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Degrees Beyond the Degree: Modeling Post-Bachelor's Graduate School Attendance

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\$734 M Research Expenditure

18 Colleges including medical and healthcare system

1,721 Tenure-line Faculty

8,926 Graduates

29,335 Undergraduates

38,261 Students





About UAIR

Team of 40+ individuals organized into 4 core teams:

1. Institutional Reporting (external focus)
2. Analytics & Reporting (internal focus)
 - i. Academic Reporting Team (student data focused)
 - ii. Administrative Reporting Team (finance, research, employee, facilities, space)
 - iii. Experience Analytics Team (internal surveys and engagement data)
3. Data Management
 - i. Architecture Team
 - ii. Engineering Team
4. Data Governance



About UAIR

We serve across data domains including:

Student, faculty/staff (employee), finance, research, facilities, space, experience and event analytics

Core Services Include:

Official external reporting (IPEDS, state compliance, ranking surveys)

Internal analytics including institution-serving dashboards

Enterprise-level data models

Large-scale internal surveys (students/faculty/staff)

Data science and advanced analytics

Data governance



Audience Poll

Does your institution track post-bachelor's graduate school enrollment?



Why This Matters

What Happens After Graduation?

- Retention ✓
- Graduation ✓
- *Graduate school enrollment* ?
- Less visibility into post-bachelor's outcomes
- Limited use in advising and strategy



Project Goals

What We Wanted to Understand

1. Which students attend graduate school?
2. What factors are associated with attendance?
3. How can we use this to inform advising?



Research Question

- **Main Question:**
 - What predicts **graduate school enrollment after receiving a bachelor's degree from our institution?**
- **Independent Variables:**
 1. GPA
 2. STEM Major Status
 3. Control for demographics and financial status



Data Sources

- **Institutional data:**
 - GPA
 - Major (STEM vs non-STEM)
 - Financial aid (pell)
 - Demographics
- **External data**
 - National Student Clearinghouse
- **Sample:**
 - **25,805** bachelor's recipients (2019-2023)



Outcome Definition

- **What Are We Predicting?**
 - Graduate school enrollment
 - *Within 5 years of graduation*
 - Binary outcome:
 - **Yes / No**

Methodology

- **Analytical Approach:**
 - Descriptive statistics
 - Logistic regression

Why Logistic Regression?

1. Works for binary outcomes
2. Interpretable
3. Common in IR



What Went Into the Model

- **Primary independent variables of interest:**
 - GPA
 - STEM major status
- **Controls:**
 - Demographics
 - Pell status

Model Validation

How Did the Model Perform?

- AUC = 0.65
- Moderate predictive power
- **Interpretation:**
 - Useful for identifying patterns
 - Not for precise individual prediction



Moving toward results

Interpreting Results

- Translating the model:
 - Odds Ratio $> 1 \rightarrow$ *increases likelihood*
 - Odds Ratio $< 1 \rightarrow$ *decreases likelihood*
 - Marginal Effect $\rightarrow$ *% change in probability*

☞ Focus on marginal effects for decision-making

Transition to Findings

Table 1. Graduate School Attendance Analysis

DV: Graduate School Attendance	Estimate	Odds Ratio	Marginal Effects
U of U GPA	1.21 (0.05)***	3.37	0.22
STEM Major	0.22 (0.03)***	1.25	0.04
Observations	25805		

Note: Standard errors in parentheses. Significance: *p < .05; ** p < .01, *** p < .001



GPA (Most Important Finding)

GPA Is the Strongest Predictor

- +1 GPA → **+22 percentage points** likelihood
- Strong, consistent relationship

STEM Major Status

STEM Majors Are More Likely to Attend

- STEM → **+4 percentage points** likelihood
- Smaller effect than GPA, still meaningful

Possible explanations

- Clearer grad pathways
- Program expectations
- Advising structures

Putting It Together

How These Factors Combine

- GPA = strongest driver
- STEM = additional boost

Important:

- *Effects are additive, not deterministic*

Example Student Profiles

Illustrative Example

- **Student A:**
 - GPA 3.8, STEM → *higher likelihood*
- **Student B:**
 - GPA 2.8, non-STEM → *lower likelihood*

Note:

- *This is not labeling students – it's illustrating patterns*



What This Model Does NOT Capture

Limits of the Data

- Student aspirations
- Career goals
- Faculty mentorship
- Graduate school awareness



From Insight to Action

What Can We Do With This?

- Move from prediction → support
- Identify opportunities for intervention



Use Case #1

Advising Applications

- Identify students with grad potential/interest
- Encourage:
 - Research experience
 - Grad school conversations



Use Case #2

Department-Level Insights

- Compare STEM vs non-STEM
- Ask:
 - Are pathways equally supported?

Use Case #3

Strategic Conversations

1. Where are gaps?
2. Which students may be overlooked?
3. How can support be expanded?

Further analysis possible at more granular levels



How We Shared Results

Implementation

- Reported to:
 - Advising leadership
 - Academic deans

Follow-up discussions = useful



Lessons Learned

What We Took Away

- “Good enough” models are still useful
- Simplicity improves adoption
- Framing matters more than complexity



Pitfalls & Challenges

What to Watch Out For

- Overinterpreting results
- Confusing prediction with causation
- Missing key variables



How to Replicate This

Getting Started at Your Institution

1. Define outcomes clearly
2. Gather internal + external data
3. Start with logistic regression
4. Focus on communication



Key Takeaways for Your Institution

What You Should Remember

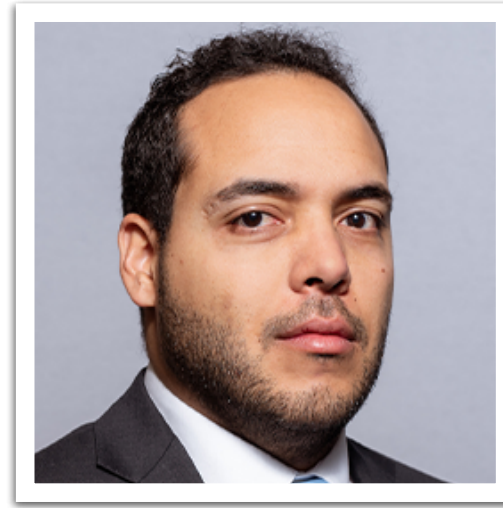
1. You can model post-grad outcomes
2. GPA and major matter most (here)
3. Insights can inform advising and strategy

Connect With Us



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Thank you!