses Global.

Gansemer-Topf, A. M., & Schuh, J. H. (2003). Instruction and academic support expenditures: An investment in retention and graduation. *Journal of College Student Retention: Research, Theory & Practice*, *5*(2), 135–145. https://doi.org/10.2190/LX9Y-3R2A-EV4T-TFXP

Gansemer-Topf, A. M., & Schuh, J. H. (2006). Institutional selectivity and institutional expenditures: Examining organizational factors that contribute to retention and graduation. *Research in Higher Education*, *47*(6), 613–642. https://doi.org/10.1007/s11162-006-9009-4

Goenner, C. F., & Snaith, S. M. (2004). Predicting graduation rates: An analysis of student and institutional factors at doctoral universities. *Journal of College Student Retention: Research, Theory & Practice*, *5*(4), 409–420. https://doi.org/10.2190/LKJX-CL3H-1AJ5-WVPE

Harrison, J. K. (2016). Predicting graduation rates at non-residential research universities [Doctoral dissertation, Florida Atlantic University]. FAU Research Repository. http://fau.digital.flvc.org/islandora/object/fau%3A33462/datastream/OBJ/download/Predicting_Graduation_Rates_at_Non-Residential_Research_Universities.pdf

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Hurwitz, M. (2012). The impact of institutional grant aid on college choice. *Educational Evaluation and Policy Analysis*, *34*(3), 344–363. https://doi.org/10.3102/0162373712448957

Jacoby, D. (2006). Effects of part-time faculty employment on community college graduation rates. *Journal of Higher Education*, *77*(6), 1081–1103. https://doi.org/10.1353/jhe.2006.0050

Kerr, E. (2020, November 9). State financial aid for college: What to know. *U.S. News*. https://www.usnews.com/education/best-colleges/paying-for-college/articles/state-financial-aid-for-college-what-to-know

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, *1*(2), 130–149. https://doi.org/10.1037/1082-989X.1.2.130

National Center for Education Statistics. (2017). *Integrated postsecondary education data system (IPEDS)*. https://nces.ed.gov/statprog/handbook/pdf/ipeds.pdf

Pascarella, E. T., & Chapman, D. W. (1983). A multi-institutional, path analytic validation of Tinto's model of college withdrawal. *American Educational Research Journal*, *20*(1), 87–102. https://doi.org/10.3102/00028312020001087

Pascarella, E. T., & Terenzini, P. T. (1991). *How college affects students: Findings and insights from twenty years of research*. Jossey-Bass Publishers.

Pike, G., Smart, J., Kuh, G., & Hayek, J. (2006). Educational expenditures and student engagement: When does money matter? *Research in Higher Education*, *47*(7), 847–872. https://doi.org/10.1007/s11162-006-9018-3

Price, D. V., & Tovar, E. (2014). Student engagement and institutional graduation rates: Identifying high-impact educational practices for community colleges. *Community College Journal of Research and Practice*, *38*(9), 766–782. https://doi.org/10.1080/10668926.2012.719481

Reynolds, C. L. (2020). The effect of dormitory residence during college on student outcomes. *Journal of Human Capital*, *14*(2), 249–289. https://doi.org/10.1086/709534

Ryan, J. F. (2004). The relationship between institutional expenditures and degree attainment at baccalaureate colleges. *Research in Higher Education*, *45*(2), 97–114. https://doi.org/10.1023/B:RIHE.0000015691.02545.61

Schumacker, R. E., & Lomax, R. G. (2016). *A beginner's guide to structural equation modeling* (4th ed.). Routledge.

Scott, M., Bailey, T., & Kienzl, G. (2006). Relative success? Determinants of college graduation rates in public and private colleges in the U.S. *Research in Higher Education*, *47*(3), 249–279. https://doi.org/10.1007/s11162-005-9388-y

Seaman, J. E., Allen, I. E., & Seaman, J. (2018). *Grade increase: Tracking distance education in the United States*. Babson Survey Research Group. https://files.eric.ed.gov/fulltext/ED580852.pdf

Sheridan, P. M., & Pyke, S. W. (1994). Predictors of time to completion of graduate degrees. *Canadian Journal of Higher Education*, *24*(2), 68–88. https://doi.org/10.47678/cjhe.v24i2.188439

Shin, J. C. (2010). Impacts of performance-based accountability on institutional performance in the U.S. *Higher Education*, *60*(1), 47–68. https://doi.org/10.1007/s10734-009-9285-y

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research*, *45*(1), 89–125. https://doi.org/10.3102/00346543045001089

Waller, L., & Tietjen-Smith, T. (2009). A national study of community college retention rates segmented by institutional degree of urbanization. *Academic Leadership: The Online Journal*, *7*(1), 4.

Waller, L., Weeks, S., Westbrook, S., & Payton, K. (2009). Equal access: A national comparison of federal grants-in-aid awarded at public and private four-year degree granting institutions. *Academic Leadership Journal*, *7*(4), 13.

Walsh, T. A. (2000, May 21–23). Identifying peer institutions for graduation rate comparisons [Paper presentation]. Association for Institutional Research 40th Annual Forum, Cincinnati, OH, United States. https://files.eric.ed.gov/fulltext/ED445646.pdf

Webber, D. A., & Ehrenberg, R. G. (2010). Do expenditures other than instructional expenditures affect graduation and persistence rates in American higher education? *Economics of Education Review*, *29*(6), 947–958. https://doi.org/10.1016/j.econedurev.2010.04.006

Wieland, A., Durach, C. F., Kembro, J., & Treiblmaier, H. (2017). Statistical and judgmental criteria for scale purification. *Supply Chain Management: An International Journal*, *22*(4), 321–328. https://doi.org/10.1108/SCM-07-2016-0230

Youmans, C. B. (2017). *The effect of tuition on graduation rate at community colleges* [Doctoral dissertation, Old Dominion University]. ODU Digital Commons. https://digitalcommons.odu.edu/cgi/viewcontent.cgi?article=1049&context=efl_etds

Yu, H. (2015). Student retention at two-year community colleges: A structural equation modeling approach. *International Journal of Continuing Education and Lifelong Learning*, *8*(1), 85–101.

Yu, H. (2017). Factors associated with student academic achievement at community colleges. *Journal of College Student Retention: Research, Theory & Practice*, *19*(2), 224–239. https://doi.org/10.1177/1521025115612484

Zong, C. (2021). *Validating and developing the structural equation model of institutional performance in graduation rate using IPEDS (Publication No. 28419347)* [Doctoral dissertation, University of Colorado Denver]. ProQuest Dissertations and Theses Global.

Author Biographies

Chen Zong, PhD, is an Institutional Research Analyst at the University of Wyoming. Her research interests include student and faculty retention in higher education, educational and psychological measurement, and large-scale data analysis for education.

Alan Davis, PhD, is a professor of Research and Evaluation Methodology at the University of Colorado Denver. His current research focuses on equity issues in higher education, including reforming introductory undergraduate STEM courses and fostering social belonging in online courses.