

Unmasking the Impact of First-generation College Students' Achievement Motivational Profiles: A Person-Centered Approach

Goal: Submit to the *Journal of First-Generation Student Success*



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Research Questions

This study sought to empirically examine the claim that FGC students studying engineering have psychological profiles that can support their academic achievement by answering the following research questions:

- RQ1. How can we describe the achievement motivational goal profiles of FGC students studying engineering?
- RQ2. In what ways do the achievement motivational goal profiles of FGC students influence their learning strategies?
- RQ3. What insights do FGC students' achievement motivational profiles provide to different psychological factors?

Achievement Goal Theory: Brief Intro.

- Achievement Goal Theory (AGT) is a motivational lens to understand how students respond to achievement challenges or setbacks.
- The type of goals students adopt have implications for resilient or counterproductive behaviors, outlooks, or reactions students subsequently embrace in the face of setbacks
 - **Mastery goals**- Focus on learning and developing competence.
 - **Performance Goals**- Focus on displaying their ability or existing competence by outperforming others.
 - **Avoidance Goals**- Focus on avoiding being outperformed or appearing academically inadequate.

“Goals provide an organizing framework through which a variety of cognitive and affective responses to achievement situations can be interpreted” (Urdan, 1997, p. 101).

Achievement
Motivational
Goals Class

$C_{k=?}$

- Latinx Students
- Gender

- Learning Strategies
- Course Self-Efficacy
- Engineering Intrinsic Interest
- Fear of Failure

Survey Measures

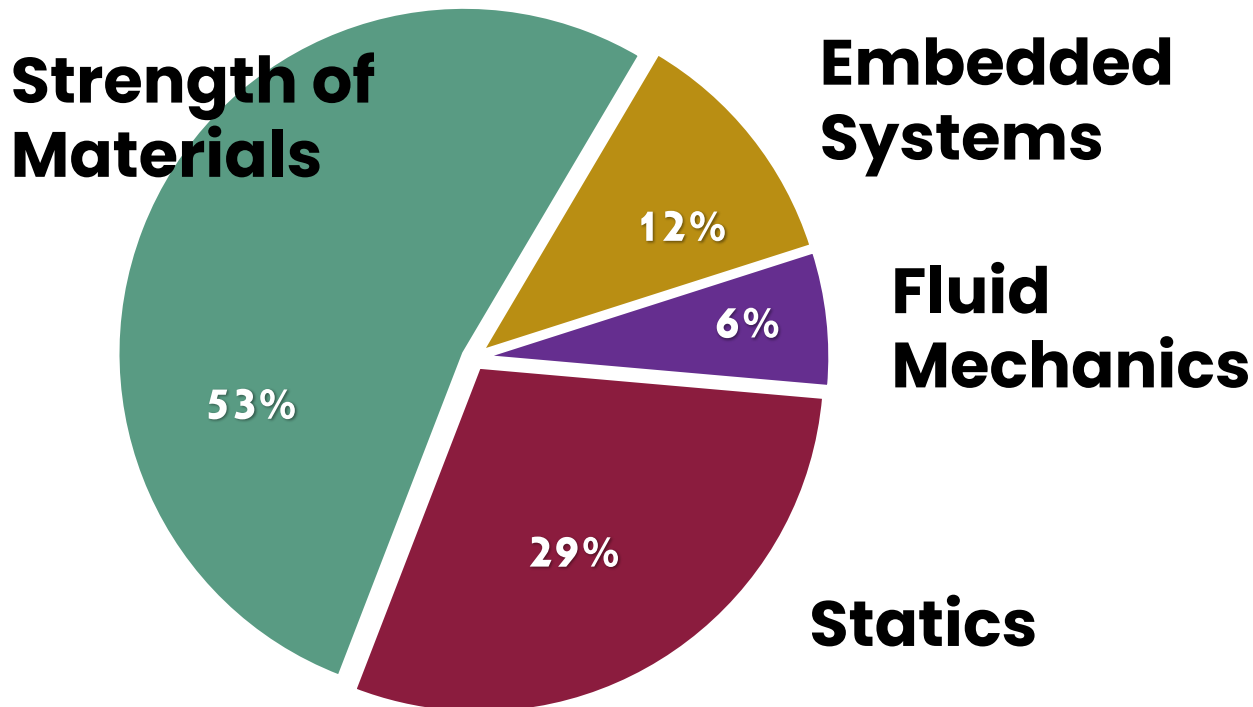
All survey measured used a 7-point anchored numeric Likert rating scale

Used to develop the achievement motivational profiles (RQ1)	Mastery goal	Focus on learning and developing competence.
	Performance goal	Focus on displaying one's ability or existing competence by outperforming others.
	Performance-avoidance goal	Focus on avoiding being outperformed or appearing academically inadequate.
Learning approaches evaluated against the different profiles (RQ2)	Deep Learning	focus on meaningful comprehension, apply critical thinking, and tend to retain information longer
	Surface Learning	rote memorization over deep understanding of the material, they focus on meeting immediate requirements (e.g., passing an exam)
Examined how achievement motivational profiles influenced different psychological factors (RQ3)	Course Self-Efficacy Beliefs	Students perception of their ability and/or competence to perform well in their engineering course.
	Engineering Intrinsic Interest	A student's genuine attraction or curiosity towards engineering topics is driven by internal motivation rather than external factors.
	Fear of Failure	Aversive consequences of failing

Overview of Participants

n = 324

**Cross-sectional
data across 3
semesters**



62% Latinx

College of Engr. average = 66%

All

**First-Generation
college students
(FGCS)**

College of Engr. average = 78%

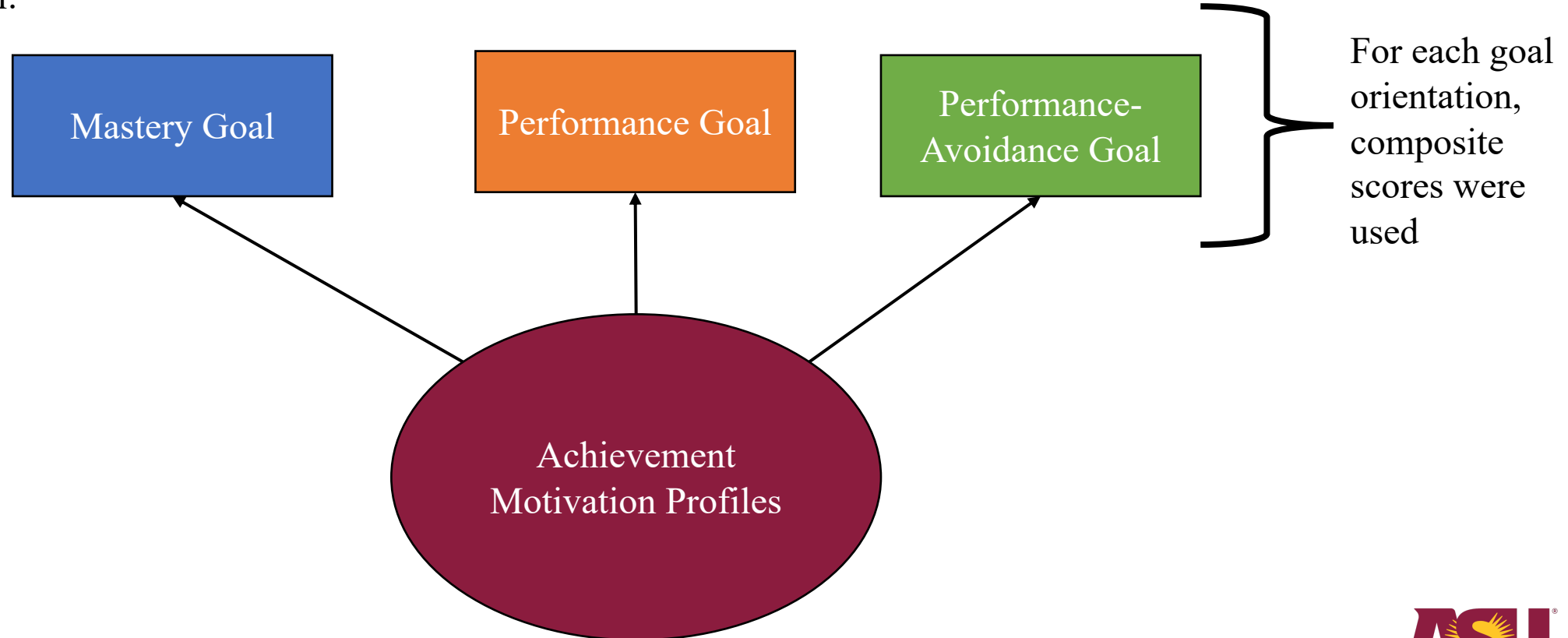
18%

**Women
+1 cisgender**

College of Engr. average = 17%

RQ1. How can we describe the achievement motivational goal profiles of FGC students studying engineering?

Measurement Model:



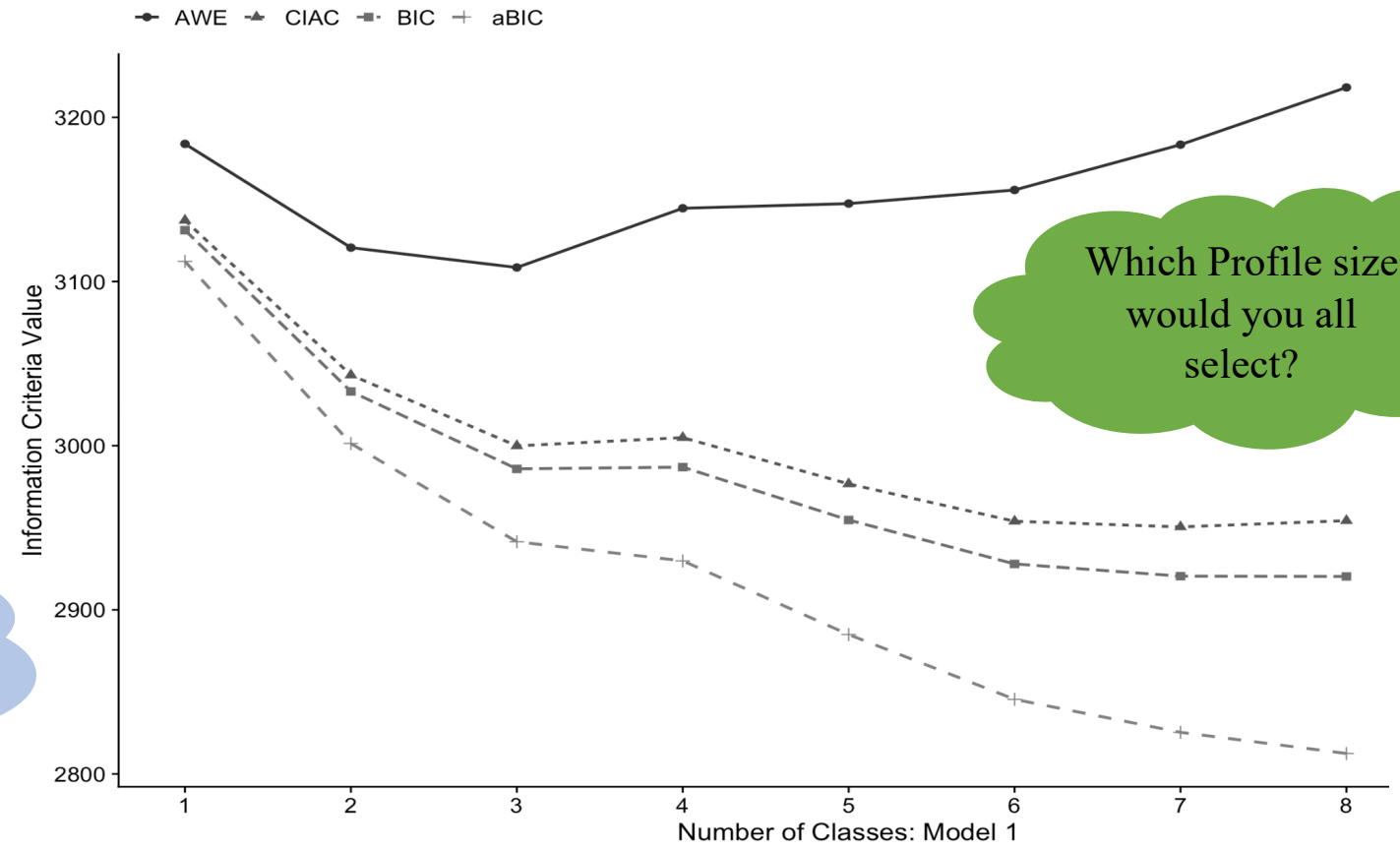
Evaluating Quality of the Measurement Model

Metrics for evaluating quality of the model

BIC, aBIC, CAIC, AWE	Lower values preferred; should be evaluated against meaningful profile sample sizes (Morgan, 2015; Nylund-Gibson et al., 2022)
BLRT and VLMR	Nonsignificant p -value suggests that the model with one less profile is preferred (Lo et al., 2001).
Number of Profiles	Researchers must consider how increasing the number of profiles may lead to a diminished return <ul style="list-style-type: none">• low profile sample size,• increased profile homogeneity, and• maintaining practical utility (Nylund-Gibson et al., 2022).
Comprehensive evaluation	No model fit indices should singularly determine the number of profiles; instead, sufficient evidence should be gathered to determine the best number of profiles (Nylund-Gibson et al., 2022)

Model 1: Equal variances, and covariances fixed to 0

When does a decrease in the information criterion become non-meaningful?



Classes	Par	LL	BIC	aBIC	CAIC	AWE	BLRT	VLMR	BF	cmPk
M1: Class1	6	-2,048	4,133	4,114	4,139	4,187	—	—	0	<0.001
M1: Class2	10	-1,969	3,999	3,967	4,009	4,089	<0.001	<0.001	0	<0.001
M1: Class3	14	-1,919	3,923	3,878	3,937	4,049	<0.001	0	0	<0.001
M1: Class4	18	-1,904	3,916	3,859	3,934	4,078	<0.001	0.05	0	<0.001
M1: Class5	22	-1,884	3,901	3,831	3,923	4,100	<0.001	0.34	0	<0.001
M1: Class6	26	-1,855	3,867	3,784	3,893	4,101	<0.001	0.04	0	<0.001
M1: Class7	30	-1,838	3,858	3,762	3,888	4,129	<0.001	0.02	0.1	0.08
M1: Class8	34	-1,824	3,853	3,745	3,887	4,160	<0.001	0.51	—	0.92

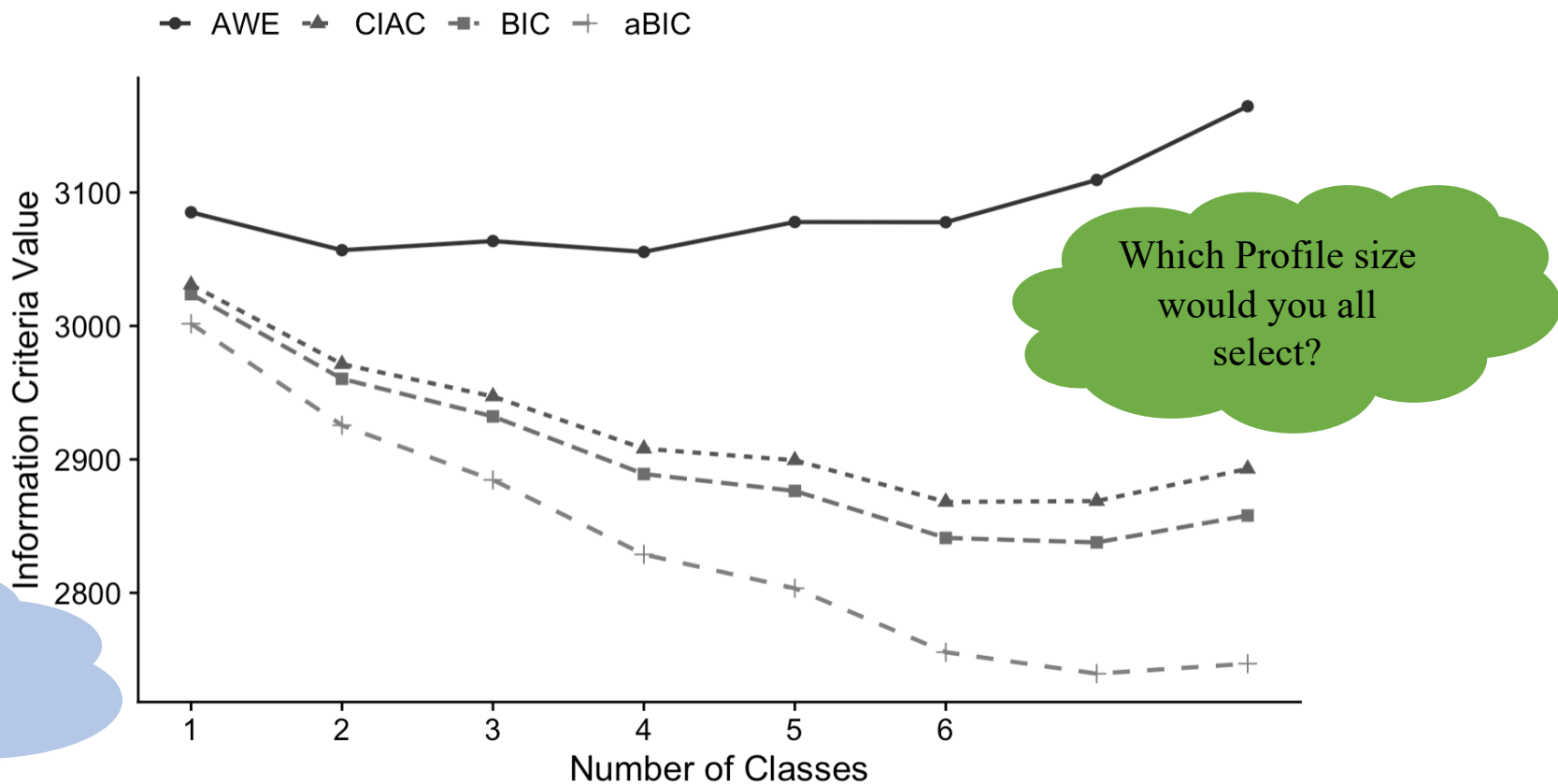
Model 2: Free variances and covariances fixed to 0

What is happening in model 2?

[illegible]

Model 3: Equal variances, and free covariances

When does a decrease in the information criterion become non-meaningful?



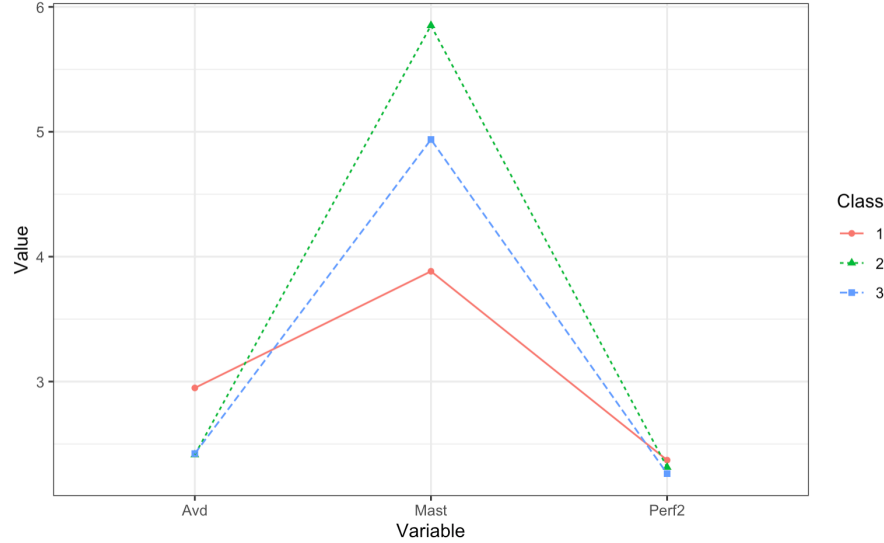
Classes	Par	LL	BIC	aBIC	CAIC	AWE	BLRT	VLMR	BF	cmPk
M3: Class1	9	-1,973	4,001	3,972	4,010	4,082	–	–	0	<0.001
M3: Class2	13	-1,919	3,916	3,875	3,929	4,034	<0.001	<0.001	0	<0.001
M3: Class3	17	-1,897	3,896	3,842	3,913	4,049	<0.001	0.16	0	<0.001
M3: Class4	21	-1,856	3,839	3,772	3,860	4,029	<0.001	0.06	0	<0.001
M3: Class5	25	-1,840	3,830	3,751	3,855	4,056	<0.001	0.01	0	<0.001
M3: Class6	29	-1,811	3,798	3,706	3,827	4,060	<0.001	0	0	<0.001
M3: Class7	33	-1,778	3,756	3,651	3,789	4,054	<0.001	0.02	>100	1
M3: Class8	37	-1,776	3,774	3,657	3,811	4,109	1	0.5	–	<0.001

Examining Sample Sizes

Researchers must consider how increasing the number of profiles may lead to a diminished return
So, **how small is too small?**

	C1	C2	C3	C4	C5	C6	C7	C8
M1: Class3	54	127	137					
M1: Class4	93	83	37	105				
M1: Class5	10	79	43	106	80			
M1: Class6	36	44	68	10	54	106		
M1: Class7	26	10	25	106	35	48	68	
M1: Class8	10	31	31	52	24	29	105	36
M3:Class2	61	257						
M3:Class3	35	194	89					
M3: Class4	87	10	174	47				
M3: Class5	10	32	55	70	151			
M3: Class6	24	30	151	10	48	55		
M3: Class7	4	6	48	53	24	32	151	
M3: Class 8	6	24	3	151	31	4	51	48

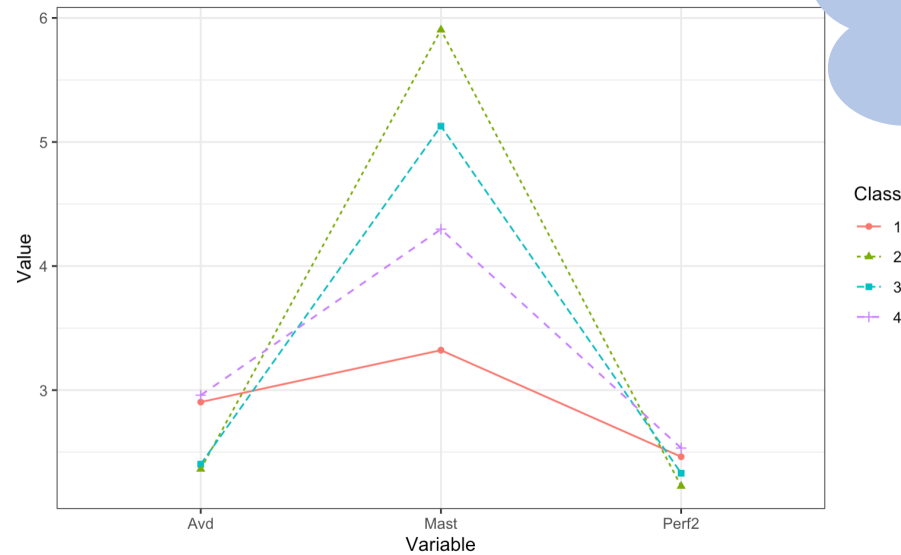
Model 3- Class 3



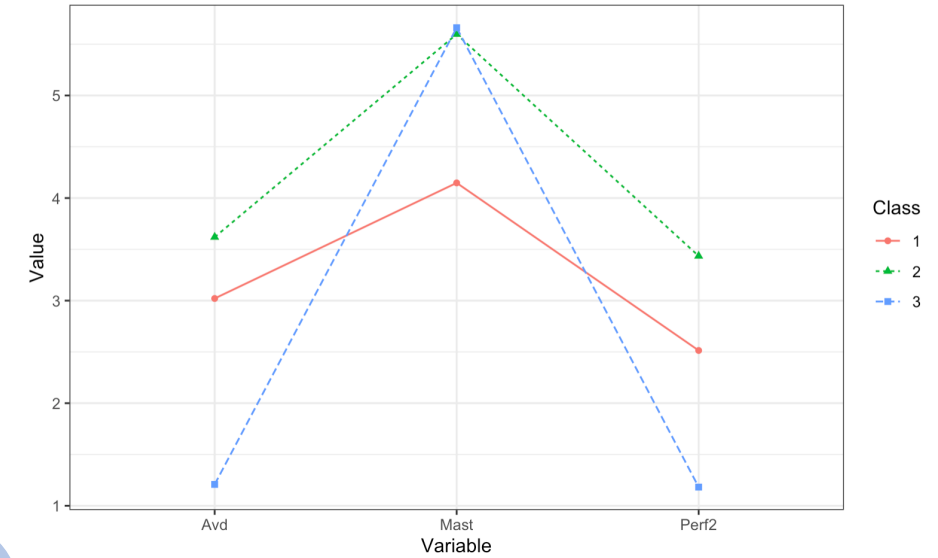
Evaluating between class homogeneity

**Model 3 solutions:
the profiles seem to
be similar, which is
not good**

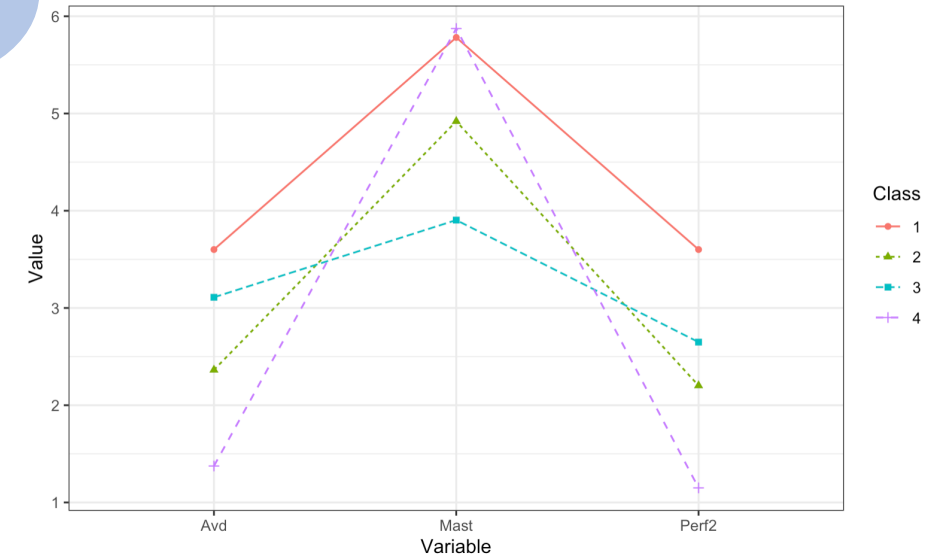
Model 3- Class 4



Model 1- Class 3




Model 1- Class 4



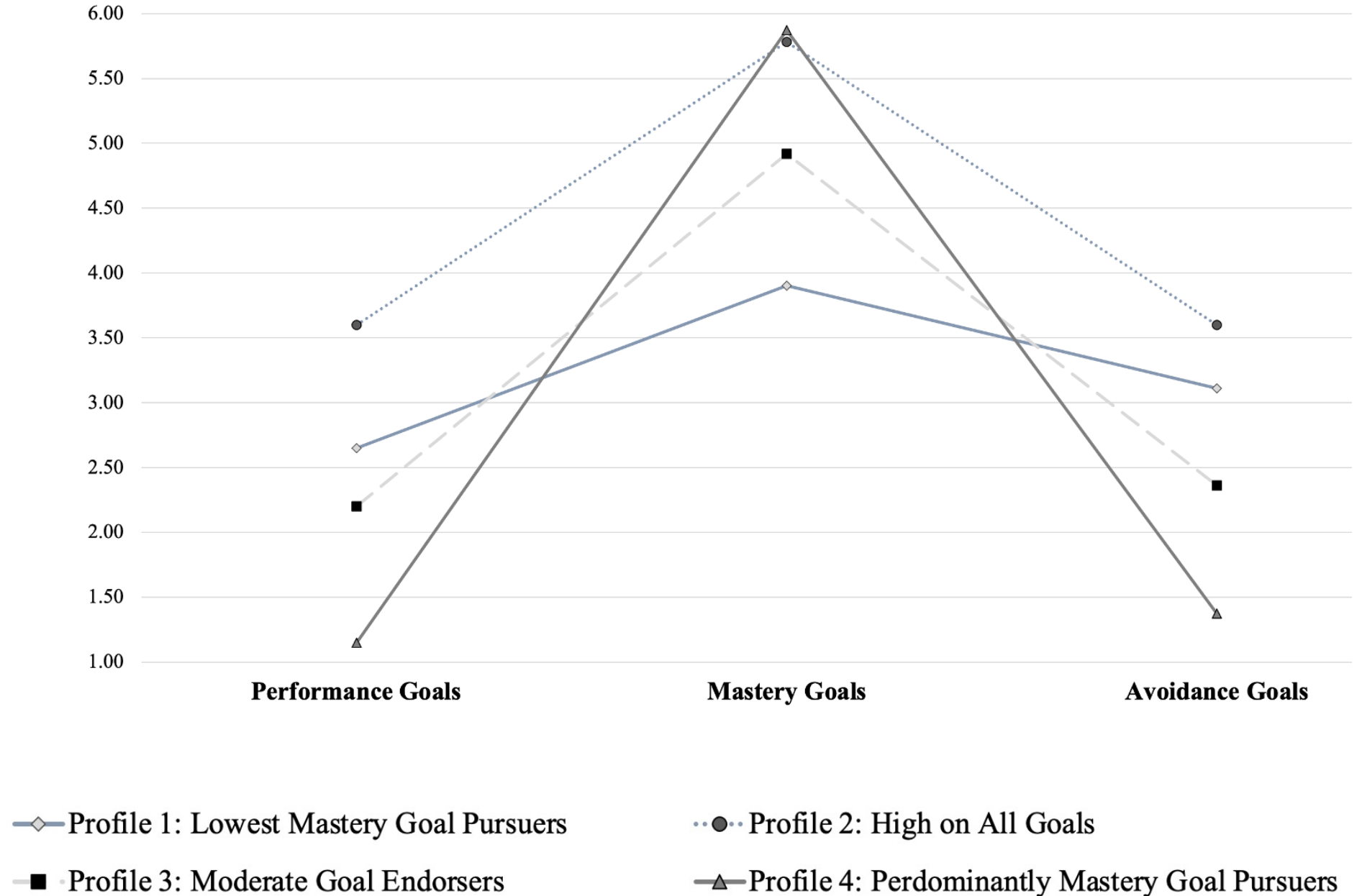
Comprehensive evaluation: In my opinion, it didn't seem like there was a clearcut solution

- How did I *honestly* decide?
 1. Sample size per profile
 2. Interpretability of each profile
 3. looked at the Information Criteria



**Was this the
right
approach?**

Final Model Selected: Model 1 with 4 profiles



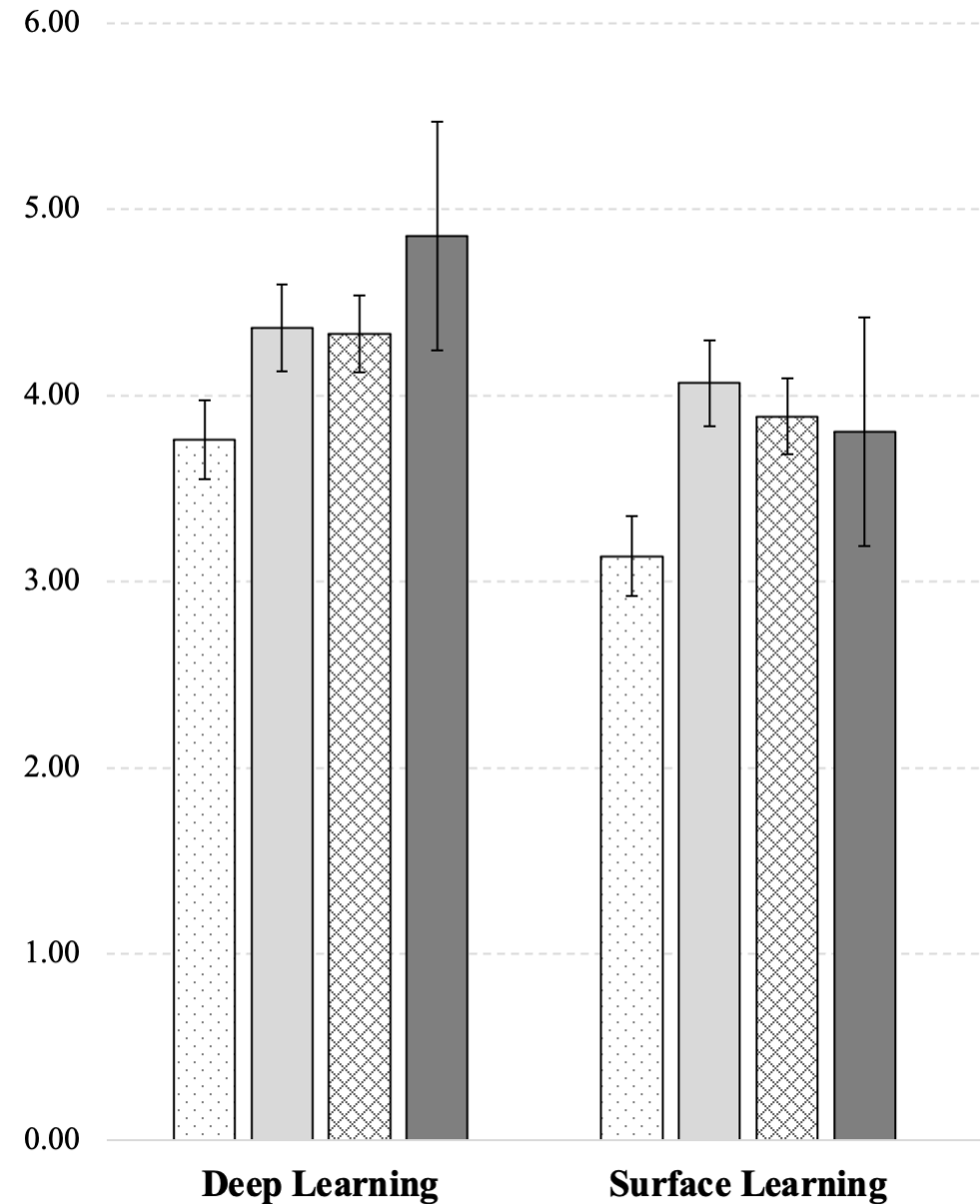
Description of Profiles



Descriptive Profile Names	Profile 1	Profile 2	Profile 3	Profile 4
	Lowest Mastery Goal Pursuers n =37	High on All Goals n =93	Moderate Goal Endorsers n =83	Predominantly Mastery Goal Pursuers n =105
Mastery Goal	3.90	5.78	4.92	5.87
Performance Goal	2.65	3.60	2.20	1.15
Avoidance Goal	3.11	3.60	2.36	1.38
% of Profile within the larger sample	12%	29%	26%	33%
% of Latinx Students by Profile	81%	82%	76%	89%
% of Women by Profile	22%	23%	11%	19%

RQ2. In what ways do the achievement motivational profiles of FGC students influence their learning strategies?

- Profile 1: Lowest Mastery Goal Pursuers
- Profile 2: High on All Goals
- ▨ Profile 3: Moderate Goal Endorsers
- Profile 4: Predominantly Mastery Goal Pursuers



RQ3. What insights do FGC students' achievement motivational profiles provide to different psychological factors?

- Profile 1: Lowest Mastery Goal Pursuers
- ▒ Profile 2: High on All Goals
- ▤ Profile 3: Moderate Goal Endorsers
- Profile 4: Predominantly Mastery Goal Pursuers

