2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC

Host Sponsor UNC Charlotte

Paper ID #50255

Exploring Mechanical Engineering Student Degree Completion Outcomes at an HSI using Machine Learning and Counterfactuals

Mr. Henry Salgado, University of Texas at El Paso

Henry is a Ph.D. candidate (ABD) in Computer Science whose research focuses on explainable AI, particularly through modeling approaches such as causal inference. His work explores how machine learning models can be made more interpretable and scientifically useful. He also studies the science of science, with interests in faculty roles in education, student persistence in engineering, and the impact of institutional contexts on these outcomes.

Dr. Meagan R. Kendall, University of Texas at El Paso

An Associate Professor at The University of Texas at El Paso, Dr. Meagan R. Kendall is a founding member of the Department of Engineering Education and Leadership. With a background in both engineering education and design thinking, her research focuses on how Latinx students develop identities as engineers and navigate moments of identity interference, student and faculty engineering leadership development through the Contextual Engineering Leadership Development framework, and promoting student motivation. Dr. Kendall is the Past Chair of the Engineering Leadership Development Division of ASEE.

Dr. Martine Ceberio, University of Texas at El Paso

Dr. Ceberio is a professor of Computer Science at the University of Texas at El Paso, currently serving as Associate Dean of Engineering for People, Culture, and Environment. She joined UTEP in 2003 after obtaining her PhD in Computer Science from the University of Nantes, France (2003). Her research revolves around reliable decision-making under uncertainty, optimization, constraint solving, solving dynamical systems, and studying neural networks with uncertainty. Her passion lies in developing reliable tools to generate reliable information about otherwise uncertain situations. She is passionate about teaching and mentoring students. She is a fierce advocate of her students' success and seizes every opportunity to provide advice and mentoring. At the University of Texas at El Paso, she is the co-lead of the Student Experience Project, which currently provides, within a community of practice, bringing together about 50 faculty and 15 graduates teaching assistants, and has so far reached over 4,500 students. As Associate Dean of Engineering, she leads a mentoring program for new faculty, which includes sessions on teaching. Outside UTEP, she mentors teachers of the local community and gets to share her passion beyond through contributed and invited talks about her teaching approach.

Dr. Angel Flores Abad, University of Texas at El Paso

Dr. Angel Flores-Abad is an associate professor in the Aerospace and Mechanical Engineering Department at the University of Texas at El Paso. His areas of interest include robotics, autonomy, and workforce development for those domains. He is committed to mentoring and guiding students to successfully and on time complete their degrees and achieve a high level of readiness for the job market. Dr. Flores-Abad is a member of the AIAA Space Automation and Robotics Committee.

Exploring Mechanical Engineering Student Degree Completion Outcomes at an HSI using Machine Learning and Counterfactuals

Introduction

This full research paper explores factors associated with engineering degree completion. Studies suggest that as many as half of undergraduates leave engineering programs before completing their degrees [1], [2]. In response to this attrition challenge, many institutions have made intentional efforts to improve persistence and support student graduation success. Within this broader effort, Hispanic-Serving Institutions (HSIs) have emerged as key contributors in educating a representative sample of the American population [3]. In fact, most Hispanic students who earn STEM degrees do so at HSIs, making these institutions important environments for understanding how to support students and improve graduation outcomes [4].

Existing research has documented the ways HSIs have attempted to support this graduation success; These efforts include, but are not limited to, the adoption of culturally relevant pedagogies, enhanced student-support structures, inclusive learning environments that affirm students' identities and experiences and faculty development [5], [6], [7], [8], [9], [10], [11]. While our study does not directly examine these institutional or pedagogical interventions, it does explore variables within student academic trajectories that may indicate where intervention may be warranted. Specifically, this study analyzes a dataset of 2,460 students enrolled in the mechanical engineering department at a four-year public HSI in Texas between 2015 and 2023. Using these data, we ask:

Which trajectory variables most strongly predict mechanical engineering degree completion at a Hispanic-Serving Institution?

The present study builds on prior work by Ortega et al. [12], which was conducted using a smaller subset of students from the same institutional context. That previous study primarily focused on evaluating the predictive performance of a neural network and briefly explored the role of demographic variables such as gender and race in graduation prediction. In contrast, the current study leverages a substantially larger sample and shifts the analytic emphasis from prediction alone toward actionability. That is, rather than asking only whether graduation outcomes can be predicted, we seek to identify which academic variables may represent plausible targets for intervention by combining machine learning models with explainability techniques (i.e., Shapley values, counterfactual analysis).

Background

A substantial body of research has examined factors associated with retention and degree completion among engineering students; comprehensive overviews are provided by [1], [13]. Prior studies suggest that persistence is influenced by a combination of academic, social, and motivational factors, including personal goals such as a sense of accomplishment or aspirations for social mobility [1]. Other work has shown that exposure to engineering through personal connections, such as knowing someone who is an engineer, can increase the likelihood of entering and remaining in the field [14]. Research has also documented that students are particularly vulnerable to leaving engineering programs during the early years, often citing heavy academic workloads, limited support structures, and low grades in foundational courses [1], [15]. Other scholars have also examined how identity and sense of belonging shape the experiences of engineering students [16], [17]. Notably, Goodman [15] found that a significant proportion of students, including many women, leave engineering despite maintaining relatively strong academic performance. Consistent with these findings, additional scholars have reported that women and students from minoritized backgrounds leave engineering at disproportionately high rates [18].

These findings align with Pascarella's *General Causal Model of Student Learning and Cognitive Development* [19], which emphasizes that student outcomes are shaped by students' backgrounds, institutional context, and their experiences during college. Within this framework, observable academic and demographic indicators can serve as proxy measures for broader processes that influence persistence. Although student retention and graduation in engineering are multifactorial phenomena that are shaped by intersecting academic, social, and structural influences, we recognize that identifying correlates of persistence is only a starting point; understanding where and how departments and institutions might intervene requires moving beyond broad associations. While we do not have access to many of these possible factors, we were able to obtain institutional data that captures proxy variables across multiple dimensions: student academic trajectory (e.g., GPA), demographic characteristics (e.g., gender, race/ethnicity), pre-college context (e.g., high school rank, participation in early college high school), academic progress (e.g., number of courses passed and failed), and performance in foundational courses (e.g., terminal grades in Calculus I, Calculus II, Statics, and Chemistry).

Methods

To address our research question, we employ two machine learning models to examine the relationship between students' trajectory variables and their graduation outcomes. Trajectory variables are used as inputs to multiple models, and outputs are analyzed to identify the most relevant variables associated with different student outcomes. The dependent variable captures three possible outcomes: *transferring to another college within the university, completing an engineering degree, or leaving college without completing a degree*. In addition, we conduct a counterfactual analysis to examine how hypothetical changes to variables alter predicted outcomes, providing insight into which factors may represent plausible targets for intervention.

Models and Implementation Details

We employ a feed-forward artificial neural network and a pruned decision tree, to balance predictive flexibility with interpretability. The neural network captures complex, potentially nonlinear relationships common in educational data, while the decision tree provides a transparent, rule-based structure that allows direct inspection of feature splits and threshold values associated with graduation outcomes. Since the neural network is a black-box model, we compute the SHAP values [20] to see how each feature contributes to the prediction. In addition, we conduct a counterfactual analysis using a boosted-tree model to examine how hypothetical changes to selected academic variables alter predicted outcomes, enabling the exploration of *"what-if"* scenarios that move beyond association toward identifying potentially actionable intervention points. All analyses were conducted in Python using NumPy and pandas for data processing, scikit-learn for data splitting, scaling, and class-weight computation, and TensorFlow Keras for model implementation. Detailed implementation procedures, including strategies for handling class imbalance, optimizer selection, and full model architectures are available in the accompanying repository: https://github.com/eigenhenry/asee26

Data and Variable Encoding

The dataset consists of records for 2,460 students enrolled in the mechanical engineering program. With respect to gender, 84% of students identified as male and 16% as female. The racial and ethnic composition of the sample was predominantly Hispanic (83%), followed by international students (6%), White non-Hispanic students (4%), Mexican international students (3%), and Black non-Hispanic students (0.1%); the remaining students were classified as unknown. The outcome variable captured students' academic pathways at the institution. Overall, 66% of students left the institution without completing an engineering degree, 30% completed their engineering degree, and 4% transferred to another college within the university.

All predictor variables were numerically encoded prior to model training. Continuous variables were standardized for the neural network model, while categorical and ordinal variables were encoded using integer mappings appropriate to their measurement scale (See table 1). Missing values in course count variables were imputed with zeros, reflecting the absence of recorded coursework.

Table 1: Variable Encoding

Variable	Type	Encoding / Transformation
No. of Passed Courses, No. of Failed Courses, GPA at Graduation, Credits Transferred, Hs rank	Cont.	Missing values imputed with 0; used as-is (standardized for NN)
Gender	Binary	M = 1, F = 0
Race/Ethnicity	Cat.	{Hispanic: 1, White Non-Hispanic: 2, Black Non-Hispanic: 3, International: 4, Asian American: 5, NH/PI: 6, Two+ races: 7, Unknown: 8, Native American: 9}
Early College HS?	Binary	Y = 1, N = 0
Terminal Grades	Ord.	A= 4, B = 3, C = 2, D = 1, S=1, F = 0, U/W = -1
Outcome	Cat.	{0: leaving college without completing a degree 1: completing an engineering degree, 2: transferring to another college}

Results

Finding 1: GPA and Passed Courses Dominates Graduation Prediction

Across both the neural network and decision tree models, GPA and the number of courses passed emerged as the strongest predictors of all three possible outcomes. The neural network achieved an overall accuracy of 96.75% on held-out test data, with particularly strong performance predicting Class 0: *leave without degree* (precision = 1.00, recall = 1.00). While the perfect metrics for Class 0 prediction may initially suggest overfitting, upon further evaluation we believe it likely reflects both the larger sample size of this outcome class (66% of students) and the clear separation in cumulative academic indicators (particularly GPA and courses passed). This is clearly seen in Fig. 1, where lower GPA values (shown in blue) push predictions strongly toward dropout. We verified that all preprocessing steps, including standardization and imputation, were fit exclusively on training data to prevent data leakage.

Class 1, *degree completion*, was also strong (precision = 0.99, recall = 0.89), while Class 2, *transfer to another college*, exhibited lower precision (0.45) but high recall (0.95). The lower precision for transfers possibly reflects the smaller sample size of this class (4% of students) and greater overlap with completion pathways, as some transfer students share academic profiles similar to those who complete degrees.

SHAP-based analysis of the neural network revealed that GPA at graduation and number of courses passed consistently dominated model predictions across all outcome classes. In the SHAP plots, each dot represents a student, positioned horizontally based on how much that feature influenced their prediction. Color encodes the feature value: red indicates higher values (e.g., high GPA), and blue indicates lower values (e.g., low GPA). Features are ordered vertically by overall importance, with those appearing at the top contributing most to the model's predictions across all students. For students predicted *leave without degree* (Class 0, Fig 1), lower GPA values (blue dots on the right) contributed most strongly toward non-completion predictions. The inverse pattern characterized students predicted *degree completion* (Class 1, Fig 2): higher GPA (red dots on the right) and a greater number of passed courses were the positive contributors. Students predicted *transfer to another college within the university* (Class 2, Fig 3) exhibited a more heterogeneous pattern, with higher GPA values often contributing positively while a lower number of passed courses also played a role. This could suggests that transfer represents a distinct academic pathway rather than a simple midpoint between dropout and completion; students may transfer with decent GPAs but fewer completed courses at the institution.

Fig 1: Leave without degree (Class 0) Lower GPA and fewer passed courses contribute most strongly toward dropout predictions.

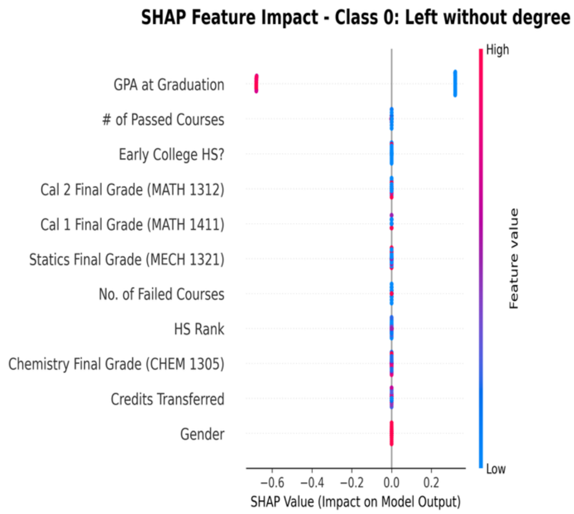


Fig 2: Degree Completion (Class 1) Higher GPA and a greater number of passed courses strongly increase the likelihood of completion.

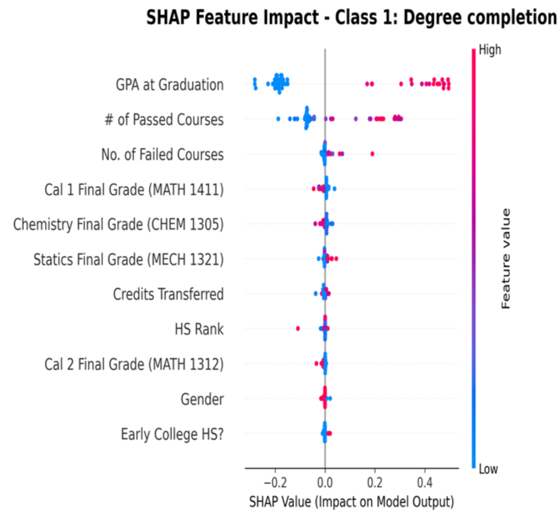
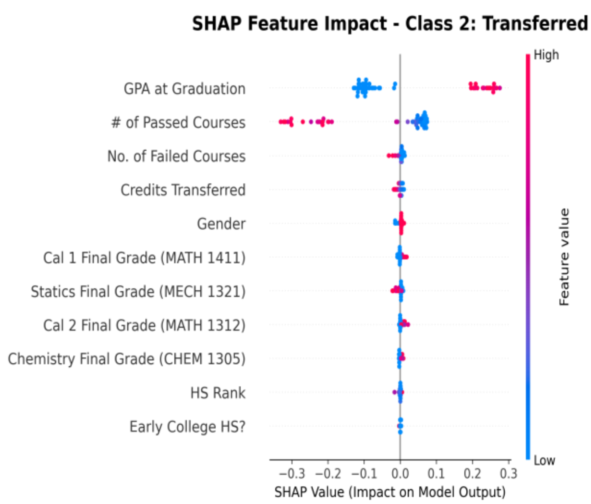


Fig 3: Transfer (Class 2) Predictions reflect mixed contributions, with higher GPA sometimes co-occurring with fewer passed courses.



The decision tree splits also corroborated these findings; GPA appeared as the root node in the tree, meaning it was the first and most important decision point the model used to categorize students.

Finding 2: Statics as a Potential Intervention

Because GPA at graduation and the number of passed courses dominated model predictions, we hypothesized these variables could be potential confounding proxies. That is, cumulative measures like GPA develop over an entire academic trajectory and represent the outcome of sustained patterns, whereas performance in specific courses occurs at defined moments in the curriculum and may be more amenable to targeted support interventions. When both variables were removed, predictive accuracy dropped sharply from approximately 95% to 53%. However, when GPA was retained and the number of passed and failed courses were excluded, model performance remained relatively stable and *Statics* performance emerged among the top predictors of engineering degree completion (Fig 4).

Notably, before removing the number of courses passed or failed, Calculus I was ranked higher than Statics across all three outcome classes in the SHAP analysis. However, once course count variables were excluded, Statics became more important for the model. A possible explanation is that Calculus I is taken early in the curriculum when students have not yet accumulated many passed or failed courses, so its performance may reflect primarily initial preparation and readiness. In contrast, Statics is typically taken later after students have progressed through coursework. Performance in Statics may therefore implicitly encode information about cumulative progression (such as how many courses a student has successfully completed to reach that point) or other unobserved factors like academic maturity and acclimation to engineering coursework. As a result, Statics performance may retain predictive power even when course count variables are explicitly removed from the model. This finding was corroborated by the decision tree (Fig 5). After initial splits on GPA and course progression, Statics appeared as a distinguishing variable in subsequent branches, while Calculus I, Calculus II, and Chemistry appeared less prominently. While this finding does not imply a causal effect, we explored counterfactual analysis on this Statics variable.

Fig 4: Statics emerges as a top predictor when we remove both number of courses passed and failed.

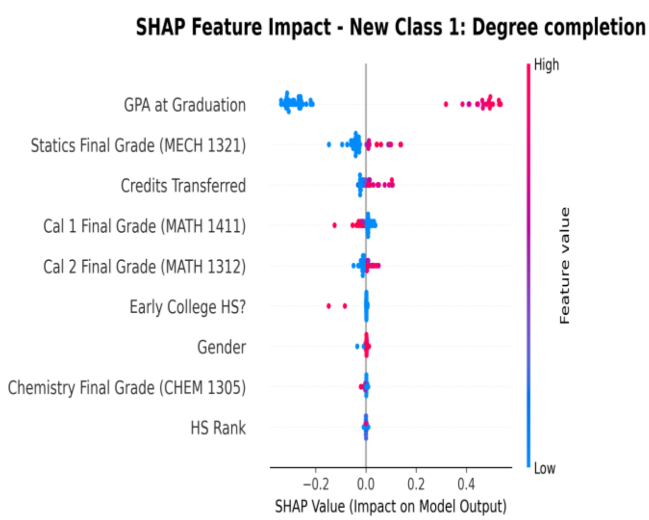
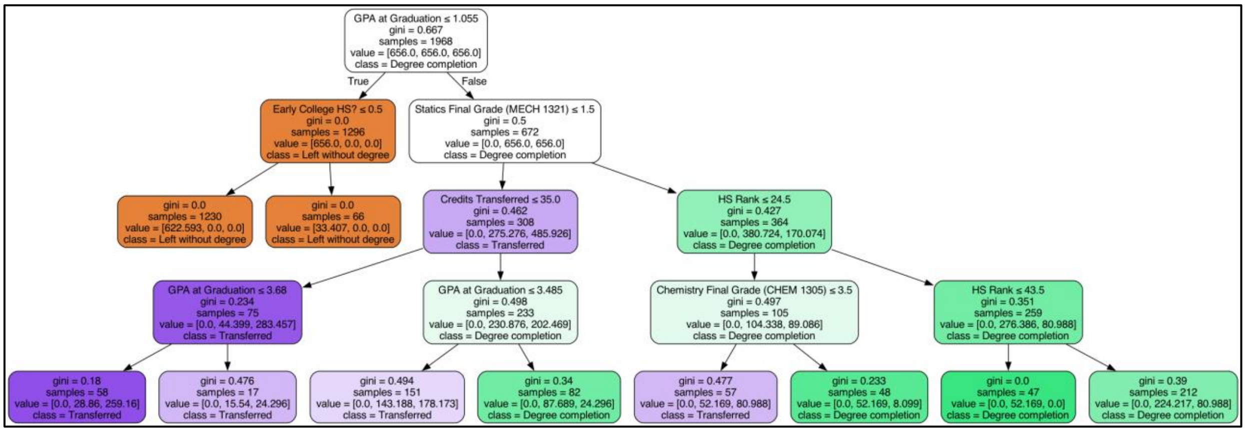


Fig 5: Cropped decision tree visualization highlighting associations between academic trajectory variables and engineering outcomes, revealing patterns consistent with neural network–based feature importance. Grade Encoding: A= 4, B = 3, C = 2, D = 1, S=1, F = 0, U/W = -1



Counterfactual Analysis

Counterfactual explanations were generated using DiCE [21] which identifies alternative feature configurations that would change the model's predicted outcome for a given student. For example, for students predicted not to complete degree, DiCE searches the feature space for minimal and diverse changes to course grades that would flip the predicted outcome to degree completion. To ensure interpretability and realism, counterfactual grade values were constrained to the valid range (1 to 4) and post-processed to snap to discrete grade levels (D to A). Rather than interpreting counterfactuals as literal predictions, we treat them as plausible academic scenarios that reveal which course improvements are most influential for altering the model's prediction.

Table 2 presents ten counterfactual scenarios for students initially predicted not to complete their degree. Across these scenarios, a pattern emerges: Statics consistently appears at the highest grade level (grade = 4, or A) in all ten counterfactuals. In contrast, Calculus I grades range from 2 to 4, Calculus II grades range from 1 to 4, and Chemistry grades range from 1 to 4. Several counterfactuals show scenarios where Statics alone reaches the maximum grade (4) while other courses remain at lower or moderate levels. For example, in CF #1, a grade of 2 (C) in Calculus I, 1 (D) in Calculus II, and 3 (B) in Chemistry is sufficient when paired with a 4 (A) in Statics. Similarly, CF #9 shows grades of 2 in Calculus I, 1 in Calculus II, and 2 in Chemistry paired with a 4 in Statics. These patterns indicate that improvements in Statics performance may be sufficient to alter predicted outcomes even without concurrent high achievement in all other courses.

Table 2: Ten counterfactual grade scenarios leading to degree completion. Encoding: A= 4, B = 3, C = 2, D = 1

CF #	Calc I	Calc II	Statics	Chemistry	Predicted
1	2	1	4	3	1
2	1	1	3	1	1
3	4	4	4	1	1
4	4	2	4	1	1
5	3	1	4	4	1
6	3	1	4	3	1
7	3	2	4	1	1
8	4	1	4	2	1
9	2	1	4	2	1
10	4	1	4	2	1

Limitations

This study has several important limitations. First, degree completion and retention are influenced by numerous academic, social, and personal factors not captured in our institutional dataset. Second, our findings reflect statistical associations rather than causal relationships. The correlation between Statics performance and degree completion may be due to unmeasured confounders. Third, this study relies on observational data and cannot establish whether interventions targeting Statics performance would actually improve completion rates.

Discussion and Conclusion

The goal of this study was to identify which variables in our dataset were most relevant for predicting engineering degree completion. Initial analyses indicated that cumulative GPA and number of courses passed were the strongest predictors of completion. However, intervening these variables typically requires early and sustained action across a student's academic trajectory. For this reason, we removed these variables to focus on course-level factors that may be more actionable at specific points in the curriculum. After excluding GPA and courses passed/failed, Statics emerged as a relevant predictor of engineering degree completion. Counterfactual analyses further suggested that improvements in Statics performance were frequently sufficient to flip model predictions from non-completion to completion, often without concurrent improvements in other courses. That is, statics appeared more often and at higher grade levels in counterfactual scenarios than Calculus I, Calculus II, or Chemistry, indicating that it may serve as a particularly influential leverage point within the model.

This finding is consistent with prior research that emphasizes statics as a bottleneck course within engineering curricula [22], [23], [24]. In general, statics course typically occupies a critical position early in mechanical engineering programs, serves as a prerequisite for subsequent courses, and has been associated with elevated D/F/W rates and delayed progression [22].

Given the role of statics identified in our analyses, several targeted interventions could be taken into consideration. First, early warning systems could flag students at risk of poor performance based on prerequisite course grades and direct them toward support resources before critical assessment points [19], [20]. Second, supplemental instruction programs, peer-led study sessions that have shown effectiveness in STEM gateway courses [26], could be expanded or prioritized for statics. Third, departments might consider restructuring statics course delivery through evidence-based pedagogical approaches such as active learning, just-in-time teaching, or mastery-based assessment that have demonstrated success in reducing DFW rates in engineering courses [27].

Finally, while we acknowledge that educational outcomes are inherently multidimensional and influenced by a wide range of academic, social, and institutional factors, these results suggest that targeted support in key courses may represent a practical intervention point for departments. This is particularly important given that a substantial proportion of engineering students do not complete their degrees [1]. Therefore, improving progression through critical courses such as Statics has implications not only for individual student success, but also for departmental capacity, institutional effectiveness, and the broader need to sustain and expand the engineering workforce.

Acknowledgements

This work was supported by the NSF Scholarships in Science, Technology, Engineering, and Mathematics Program (S-STEM), with award number 2221498. We would also like to thank Elizabeth Barrera from the office of Research Innovation and Impact for helping us compile the dataset.

Use of Generative AI

We used generative ai tools to assist with literature review, specifically Google's Scholar Labs and ChatGPT's Deep Research. All outputs were verified and edited by the authors to ensure accuracy and integrity.

References

[1] B. N. Geisinger and D. R. Raman, "Why They Leave: Understanding Student Attrition from Engineering Majors," 2012.
[2] W. Wulf and G. M. C. Fisher, "A Makeover for Engineering Education," Issues in Science and Technology. Accessed: Dec. 30, 2025. [Online]. Available: https://issues.org/p_wulf/
[3] HACU, "2024 Fact Sheet." Accessed: Mar. 17, 2025. [Online]. Available: https://www.hacu.net/NewsBot.asp?ID=4597&MODE=VIEW
[4] Excelencia in Education, "30 years of Hispanic-Serving Institutions (HSIs): Improving Access to Quality for 30% | Excelencia in Education," Excelencia Education. Accessed: May 01, 2025. [Online]. Available: https://www.edexcelencia.org/research/publications/hispanic-serving-institutions-hsis-factbook

[5] S. Hurtado and D. F. Carter, "Effects of college transition and perceptions of the campus racial climate on Latino college students' sense of belonging," *Sociology of Education*, vol. 70, no. 4, pp. 324–345, 1997, doi: 10.2307/2673270.
[6] "Exploring Hispanic-Serving Institution (HSI) Faculty Members' Experiences with Culturally Sustaining Teaching Practices: Journal of Latinos and Education: Vol 24 , No 2 - Get Access." Accessed: Jan. 07, 2026. [Online]. Available: https://www.tandfonline.com/doi/full/10.1080/15348431.2024.2381034?src=&utm_source=chatgpt.com
[7] R. Covarrubias, G. Laiduc, K. Quinteros, and J. Arreaga, "LESSONS ON SERVINGNESS FROM MENTORING PROGRAM LEADERS AT A HISPANIC SERVING INSTITUTION," vol. 9, no. 2.
[8] G. Lozano, M. Franco, and V. Subbian, "Transforming STEM Education in Hispanic Serving Institutions in the United States: A Consensus Report," *SSRN Journal*, 2018, doi: 10.2139/ssrn.3238702.
[9] M. R. Kendall, A. C. Strong, G. Henderson, and I. Basalo, "PERCEPTIONS OF ENGINEERING FACULTY ON EDUCATIONAL INNOVATION AT HISPANIC-SERVING INSTITUTIONS," *J Women Minor Scien Eng*, vol. 27, no. 6, pp. 21–57, 2021, doi: 10.1615/JWomenMinorScienEng.2021034722.
[10] A. Strong, M. Kendall, G. Henderson, and I. Basalo, "Impact of Faculty Development Workshops on Instructional Faculty at Hispanic-serving Institutions," in *2019 ASEE Annual Conference & Exposition Proceedings*, Tampa, Florida: ASEE Conferences, Jun. 2019, p. 32931. doi: 10.18260/1-2--32931.
[11] A. Coso Strong, M. R. Kendall, and G. Henderson, "Voices of Engineering Faculty at the Margins: Supporting Professional Agency through Faculty Development," in *Handbook of STEM Faculty Development*, S. M. Linder, C. Lee, and K. High, Eds., 2022.
[12] A. Ortega, M. Kendall, A. Flores Abad, V. Bonilla, and L. Everett, "Predicting Outcomes of Aerospace and Mechanical Engineering Students via Artificial Intelligence," Jun. 2024. doi: 10.18260/1-2--47857.
[13] National Academies of Sciences, Engineering, and Medicine, "Understanding the Educational and Career Pathways of Engineers." Accessed: Jan. 06, 2026. [Online]. Available: https://www.nationalacademies.org/read/25284/chapter/10
[14] J. Martin, S. Yu, C. Waight, K. s Zerda, and T.-L. Sha, "The Relations of Ethnicity to Female Engineering Students' Educational Experiences and College and Career Plans in an Ethnically Diverse Learning Environment," *Journal of Engineering Education*, vol. 97, pp. 449–465, Oct. 2008.
[15] I. F. Goodman *et al.*, "GOODMAN RESEARCH GROUP, INC.," 2002.
[16] A. Prybutok, A. D. Patrick, M. J. Borrego, C. C. Seepersad, and M. J. Kirisits, "Cross-sectional Survey Study of Undergraduate Engineering Identity," presented at the 2016 ASEE Annual Conference & Exposition, Jun. 2016. Accessed: Apr. 20, 2026. [Online]. Available: https://peer.asee.org/cross-sectional-survey-study-of-undergraduate-engineering-identity?utm_source=chatgpt.com
[17] A. Patrick, M. Andrews, C. Riegle-Crumb, M. R. Kendall, J. Bachman, and V. Subbian, "Sense of belonging in engineering and identity centrality among undergraduate students at Hispanic-Serving Institutions," *Journal of Engineering Education*, vol. 112, no. 2, pp. 316–336, 2023, doi: 10.1002/jee.20510.

[18] R. Marra M., K. A. Rodgers, D. Shen, and R. Bogue, “Leaving Engineering: A Multi-Year Single Institution Study.” Accessed: Jan. 06, 2026. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/j.2168-9830.2012.tb00039.x
[19] E. T. Pascarella and P. T. Terenzini, *How College Affects Students: A Third Decade of Research. Volume 2*. Jossey-Bass, An Imprint of Wiley, 2005.
[20] S. Lundberg and S.-I. Lee, “A Unified Approach to Interpreting Model Predictions,” Nov. 25, 2017, *arXiv*: arXiv:1705.07874. doi: 10.48550/arXiv.1705.07874.
[21] R. K. Mothilal, A. Sharma, and C. Tan, “Explaining Machine Learning Classifiers through Diverse Counterfactual Explanations,” in *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, Jan. 2020, pp. 607–617. doi: 10.1145/3351095.3372850.
[22] I. E. Salami, S. S. Oladipo, and L. A. Perry, “Exploring High DFW Rates in an Engineering Statics Course: Insights from Faculty and Teaching Assistants,” presented at the 2024 ASEE Midwest Section Conference, Sep. 2024. Accessed: Jan. 07, 2026. [Online]. Available: https://peer.asee.org/exploring-high-dfw-rates-in-an-engineering-statics-course-insights-from-faculty-and-teaching-assistants
[23] S. Takahira, D. J. Goodings, and J. P. Byrnes, “Retention and Performance of Male and Female Engineering Students: An Examination of Academic and Environmental Variables,” *Journal of Engineering Education*, vol. 87, no. 3, pp. 297–304, 1998, doi: 10.1002/j.2168-9830.1998.tb00357.x.
[24] I. E. Salami and L. A. Perry, “Challenges in Engineering Statics: Students’ Perceptions of Their Difficulties,” presented at the 2025 ASEE Annual Conference & Exposition, Jun. 2025. Accessed: Jan. 07, 2026. [Online]. Available: https://peer.asee.org/challenges-in-engineering-statics-students-perceptions-of-their-difficulties
[25] L. Pinkus, “Using Early-Warning Data to Improve Graduation Rates: Closing Cracks in the Education System.” Alliance For Excellent Education, 2008.
[26] D. Drane, M. Micari, and G. Light, “Full article: Students as teachers: effectiveness of a peer-led STEM learning programme over 10 years,” 2014, Accessed: Feb. 15, 2026. [Online]. Available: https://www.tandfonline.com/doi/full/10.1080/13803611.2014.895388?casa_token=mq8h92jEjV0AAAAA%3Amf9CJiZ2SSthLa2gXyQ3t3YlZFMXO9xx31Kr2FTzvB-QULMaGpfMiTY-Aw7_U_FpyNyhVkCqGONfXg
[27] A. Battistini, M. S. Haque, W. A. Kitch, and S. Kum, “Improving Student Success, Retention, and Equity in Engineering Statics and Dynamics Using Experiential Learning Modules and Mastery Based Grading,” presented at the 2025 ASEE Annual Conference & Exposition, Jun. 2025. Accessed: Feb. 15, 2026. [Online]. Available: https://peer.asee.org/improving-student-success-retention-and-equity-in-engineering-statics-and-dynamics-using-experiential-learning-modules-and-mastery-based-grading