



JMU ISSAQ Validity Results

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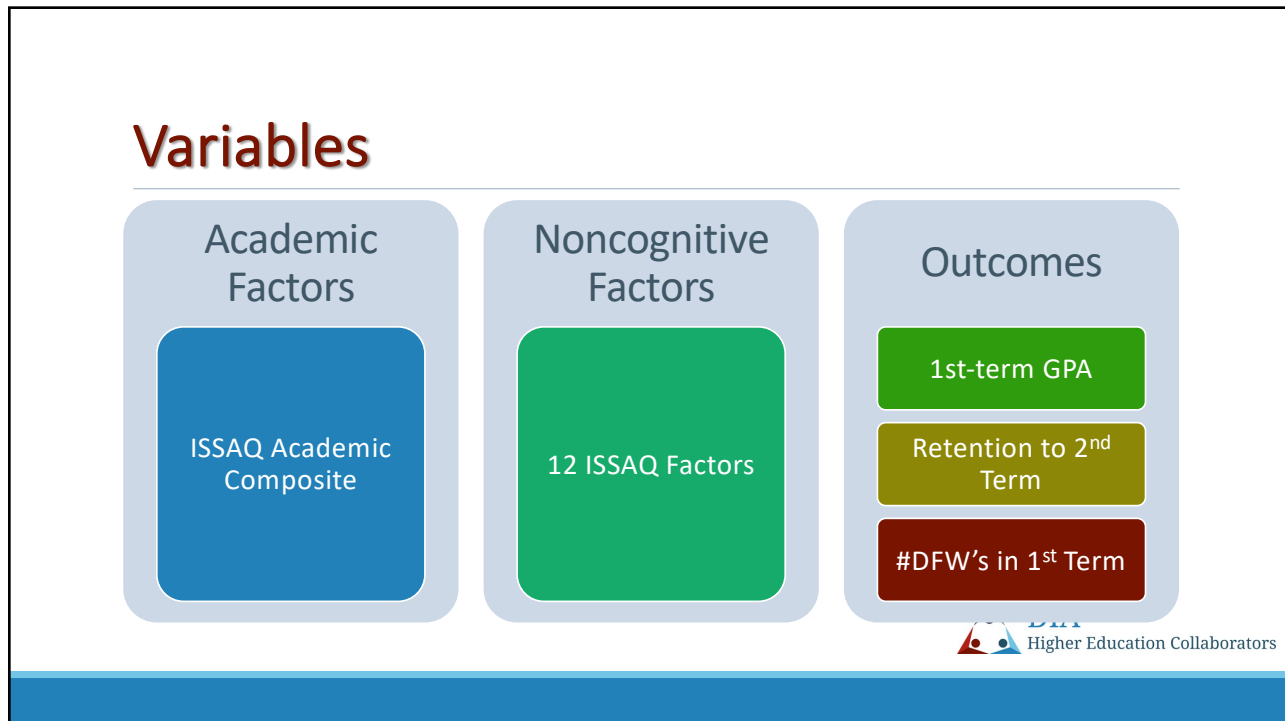
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Data Collection

- 4,253 ISSAQ Student Survey responses gathered between June 27th and August 12th, 2023
 - Responses validated by JMU to ensure ID/name/email match
- Matched to outcomes file provided by OIR
 - Resulting sample size for these analyses = 3,767 (88.6%)



2



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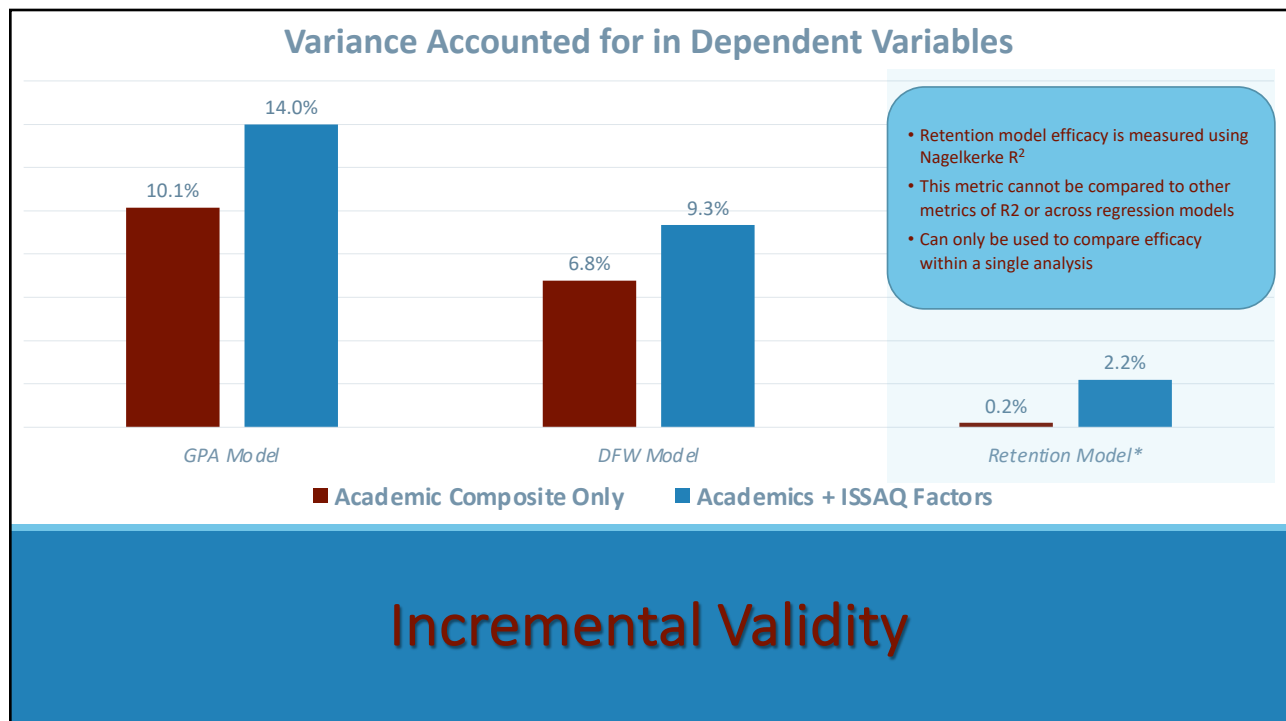
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Examining Predictive Efficacy

- The most common means of examining predictive efficacy is to compare the incremental predictive validity of noncognitive factors above and beyond academic markers (Markle et al., 2013; Robbins et al., 2004)
- To do this, regression models are created that test compare a model containing academic and noncognitive factors to one containing academic factors alone
- Because of missing data, academic markers are represented here by an “Academic Composite2” takes the average of any available SAT, ACT, HSGPA, or TSIA2 data (standardized to allow comparability across scales)



5



6

Phase 2: *Known-groups Validity*



7

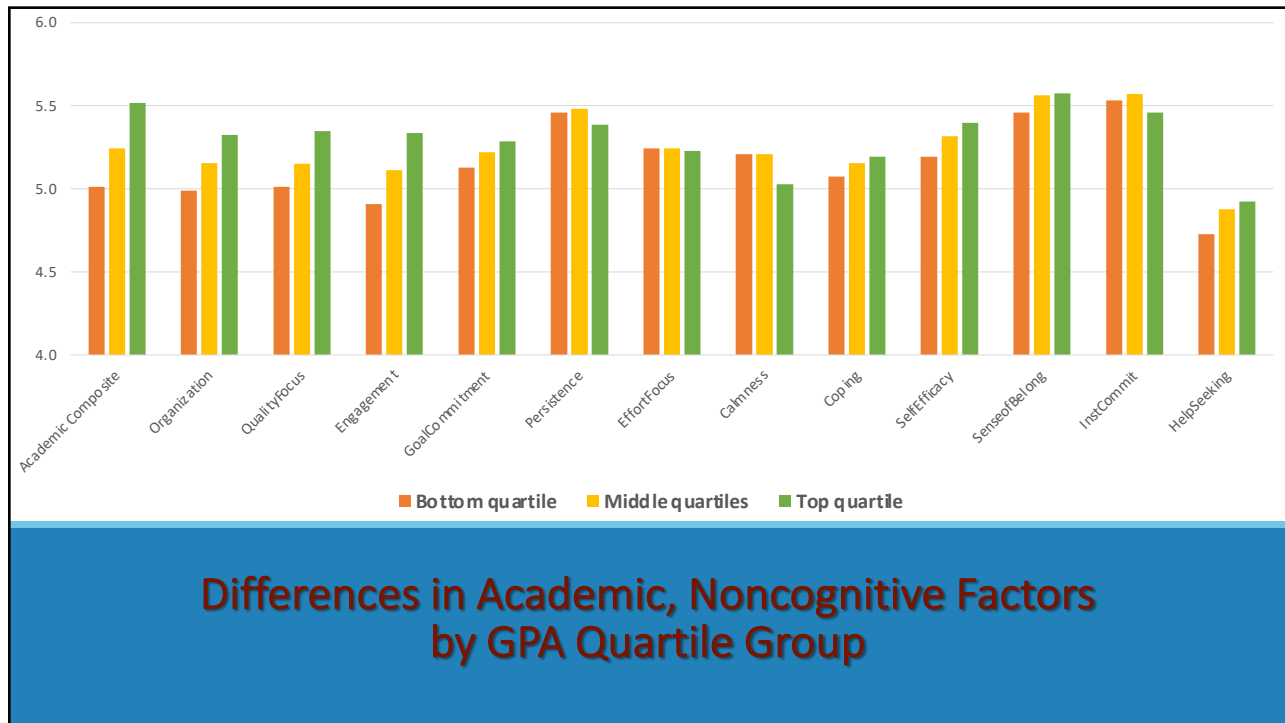
Methodological Notes

- The goal of regression-based approaches is to identify models that are both predictive and parsimonious
- Thus, regression-based approaches are helpful for eliminating irrelevant data, but interpreting these models for the purposes of identifying individual predictive factors can be complicated
- Thus, outcome group comparisons allow a simple interpretation of the relationship between a predictor and a specific outcome

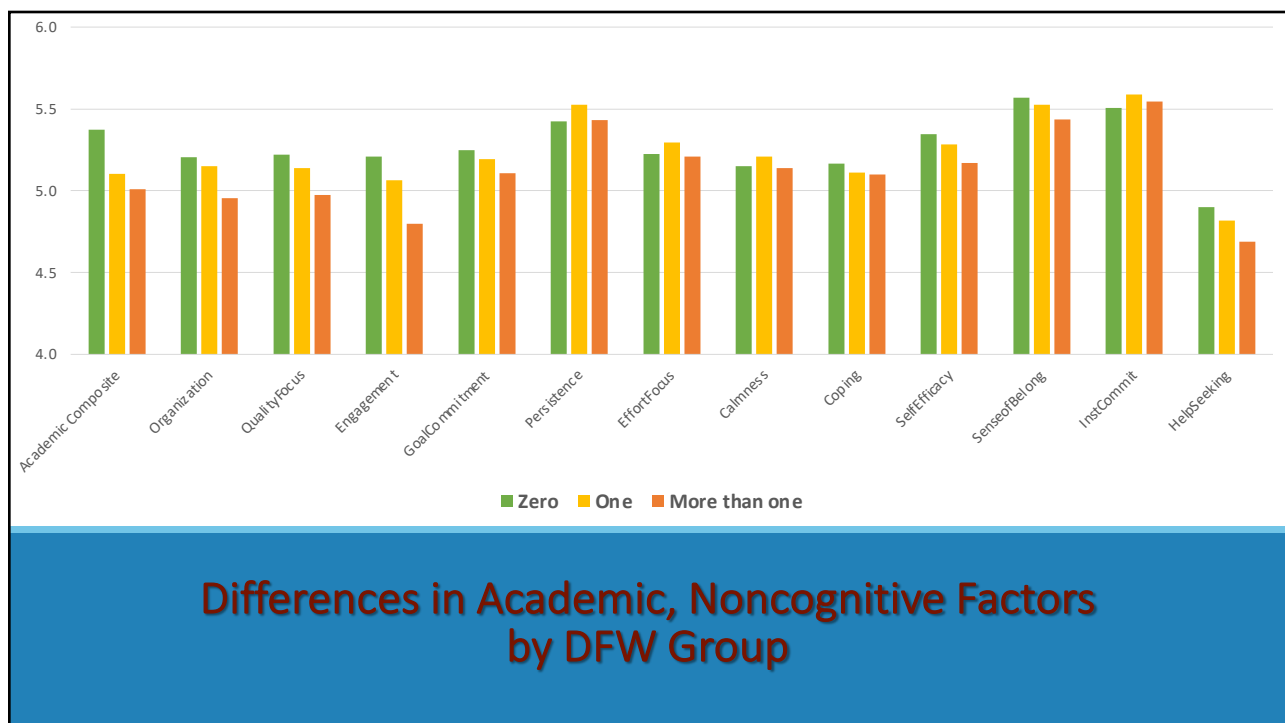
- Note that these analyses only refer to the Fall 2021 FTIC sample



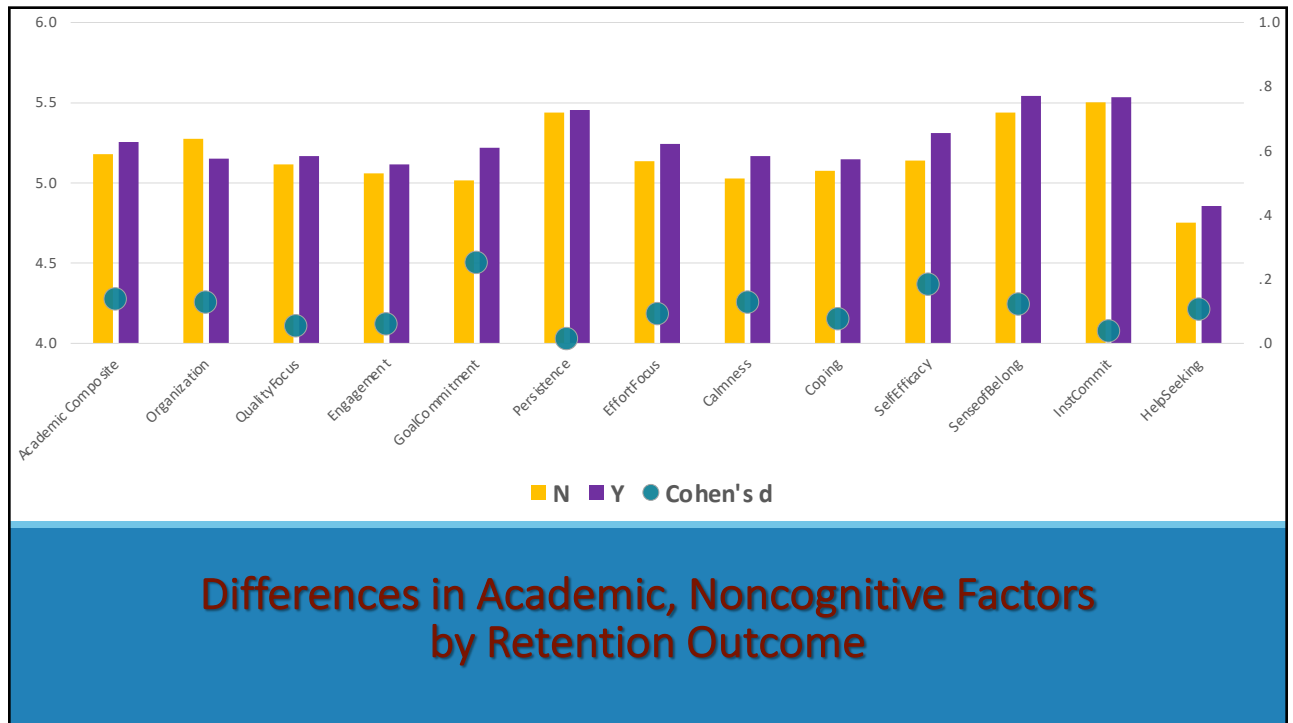
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Phase 3:
Comparing Subgroups

ISSAQ

12

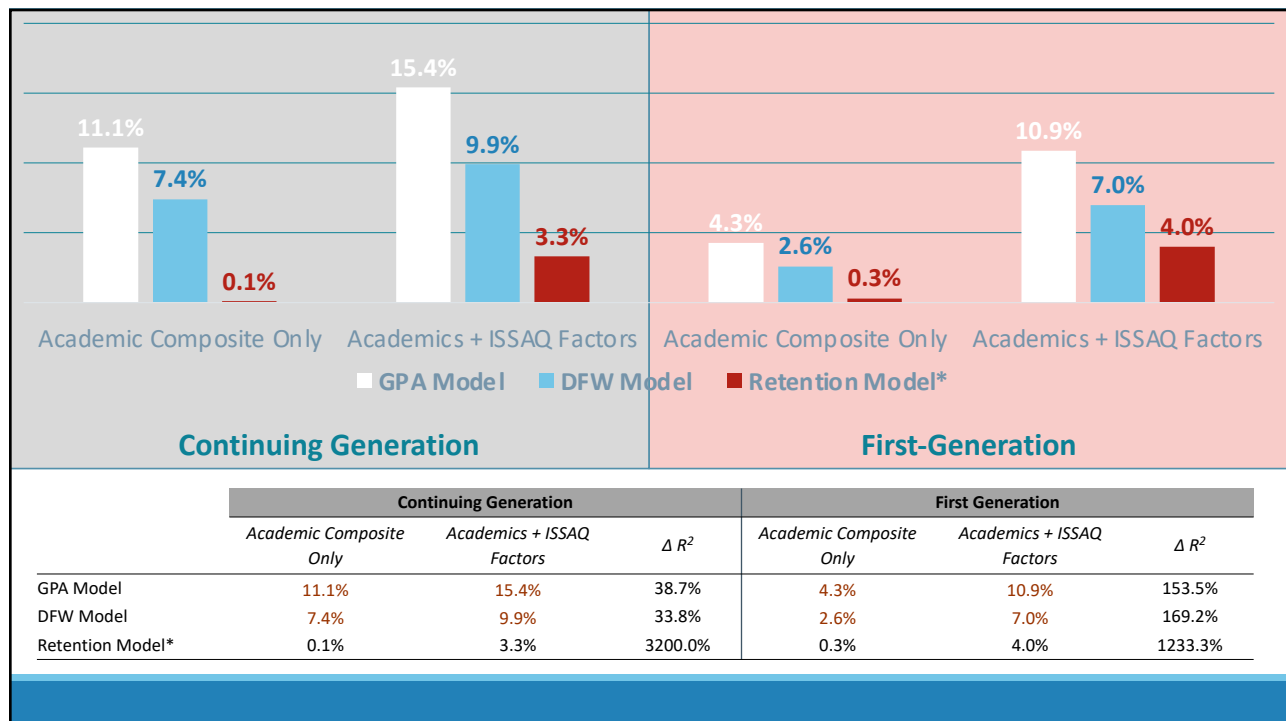
Comparing Predictive Models: First-Generation Status

- In addition to simply comparing scores, one of the other ways these data can be used to understand incoming populations is to look at how predictors vary across subgroup status.
- Here, we first will look at overall model performance for first and continuing-generation students
- Then we will compare specific predictors as they relate to student outcomes

First-Gen Status	Frequency	Percent
N	3367	89.4
U	15	0.4
Y	385	10.2



13



14

Variable	Continuing Generation			First Generation		
	Term GPA	DFW	Retention	Term GPA	DFW	Retention
Academic Composite	.333**	-.273**		.207**	-.161**	
Organization	.132**	-.089**		.100*		
QualityFocus	.106**	-.085**				
Engagement	.172**	-.152**		.107*		
GoalCommitment	.079**	-.057**	.050**			
Persistence						
EffortFocus					.102*	
Calmness	-.054**			-.111*		
Coping				.119*		
SelfEfficacy	.073**	-.074**	.050**			
SenseofBelong	.046**	-.056**				
InstCommit						
HelpSeeking	.073**	-.064**			-.127*	



15

Summary of Findings

1. Overall, ISSAQ does add to the prediction of first-term GPA, #DFW's, and retention
 1. The ability to predict retention, overall, is relatively weak, likely due to the low base rate of attrition (3.2%)
2. Using a known validity groups approach, several ISSAQ factors showed the ability to distinguish between high vs. low academic achievement and retention at JMU.
3. Comparing models for continuing and first-generation college students showed that ISSAQ improved the prediction of outcomes more for first-gen students, though both models were statistically significant.
4. Bivariate correlations suggest qualitative differences in the prediction of outcomes based on first-gen status.

16