The Best Three Years of Your Life: A Prediction of Three-Year Graduation with Diagnostic Classification Model

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Abstract

The 3-year graduation rate is a rarely measured metric in higher education compared to its 4- or 6- year graduation rate counterparts. For the first time in college (FTIC) students to graduate in three years, they must come with certain skills, abilities, plans, supports, or motivations. This project considers two distinct but interrelated ways of using advanced and novel statistical models, the Log-linear Cognitive Diagnostic Model (LCDM) and the Logistic Regression model (LR), to look at both students' ability to graduate in three years and the characteristics that contribute to this ability. The results indicate that the LCDM is a reliable and efficient statistical model which can provide accurate prediction of students' ability to graduate early. In addition, student enrolled credit hours in the semester, transfer credit hours, student high school GPA, and student socioeconomic status (EFC) were statistically significant predictors contributing to three-year graduation. The significant interaction between students' EFC status and transfer credit hours has a meaningfully practical impact on enrollment strategies and institutional policies. Future studies could use the same LCDM model to consider the degree to which these or other characteristics contribute to 4-, 5-, and 6-year graduation rates. Identification of these characteristics could have policy, student support, and admissions implications. Additionally, the success of the LCDM model in predicting ability could be used for predicting abilities unrelated to graduation, including the ability to pay off loans, succeed in an internship, or give back financially to a university.

Keywords: three-year graduation, Log-linear Cognitive Diagnostic Model, logistic regression model, classification, prediction

1. Introduction

In the field of collegiate metrics, student graduation rates matter. Moving past a monolithic (and perhaps antiquated) 4-year graduation rate, universities are looking at 6-year graduation rates to determine institutional ability to meet expectations of "normal" matriculation. Graduation rates are considered for value of degree, competency of program, advising, and overall program health. Moreover, graduation rates reflect the health of the overall institution and their collective ability to serve students. While 4- and 6- year graduation rates are most common as they are required for some discipline-level accreditors and for external surveys and reports, 3-year graduation rates are less examined. For first time in college (FTIC) students to graduate in three years, they must come with certain identifiable factors, tactics, supports, or motivations.

The purpose of this study was to considers two distinct but interrelated ways of using advanced and novel statistical models, the Log-linear Cognitive Diagnostic Model (LCDM) and the Logistic Regression Model (LR), to look at both students' ability to graduate in three years and the characteristics that contribute to this ability.

2. Literature Review

The national 6-year graduation rate for students starting an undergraduate degree in 2011 and finishing at the same institution was 60%. Specifically, the 6-year graduation rate was 60% at public institutions, 66% at private non-profit institutions, and 21% at private-for profit institutions (NCES, 2019). For 4-year graduation rates, the numbers drop significantly. Overall, the 4-year graduation rate was only 42% for the same 2011 cohort. Trends in rates for 4-year graduation mirrored that of 6-year graduation; 37% of students at public institutions, 54% of students at private nonprofit institutions, and only 15% of students at private for-profit institutions graduated within 4 years (NCES, 2018). Less attention has been paid to 3-year graduation rates as they are not required by most reporting bodies.

Invariably, research conversations regarding graduation rate revolve around demographic factors like race (Tracey & Sedlacek, 2018), gender, and (dis)ability (Pingry O'Neill, Markward, & French, 2012). Extended conversations consider environment and support structures available to students as they measure persistence and retention. While it stands to reason that some characteristics may more clearly contribute to quicker matriculation and completion (transfer hours, average hours taken each semester, etc.), little research has examined the degree to which these factors influence graduation rate.

Available information on 3-year graduation rates usually involves student advice on how to graduate early (Clark, 2017; Alexander, 2009) or commentary on why more 3-year opportunities should be offered (Fant, 2009). For the student, the benefits of graduating in three years include financial reprieve and time to either take a "gap year" or start a career earlier than their peers. For the university or college, 3-year graduates give both hope and insight to administrators who wish to curb the national trend of a lengthening college stay.

In addition to tracking graduation, researchers are becoming more and more interested in crafting predictive models that help identify students with early or on-time graduation potential and students who may need more time or are unlikely to graduate at all. Identifying these students in the application process can help recruit a strong incoming class, and identifying these students who have already enrolled help administrators target policies and practices that encourage early or on-time graduation.

Two statistic models are proposed to study the 3-year graduation: The Log-linear Cognitive Diagnostic Model (LCDM) and the Logistic Regression Model (LR).

The LCDM model has been widely applied to estimate examinees' mastery status of abilities on large-scale assessment (George & Robitzsch, 2014; Lee & Sawaki, 2009; Ravand, 2016; Sedat & Arican, 2015). Some studies have also successfully demonstrated the utility of LCDM in test development (Bradshaw, Izsák, Templin, & Jacobson, 2014). Though the LCDM model can be used to predict a subject's latent ability to meet a desired goal, the LCDM has not been introduced into or used in higher education. The LCDM model is designed to classify categorical latent factors (Rupp, Templin, & Henson, 2010) and consider how the same set of factors may contribute to ability as replicated into multiple combinations. Applying the LCDM to student latent abilities in higher education is an appropriate and heretofore unconsidered predictive breakthrough. The LCDM brings significant insight for faculty and administrators who wish to understand students' math, verbal, or research abilities and provides critical support for respective stakeholders to make strategic decisions based on a study of students' ability to graduate in 3 years, 4 years, or 6 years.

In contrast to LCDM, the LR model has been widely used in higher education to predict various categorical outcomes, such as student retention, 4-year graduation, 6-year graduation, mental health, and language learning, among others (Peng, So, Stage, & John, 2002; Cabrera, 1994; Peng, Lee, & Ingersoll, 2002; Larsen & Merlo, 2005). It is a traditional statistical technique that has been used frequently to investigate the impact of predictors on categorical outcomes.

The purpose of this study is to help stakeholders understand college students' abilities to graduate early and to explore contributing factors' impacts on this ability. Specifically, the application of the LCDM model opens news doors for research as it can be applied across several dimensions of higher education research. The second study contributes significantly to administrators' abilities to identify factors that may contribute to early graduation.

3. Methods

In an effort to best understand the characteristics that may influence the ability of students to graduate early, two simulation studies were conducted to predict if current undergraduate students can graduate in three years and to explore what factors contribute to students' early graduation.

3.1 Study 1

Study 1 focuses on utilizing the Log-linear Cognitive Diagnostic Model (LCDM) to classify students into two categories: students with sufficient ability to graduate in three years (1) or students with insufficient ability to graduate in three years (0).

3.1.1 Log-linear Cognitive Diagnostic Model (LCDM)

The LCDM model is a measurement model that evaluates students' mastery status based on a set of categorical latent attributes and items (Rupp, Templin, & Henson, 2010). It provides multidimensional diagnostic information to support educators' decision making. Similar to the Latent Class Analysis (LCA), LCDM utilizes the discrete latent variables and item responses to classify students into different latent classes (Goodman, 1974; Lazarsfeld & Henry, 1968). In this study, only dichotomous latent factors and item responses are included.

Let $\boldsymbol{i} = (1, \ldots, I)$ denotes numbers of items, $\boldsymbol{x}_i = (x_1, \ldots, x_I)$ denotes the item responses of items, $\boldsymbol{r} = (1, \ldots, R)$ denote numbers of students, and $\boldsymbol{\alpha}_r = (\alpha_1, \ldots, \alpha_R)$ denote a categorical latent attribute for one student. Equation 1 estimates the probability of a student r identifying "sufficient ability" on an item i given one's latent attribute α_r.

$$\pi_{ri} = P(x_{ri} = 1|\alpha_r) = \frac{exp(\lambda_{i,0} + \lambda_{i,1}\alpha_r)}{1 + exp(\lambda_{i,0} + \lambda_{i,1}\alpha_r)} \qquad \text{Equation 1}$$

$\lambda_{i,0}$ is the intercept loading, representing the log of odds that a student identifies "sufficient ability" on an item by guessing. $\lambda_{i,1}$ is the main effect, representing the log of odds for a student who has sufficient ability to graduate in three years (Bradshaw & Madison, 2016).

3.1.2 Data Simulation

10 binary items and 1000 students' responses were simulated with 100 replications in R, version 3.6.3 (R Core Team, 2019) based on the LCDM in the study 1. Two stages of data generation were developed:

(1) The probability of having sufficient ability to graduate in three years for the latent attribute was set to 0.4 in the study for purpose of the research.

$$P(\alpha_r = 1|x_r) = 0.4 \qquad \text{Equation 2}$$

(2) The item responses were generated from the linear predictors of the probability of having sufficient ability to graduate in three years. An intercept and a slope parameter were simulated from a normal distribution to form the linear predictors.

$$\lambda_{i,0} \sim N(-1.5, 0.1)$$
$$\lambda_{i,1} \sim N(1.5, 0.1) \qquad \text{Equation 3}$$

A $1000\ x\ 10$ data structure was generated for further classification analysis.

3.1.3 Analysis

A Maximum Likelihood (ML) algorithm was used to estimate model parameters in *Mplus*, 6th Edition (Muthen, Muthen, 1998 – 2011). Intercepts, slopes, and the probability of latent attribute were estimated in the LCDM model. The classification accuracy was estimated by the bias of the estimated probability of latent attribute. The bias of the estimated probability of attribute was the difference between the estimated and the simulated "true" probability of having "sufficient ability" on the latent attribute. The estimated classification rate was obtained by applying 0.4 as the cutoff point. A student with an estimated probability larger than 0.4 would be classified into "sufficient ability to graduate in three years" group, vice versa.

$$Bias = \frac{\sum\left(P^{est}(\alpha_r = 1|x_r) - P^{true}(\alpha_r = 1|x_r)\right)}{Replications} \qquad \text{Equation 4}$$

3.2 Study 2

Once each student was classified into two groups (with sufficient ability to graduate in three years or with insufficient ability to graduate in three years) based on their item responses and latent attribute, study 2 focuses on exploring student-level factors that contribute to three-year graduation.

3.2.1 Logistic Regression (LR)

Logistic regression modeling was used in study 2 to explore the relationships between student-level predictors (enrolled term credit hours, high school GPA, transfer credit hours, Pell amount, and expected family contribution or EFC) and the classification on three-year graduation. LR is a traditional generalized linear model used to predict binary or categorical outcomes.

Let $\boldsymbol{p} = (0, \ldots, P)$ be a number of parameters, $\boldsymbol{\beta}_p = (\beta_0, \beta_1 \ldots, \beta_P)$ be the coefficient parameters, and $\boldsymbol{X} = (X_{CH}, \ldots, X_{EFC})$ be a set of predictors: enrolled term credit hours (X_{CH}), high school GPA (X_{GPA}), transfer credit hours(X_{TCH}), Pell amount (X_{PELL}), and expected family contribution (X_{EFC}). Equation 5 estimates the probability of a student r being classified in the "sufficient ability to graduate in three years" given predictors in the main effect model.

$$P(\alpha_r = 1|\boldsymbol{X}) = \frac{exp(\beta_0 + \beta_1 X_{CH} + \beta_2 X_{GPA} + \beta_3 X_{TCH} + \beta_4 X_{PELL} + \beta_5 X_{EFC})}{1 + exp(\beta_0 + \beta_1 X_{CH} + \beta_2 X_{GPA} + \beta_3 X_{TCH} + \beta_4 X_{PELL} + \beta_5 X_{EFC})} \quad \text{Equation 5}$$

Equation 6 estimates the probability of a student r being classified in the "sufficient ability to graduate in three years" given predictors in the interaction model.

$$P(\alpha_r = 1|\boldsymbol{X}) = \frac{exp\begin{pmatrix} \beta_0 + \beta_1 X_{CH} + \beta_2 X_{GPA} + \beta_3 X_{TCH} + \\ \beta_4 X_{PELL} + \beta_5 X_{EFC} + \beta_6 X_{CH} * X_{EFC} + \\ \beta_7 X_{GPA} X_{EFC} + \beta_8 X_{TCH} * X_{EFC} + \\ \beta_9 X_{PELL} * X_{EFC} \end{pmatrix}}{1 + exp\begin{pmatrix} \beta_0 + \beta_1 X_{CH} + \beta_2 X_{GPA} + \beta_3 X_{TCH} + \\ \beta_4 X_{PELL} + \beta_5 X_{EFC} + \beta_6 X_{CH} * X_{EFC} + \\ \beta_7 X_{GPA} X_{EFC} + \beta_8 X_{TCH} * X_{EFC} + \\ \beta_9 X_{PELL} * X_{EFC} \end{pmatrix}} \quad \text{Equation 6}$$

β_0 is the intercept, representing the base probability of a student being classified into "sufficient ability" group without any predictions. β_1, β_2, β_3, β_4, and β_5 are partial regression coefficients of each predictor, respectively, measuring the expected changing in the probability of classification by a unit change in one predictor while holding other predictors constant. β_6, β_7, β_8, and β_9 are interaction effects. For example, β_6 measures the effect of students' enrolled credit hours on the classification of three-year graduation is different for different values of students' EFC status.

3.2.2 Data simulation

Enrolled term credit hours, high school GPA, transfer credit hours, Pell amount, and EFC were simulated in R, version 3.6.3 (R Core Team, 2019) based on real undergraduate students' data at private research university. A $1000\ x\ 5$ data structure was simulated for later LR analysis.

$$X_{CH} \sim N(15, 1.5),\ X_{GPA} \sim N(3.00, 0.6),\ X_{TCH} \sim N(10, 4)$$
$$X_{PELL} \sim N(4410, 500),\ X_{EFC} \sim rbinom(1000, 1, 0.35) \quad \text{Equation 7}$$

3.2.3 Analysis

A Maximum Likelihood (ML) algorithm was adopted to estimate parameters in LR, which was implemented in the R, version 3.6.3, by using the glm function in the stats package (R Core Team, 2019). The logits of intercept, partial regression coefficients, and interaction coefficients were estimated in the LR model. The goodness of model fit was conducted by the Likelihood Ratio Test (LRT). The LRT compares the likelihood of the null model, the model with only an intercept, against the likelihood of the main effect model, the model with predictors, and the likelihood of the interaction model, the model with main effects and interactions between predictors. A significant p-value ($p < .05$) represents the model with more parameters has a better model fit than the null model. In addition, a lower Akaike Information Criterion (AIC), residual variance, and a higher Pseudo R squares also indicated a better model fit. The statistical significance of each coefficient in the Wald test evaluated if a predictor needs to be included in the model.

4. Results

4.1 Study 1

4.1.1 Classification Accuracy

Parameters in the LCDM were converged under the ML estimation ($LogLikelihood^{change} < 0.000001$). The average estimated probability of being identified as "sufficient ability to graduate in three years" was 0.381 across 100 replications. The bias of the classification accuracy of latent attribute was 0.01, meaning that the probability of identifying a student as "sufficient ability" when the one was not is 0.01. The small bias suggested a high classification accuracy given latent attribute and item responses. Table 1 shown an example of students' classification based on the estimated probability of being identified as "sufficient ability" on the latent attribute.

Table 1. Classification of students' ability to graduate in three years.

Probability of not graduating in three years $P(\alpha_r = 0 \mid x_r)$	*Probability of graduating in three Years* $P(\alpha_r = 1 \mid x_r)$	*Student Classification*
0.6611	0.3388	1
0.8697	0.1303	1
0.9934	0.0065	1
0.0402	0.9597	2
0.9738	0.0261	1
0.1032	0.8967	2
0.3485	0.6514	2

4.2 Study 2

4.2.1 Descriptive

A total of 1000 simulated students were included in study 2. 619 students were coded as insufficient ability (0) and 381 students were coded as sufficient ability (1) in the outcome variable. Table 2 shown descriptive of simulated predictors in study 2.

Table 2. A summary table of predictors.

Predictors	*Minimum*	*Median*	*Mean*	*Max*
Enrolled Term Credits	1	15	15.2	22
High School GPA	0	3.3	3.26	4
Transfer Credits Hours	1	9	12	30
Pell Amount	$ 17	$5,500	$4,410	$5,775
EFC	EFC Zero (0)	EFC Non-Zero (1)		
	350	650		

The continuous predictors were centered at the mean in the LR analysis so that 0 stands for the mean of the predictor.

4.2.2 Regression coefficient

Three LR models were developed in the analysis: null model, main effect model, and interaction model. AIC, residual variances, and Likelihood Ratio Test (LRT) were conducted to evaluate the model fit. The results were reported based on the final model that was selected from the model fit indices.

Null model

The null model was only predicted by the intercept, representing the expected odds of classification without any predictors ($AIC = 564$; $\varepsilon^2 = 562$). As shown in Table 3, the expected odds for students who were truly with sufficient ability to graduate in three years to be classified into the "sufficient ability" group without any predictors was 0.006.

Table 3. Parameter estimations in the null LR model.

Parameters	*Logit*	*Odds*	*p*
β_0	-5.11	0.006	***

Main effect model

The main effect model was predicted by an intercept and five predictors ($AIC = 355$; $\varepsilon^2 = 343$). Five predictors contributed 38% variances to classification accuracy ($Psudo\ R^2 = 0.38, df = 5$). Of the five independent predictors in the Equation 5, three predictors indicated statistically significant relationships to the prediction of classifications as shown in Table 4.

Table 4. Parameter estimations in the main effect LR model

Parameters	*Logit*	*Odds*	*p*
β_0	-5.56	0.03	***
β_1	0.39	1.47	***
β_2	1.33	3.78	**
β_3	0.09	1.09	***
β_4	0.00	1	0.43
β_5	-0.55	0.57	0.1

* $p < 0.5$, ** $p < 0.01$, *** $p < .001$

The expected odds to graduate in three years with sufficient ability increased 1.47 for every 1 credit hour increased in students' enrolled term credit hours, when holding other predictors constant. Likewise, the expected odds to graduate in three years with sufficient ability increased 3.78 for every 1 unit increased in high school GPA, when holding other predictors constant. In addition, the expected odds to graduate in three years with sufficient ability increased 1.09 for every 1 credit hour increased in transfer credit hours, when holding other predictors constant. The Pell grant amount and EFC did not significantly affect students' classification on graduation ability in the main effect model.

Interaction model

The interaction model was predicted by an intercept, five main effects, and four interaction effects ($AIC = 356$; $\varepsilon^2 = 336$) as Equation 6. Interaction effect contributed additional 2% variance on the classification accuracy ($Psudo\ R^2 = 0.02, df = 10$). The effect of students' transfer credit hours on the classification of three-year graduation was different depends on students' EFC status ($Odds_{\beta_8} = 1.04, p <\ .05$). For every 1 unit increased on students' transfer credit hours, the odds to graduate in three years with sufficient ability for EFC zero students was 0.57, and the odds for EFC non-zero students was 1.04 higher than EFC zero students.

Table 5. Parameter estimations in the interaction effect LR model

Parameters	*Logit*	*Odds*	*p*
β_0	-5.51	0.003	***
β_1	0.42	1.47	***
β_2	1.53	3.78	**
β_3	0.08	1.09	***
β_4	0.00	1	0.43
β_5	-0.66	0.57	0.1
β_6	-0.05	0.95	0.79
β_7	-0.39	0.67	0.70
β_8	0.04	1.04	*
β_9	0.00	1	0.37

* $p < 0.5$, ** $p < 0.01$, *** $p < .001$

The interaction model was not statistically better fitted data than the main effect model in the LRT analysis ($\chi^2 = 1.702, p > 0.05$); however, the interaction model had a lower AIC and residual errors, the statistically significant main effects and interaction effects were kept in the final model for the reporting purpose.

Final model

The final LR model has a $AIC = 350$ and residual errors $\varepsilon^2 = 328$ as 8.

$$P(\alpha_r = 1|\boldsymbol{X}) = \frac{exp\begin{pmatrix}\beta_0 + \beta_1 X_{CH} + \beta_2 X_{GPA} + \beta_3 X_{TCH} + \\ \beta_4 X_{EFC} + \beta_5 X_{TCH} * X_{EFC}\end{pmatrix}}{1 + exp\begin{pmatrix}\beta_0 + \beta_1 X_{CH} + \beta_2 X_{GPA} + \beta_3 X_{TCH} + \\ \beta_4 X_{EFC} + \beta_5 X_{TCH} * X_{EFC}\end{pmatrix}} \qquad \text{Equation 8}$$

As shown in the Wald test in Table 6, the expected odds for students who were truly with sufficient ability to graduate in three years to be classified into the "sufficient ability" group on the outcome (three-year graduation) without any predictors was 0.005. The main effect and interaction effect together contributed to a 40% higher classification accuracy beyond and above the null model $(Psudo\ R^2 = 0.40, df = 6)$.

Table 6. Parameter estimations in the final LR model

Parameters	*Logit*	*Odds*	*p*
β_0	-5.16	0.005	***
β_1	0.40	1.49	***
β_2	1.39	4.00	**
β_3	0.08	1.08	***
β_4	-1.32	0.26	*
β_5	0.04	1.04	*

* $p < 0.5$, ** $p < 0.01$, *** $p < .001$

For every 1 credit hour increased in the students' term enrolled credit hours, the odds for students to be classified into the "sufficient ability" group to graduate in three years increased 1.49. In addition, for every 1 unit increased in students' high school GPA, the odds for students to be classified into the "sufficient ability" group increased 4. Moreover, for every 1 credit hour increased in the students' transfer credit hours, the odds for EFC zero students to be classified into the "sufficient ability" group to graduate in three years was 0.26, the odds for EFC non-zero students to be classified into the "sufficient ability" group to graduate in three years was 1.04 higher than the EFC zero students, which was 1.30.

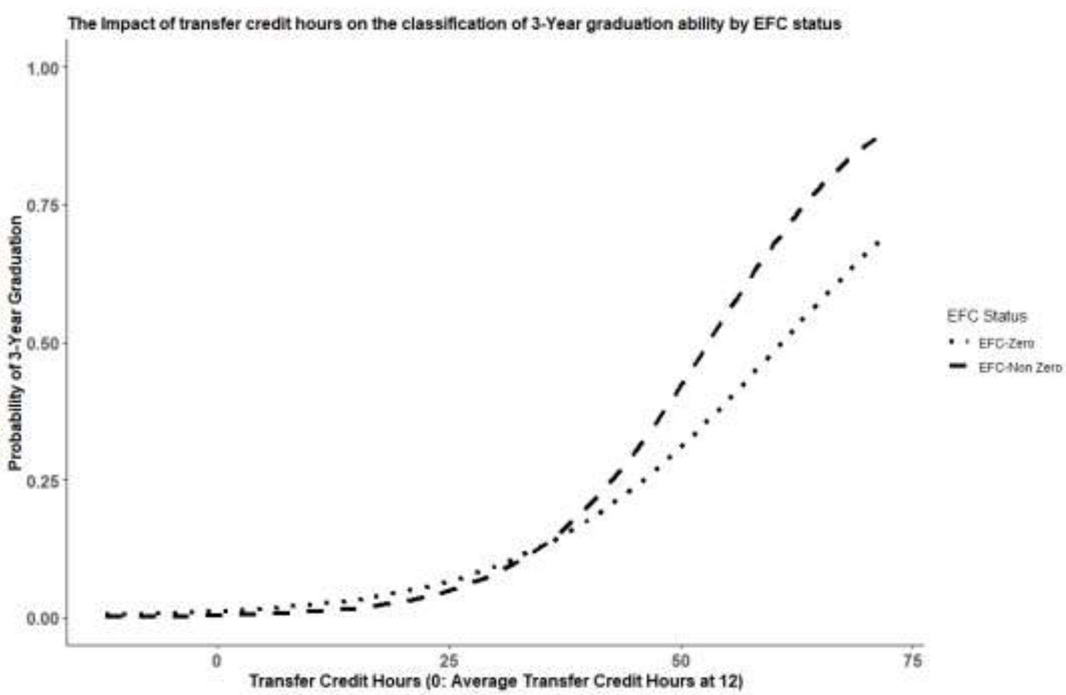

Figure 1. Interaction between EFC status and Transfer Credit Hours.

5. Conclusion and Implications

In summary, the LCDM is a reliable statistical technique that accurately classifies students' abilities of early graduation in the first study. The prediction of student latent ability was closely matched with the generated data. In the second study, the LR model indicated that student semester-enrolled credit hours, transfer credit hours, student high school GPA, and student socioeconomics (EFC status) were statistically significant predictors contributing to three-year graduation at the researched university. Particularly, the significant interaction between students' EFC status and transfer credit hours could have a meaningful practical impact on a variety of topics in higher education, such as admission strategies, budget plan, and financial aid applications.

As universities nation-wide seek ways to improve their 6- and 4-year graduation rates, identifying factors that help predict 3-year graduation can be a silver bullet. While some factors (high school GPA and Pell amount) did not significantly affect the 3-year graduation rate, others (credits taken per semester, credits transferred, and EFC) had a significant and actionable effect. As Chief Academic Officers and Presidents consider ways to increase the number of students who graduate in 3, 4, 5, and 6 years or less, they would be wise to consider ways to recruit students who come with transfer hours. Though it makes sense that those who come in with more hours are more likely to graduate earlier, it is important to understand that the number of hours matters. Each hour increase is an increase in the likelihood of early graduation. Universities also should consider encouraging students who are properly supported to take more than 12 hours a semester. Flat rate tuition at many colleges incentivizes addition hours as all students pay a fixed tuition amount regardless of hours taken. Responsibly introduced, this kind of policy could help students increase average hours per semester. Finally, financial-aid-blind admissions policies may need to consider the role that an EFC greater than 0 may have on students' abilities to matriculate and graduate on time or early.

Additionally, the successful application of the LCDM model to latent factors that contribute to students' ability to graduate in three years suggests a wide variety of new applications. LCDM may be used to give insight into a number of questions both faculty and administrators have about student success across multiple metrics but also faculty abilities to publish, successfully navigate tenure, or receive grants. There are no limits to what the LCDM model could be used for across campuses.

6. Discussions

This study has successfully applied the LCDM model to the assessment of three-year graduation in higher education. Three-year graduation rates are a rarely cited statistic in current higher education literature compared to 4- and 6-year graduation rates. Identifying students' early-graduation ability as well as factors that potentially impact on this ability provide meaningful insights for top administrative and practitioners to discuss how it may affect enrollment strategies, financial budgets, and institutional policy adjustments. There are several advantages of using the LCDM model and LR model in this study. First, previous studies rarely focused on categorizing students' latent ability. Unlike the traditional factor analysis, the LCDM model provided each student a classification of their graduation ability, showing deeper qualitative information to support quantitative information. Second, the LCDM model had a highly accurate classification rate. A low bias rate of the LCDM model validated the inferences drawn from the student classification. Third, the combination of the LCDM model and LR model in this study improved the accessibility and usefulness of applying psychometrical models to address higher educational topics for future researchers and practitioners.

This study is limited within the simulation scope. Future studies could use the same LCDM model to consider the degree to which the same or other characteristics contribute to 4-, 5-, and 6-year graduation rates with the empirical data. Identification of these characteristics could have policy, student support, and admissions implications. As the value of a degree continues to be questioned and evaluated from different angles, administrators must make lasting changes that increase graduation rates and decrease time to graduation.

Finally, the power of LCDM has been well documented in other fields but now can be applied to additional areas of interest in higher education. Understanding what students, faculty, and programs have the ability to meet goals based on a collection of factors can be a tremendous leap forward for both predictive research in education and policy production.

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