Generative AI to Streamline Institutional and System Workflows

Zachary A. Pardos & Conrad Borchers
March 23rd, 2026

What is AI?

Anything that pushes the boundary between the tasks that computers are good at and the tasks that only humans are good at

Artificial Intelligence > Machine Learning > Neural Networks > Generative AI

Game Play

Driving

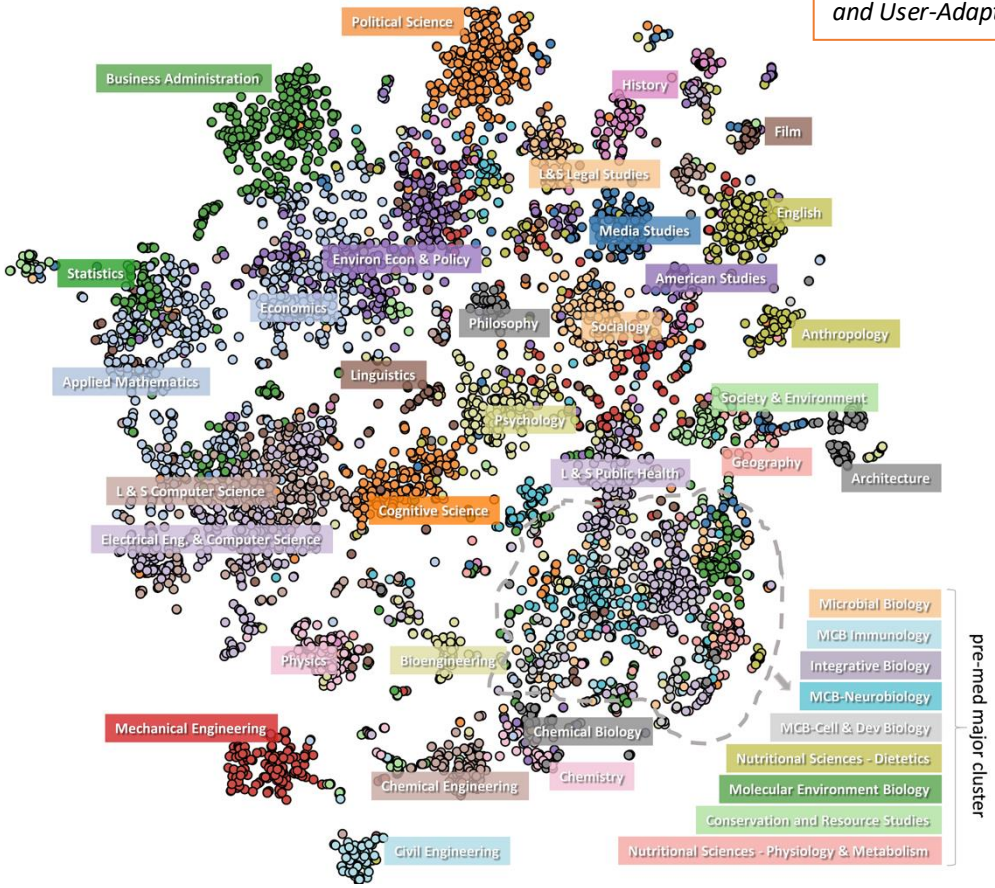
Translation

ChatGPT

Natural language

Learning about majors from student enrollment data

Pardos, Z.A., Fan, Z., Jiang, W. (2019) **Connectionist Recommendation in the Wild: On the utility and scrutability of neural networks for personalized course guidance**. *User Modeling and User-Adapted Interaction* (**UMUAI**).



Visualization of all undergrad students the semester before they graduate

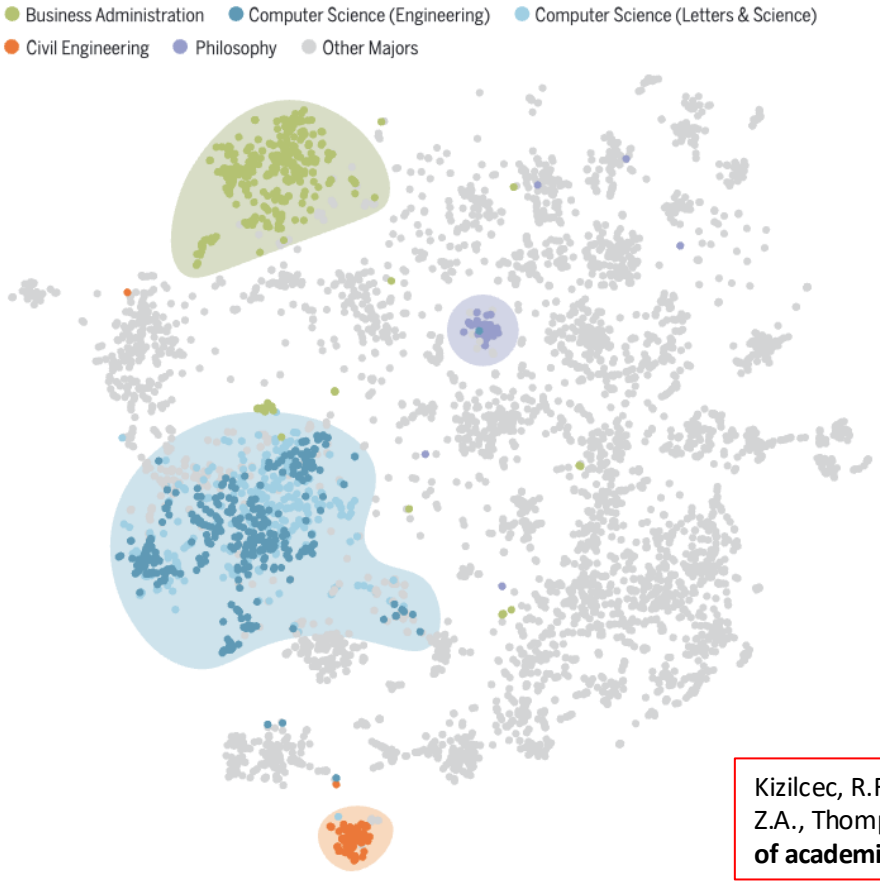
DATASET

Fall 2008 to Fall 2016

- 108,033 undergraduates
- 2.2M course enrollments
- 9,714 unique courses
- 197 subject areas

Mapping course enrollment pathways

Pathways are visualized for 6103 UC-Berkeley undergraduates across all majors from matriculation to their last year. Each point reflects a student, and a smaller distance between points reflects more similar course sequences taken. Some majors (e.g., computer science, business administration) accommodate wider variation in paths, whereas others reflect more narrow paths (e.g., civil engineering, philosophy).



POLICY FORUM

HIGHER EDUCATION

From pipelines to pathways in the study of academic progress

Students and administrators can benefit from new analytics

"Education Data Science"

"Learning Analytics"

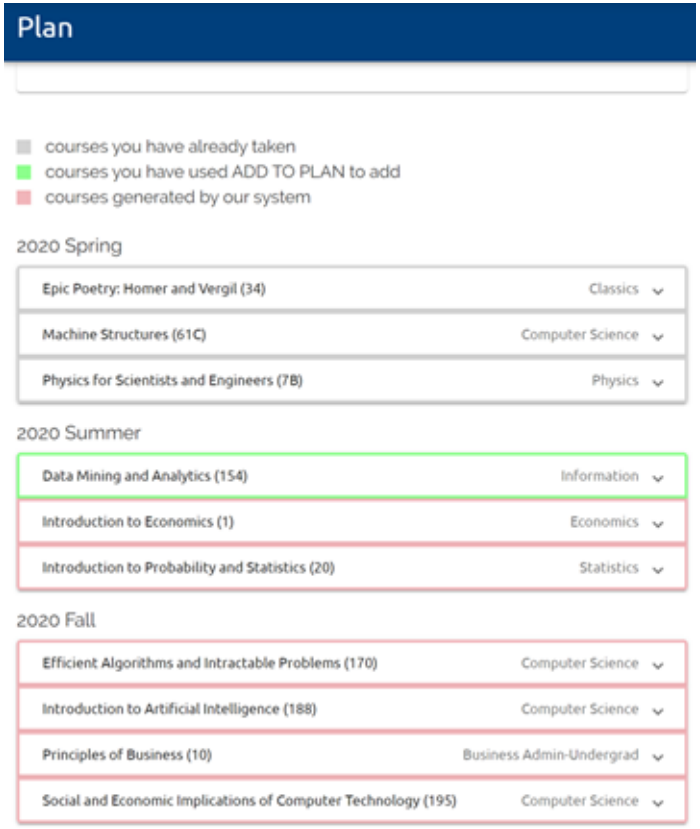
"**Higher Ed Administration**"

Kizilcec, R.F., Baker, R.B., Bruch, E., Cortes, K.E., Hamilton, L.T., Lang, D.N., Pardos, Z.A., Thompson, M.E., Stevens, M.L. (2023). **From pipelines to pathways in the study of academic progress**. *Science*, 380, 344-347.

AI virtual advising research

Course Recommendation

Academic Plan Generation

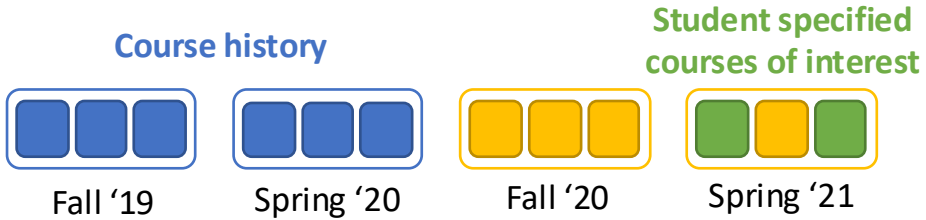


Beginning of the story

Student specified end to the story

Once upon a time .... *the hero slayed the dragon*.

- Transformer model imputes the tokens in the middle of the sequence (i.e., GP**T**)



Courses personalized by AI algorithm

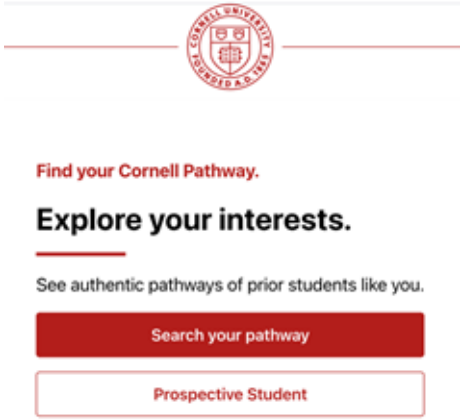
- Prioritizes graduation requirements

Shao, E., Guo, S., & Pardos, Z. A. (2021) **Degree Planning with PLAN-BERT: Multi-Semester Recommendation Using Future Courses of Interest**. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 35, No. 17, pp. 14920-14929).

Emerging Algorithmic Pathways Research

- Recommending courses as semester bundles (not individually) leads to more effective recommendations (Khan & Polyzou, 2024).

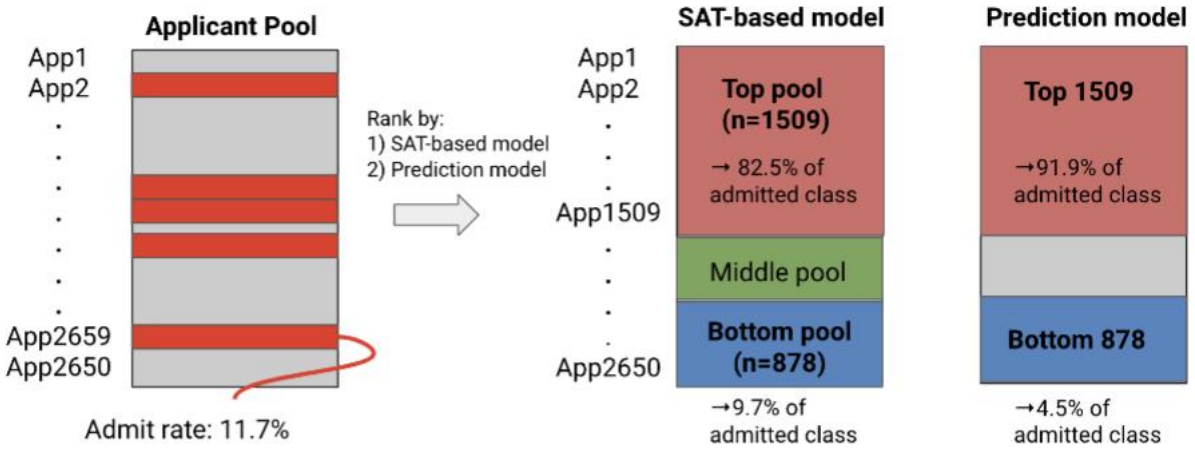
- Visualizing real student course pathways helps students explore interests and discover new, unexpected options (Chen et al., 2022).



https://pathways.cornell.edu/

AI admissions research

ML as a replacement for standardized tests



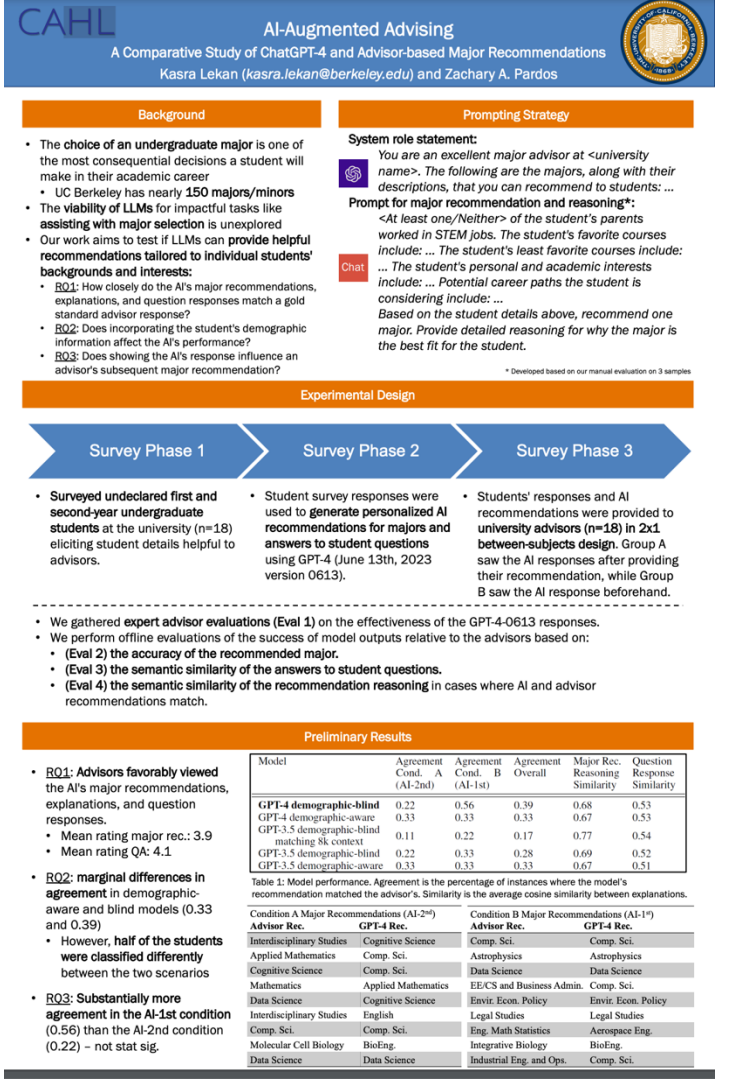
Lee, H., Kizilcec, R. F., & Joachims, T. (2023). Evaluating a learned admission-prediction model as a replacement for standardized tests in college admissions. In *Proceedings of the Tenth ACM Conference on Learning@Scale* (pp. 195-203).

AI virtual advising research

Major Recommendation

- AI recommendations matched advisor recommendations for ~33% of students
- Campus advisors at UC Berkeley (n=25) rated personalized AI major recommendations and explanations favorably (4.0 out of 5)

Lekan, K., Pardos, Z.A. (2025). **AI-Augmented Advising: A Comparative Study of ChatGPT-4 and Advisor-based Major Recommendations.** *Journal of Learning Analytics, 12(1), 110-128.*



CAHL

AI-Augmented Advising

A Comparative Study of ChatGPT-4 and Advisor-based Major Recommendations

Kasra Lekan (*kasra.lekan@berkeley.edu*) and Zachary A. Pardos

Background

- The **choice of an undergraduate major** is one of the most consequential decisions a student will make in their academic career
  - UC Berkeley has nearly **150 majors/minors**
- The **viability of LLMs** for impactful tasks like **assisting with major selection** is unexplored
- Our work aims to test if LLMs can **provide helpful recommendations tailored to individual students' backgrounds and interests:**
  - RQ1: How closely do the AI's major recommendations, explanations, and question responses match a gold standard advisor response?
  - RQ2: Does incorporating the student's demographic information affect the AI's performance?
  - RQ3: Does showing the AI's response influence an advisor's subsequent major recommendation?

Prompting Strategy

System role statement:

You are an excellent major advisor at <university name>. The following are the majors, along with their descriptions, that you can recommend to students: ...

Prompt for major recommendation and reasoning*:

<At least one/Neither> of the student's parents worked in STEM jobs. The student's favorite courses include: ... The student's least favorite courses include: ... The student's personal and academic interests include: ... Potential career paths the student is considering include: ...

Based on the student details above, recommend one major. Provide detailed reasoning for why the major is the best fit for the student.

Chat

* Developed based on our manual evaluation on 3 samples

Experimental Design

Survey Phase 1

- **Surveyed undeclared first and second-year undergraduate students** at the university (n=18) eliciting student details helpful to advisors.

Survey Phase 2

- Student survey responses were used to **generate personalized AI recommendations for majors and answers to student questions** using GPT-4 (June 13th, 2023 version 0613).

Survey Phase 3

- Students' responses and AI recommendations were provided to **university advisors (n=18) in 2x1 between-subjects design.** Group A saw the AI responses after providing their recommendation, while Group B saw the AI response beforehand.

- We gathered **expert advisor evaluations (Eval 1)** on the effectiveness of the GPT-4-0613 responses.
- We perform offline evaluations of the success of model outputs relative to the advisors based on:
  - **(Eval 2) the accuracy of the recommended major.**
  - **(Eval 3) the semantic similarity of the answers to student questions.**
  - **(Eval 4) the semantic similarity of the recommendation reasoning** in cases where AI and advisor recommendations match.

Preliminary Results

- RQ1: **Advisors favorably viewed** the AI's major recommendations, explanations, and question responses.
  - Mean rating major rec.: 3.9
  - Mean rating QA: 4.1
- RQ2: **marginal differences in agreement** in demographic-aware and blind models (0.33 and 0.39)
  - However, **half of the students were classified differently** between the two scenarios
- RQ3: **Substantially more agreement in the AI-1st condition** (0.56) than the AI-2nd condition (0.22) – not stat sig.

Model	Agreement Cond. A (AI-2nd)	Agreement Cond. B (AI-1st)	Agreement Overall	Major Rec. Reasoning Similarity	Question Response Similarity
GPT-4 demographic-blind	0.22	0.56	0.39	0.68	0.53
GPT-4 demographic-aware	0.33	0.33	0.33	0.67	0.53
GPT-3.5 demographic-blind matching 8k context	0.11	0.22	0.17	0.77	0.54
GPT-3.5 demographic-blind	0.22	0.33	0.28	0.69	0.52
GPT-3.5 demographic-aware	0.33	0.33	0.33	0.67	0.51

Table 1: Model performance. Agreement is the percentage of instances where the model's recommendation matched the advisor's. Similarity is the average cosine similarity between explanations.

Condition A Major Recommendations (AI-2nd) Advisor Rec.	GPT-4 Rec.
Interdisciplinary Studies	Cognitive Science
Applied Mathematics	Comp. Sci.
Cognitive Science	Comp. Sci.
Mathematics	Applied Mathematics
Data Science	Cognitive Science
Interdisciplinary Studies	English
Comp. Sci.	Comp. Sci.
Molecular Cell Biology	BioEng.
Data Science	Data Science

Condition B Major Recommendations (AI-1st) Advisor Rec.	GPT-4 Rec.
Comp. Sci.	Comp. Sci.
Astrophysics	Astrophysics
Data Science	Data Science
EE/CS and Business Admin.	Comp. Sci.
Envir. Econ. Policy	Envir. Econ. Policy
Legal Studies	Legal Studies
Eng. Math Statistics	Aerospace Eng.
Integrative Biology	BioEng.
Industrial Eng. and Ops.	Comp. Sci.

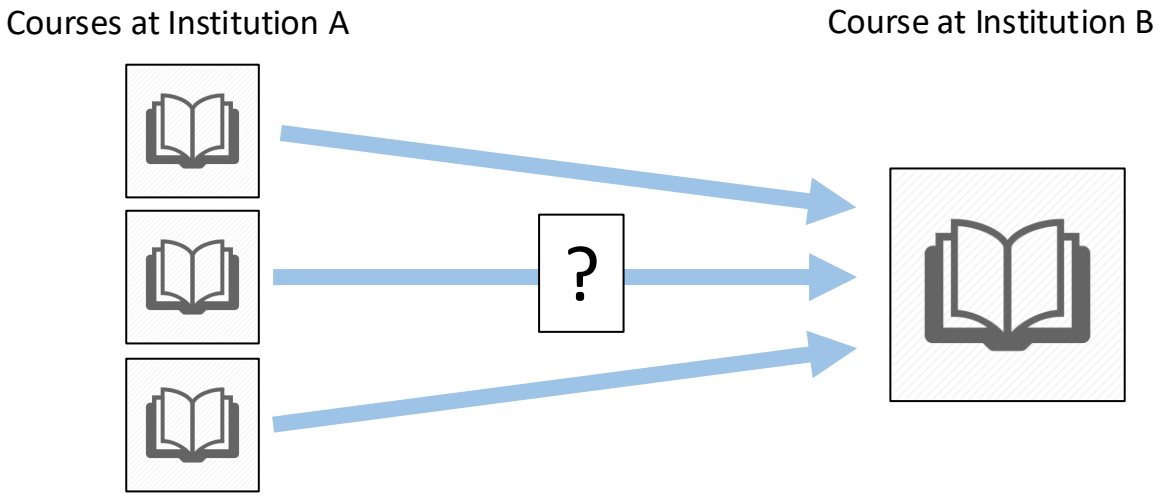
European Credit Transfer and Accumulation System (ECTS)

Awarding Credit

Wagenaar, R. (2006). An introduction to the European credit transfer and accumulation system (ECTS). *Bologna Handbook–"Making Bologna Work"(B. 2.4-1). Berlin, Stuttgart: Dr. Josef Raabe Verlag*.

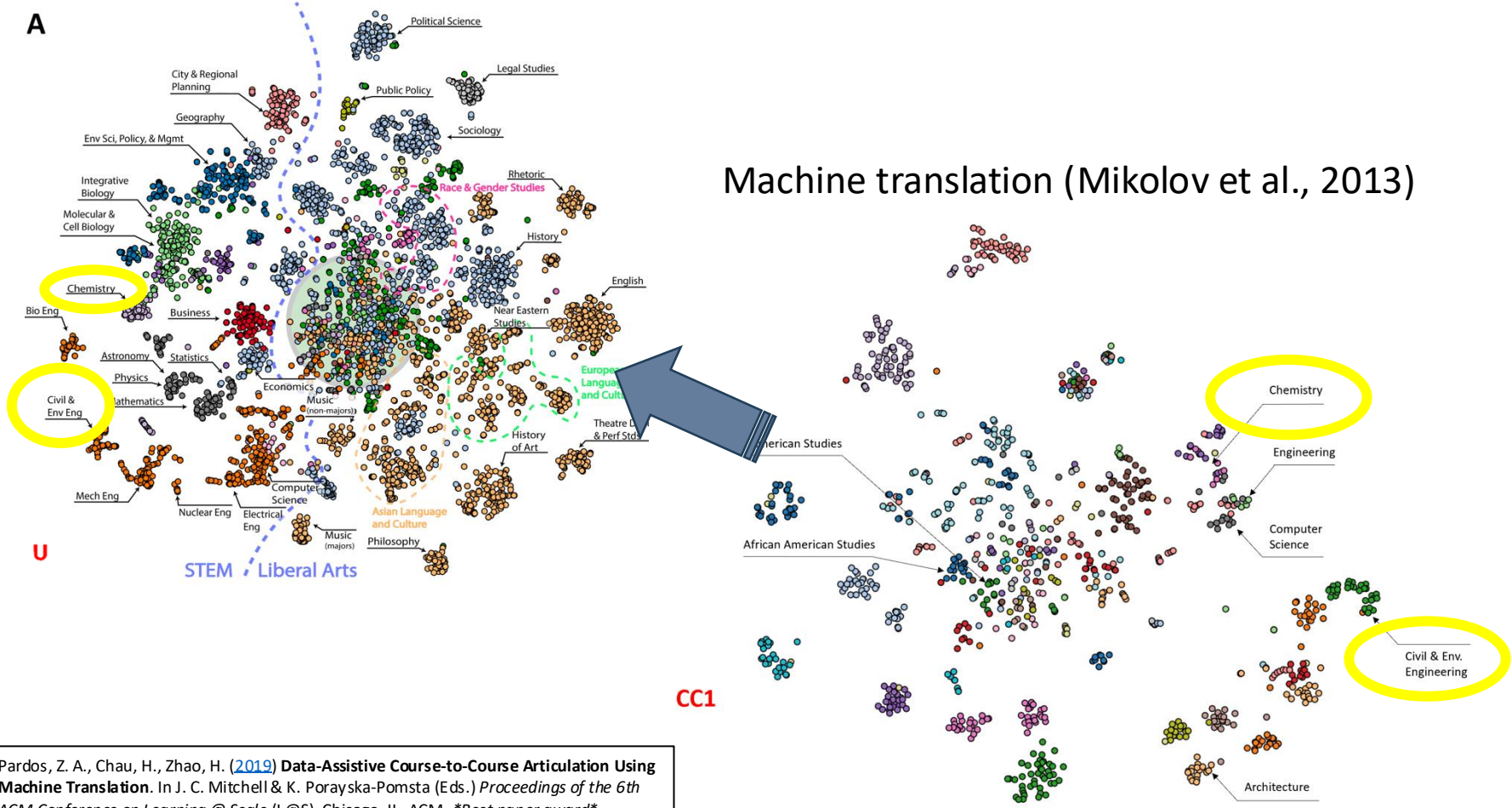
Course-to-Course Articulation

Which course (if any) at Institution A is academically equivalent to a course at Institution B?



Taking courses at Institution A that satisfy degree-credit at Institution B is often required to qualify for transfer to Institution B

Translating between institutions (articulation/equivalency)



Pardos, Z. A., Chau, H., Zhao, H. (2019) **Data-Assistive Course-to-Course Articulation Using Machine Translation**. In J. C. Mitchell & K. Porayska-Pomsta (Eds.) *Proceedings of the 6th ACM Conference on Learning @ Scale* (L@S). Chicago, IL. ACM. **Best paper award**

US Challenges transfer course evaluation process

Requires substantial time and effort from faculty and staff for manual review

- 70% of articulation experts cite ***"Excessive workload"*** [1]

Manual review often leads to inconsistency due to different interpretations of credit acceptance norms[2]

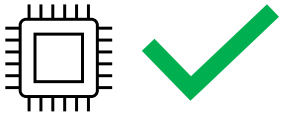
High financial cost:

- $1.2M initial investment in Alabama (1994)[3]
- $105M appropriated by California (2022-2023)[4]

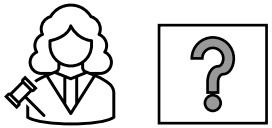
Pizarro Milian, R., Aurini, J.(2025). Barriers to Articulation: Resource Dependencies, Networks and Status Dynamics. *High Educ Policy*. https://doi.org/10.1057/s41307-025-00423-1

[1]Xu, L., Pardos, Z. A., & Pai, A. (2023). Convincing the Expert: Reducing Algorithm Aversion in Administrative Higher Education Decision-making. In *Proceedings of the Tenth ACM Conference on Learning@ Scale* (pp. 215-225).
[2]Barry, R. J., & Barry, P. A. (1992). Establishing equality in the articulation process. *New directions for community colleges*, *78*(2), 35-44.
[3]Katsinas et al. (2016). Alabama articulation and general studies committee & statewide transfer and articulation reporting system: Evaluation project final report.
[4]Assembly Budget Committee. *Floor Report of the 2022-2023 Budget* (California State Assembly, 2022).

Is it working?

- Algorithmically, yes 
  > accuracy measures up from 60% (2019) to 92% (2026)

- According to stakeholders: ~60% adoption of recommendations



Kwak, Y., Adelkar, S., & Pardos, Z. A. (2026). Advancing credit mobility through stakeholder-informed AI design and adoption. arXiv preprint arXiv:2601.05666.

Editors' Picks

Students Retention

Accreditors Encourage AI Use to Boost Credit Transfer Process

October 06, 2025

Other Emerging AI Applications

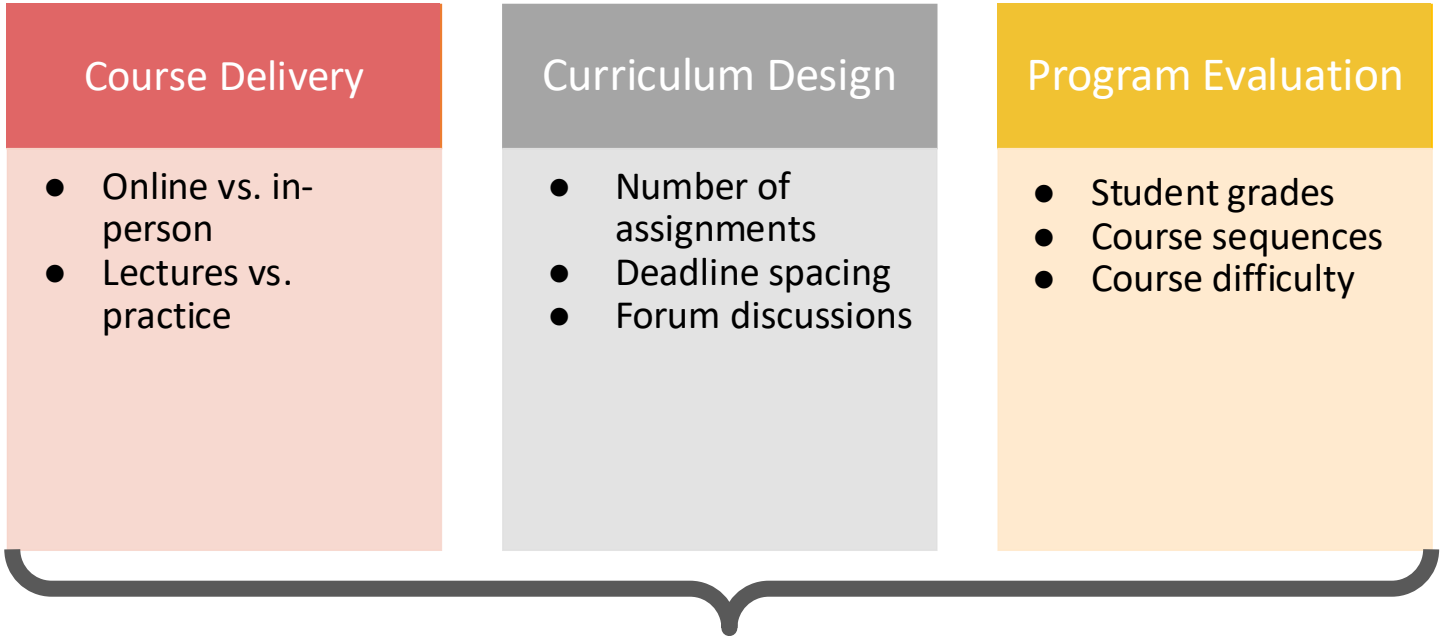
Credit mobility & transfer

- **ATAIN.org**: AI-supported course equivalency and transfer pathways across institutions (scaled to 70 institutions)
- **Pathways Tool** (Cornell): Personalize course pathway recommendations based on interest + historical data

Advising & course planning platforms

- **ATLAS (U. Michigan)**: data-driven course planning, degree progress, and curriculum insights for students & advisors
- **Ellucian “Smart Plan” / Ivy / AVA**: AI-supported advising, scheduling, and student guidance tool

Curriculum Analytics (Greer et al., 2016)



Institutional data that predict course outcomes, dropout, **workload**, and well-being.

Credit Hours Are Not Enough

Credit hours only explain **6% of students' perceived course load**.

Learning management system features explain **36%** (Pardos et al., 2023).

Pardos, Z. A., Borchers, C., & Yu, R. (2023). Credit hours is not enough: Explaining undergraduate perceptions of course workload using LMS records. The Internet and Higher Education, 56, 100882.

Proposed Solution

Course load analytics (CLA): A machine learning approach to producing metrics about course workload relevant to student course selection.

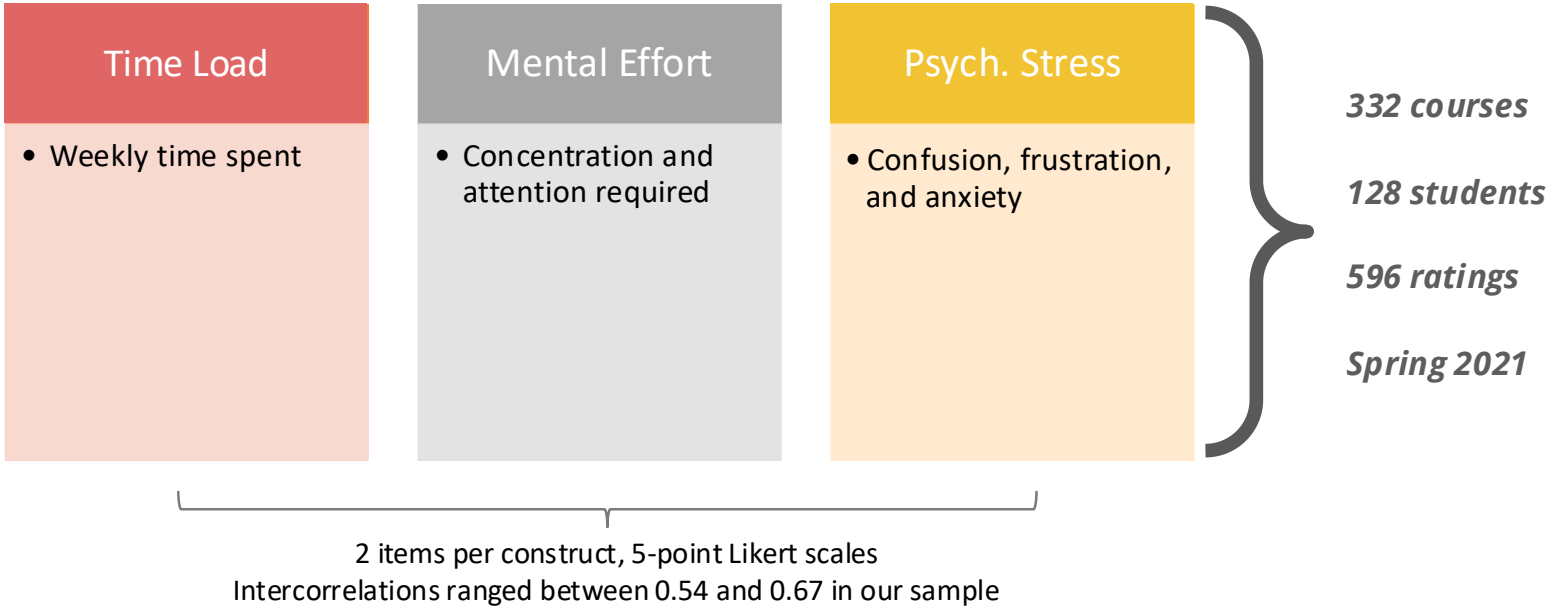
Novelty:

Multidimensional accounts of workload in higher education

Actionable for curricular redesign (e.g., assignment deadline features)

Course Workload Survey

Adapted Subjective Workload Assessment Technique (SWAT; Reid & Nygren, 1988).



Machine Learning Predictions of Workload

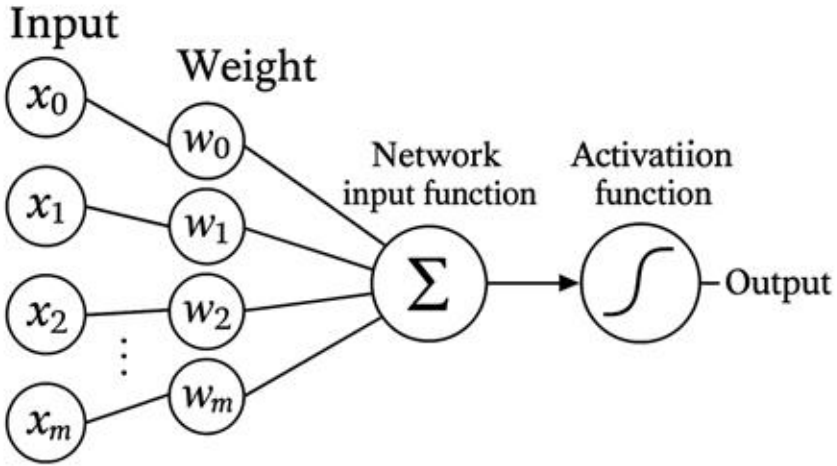
(LMS) # of Assignments

(LMS) Spread of Deadlines

…

(Enrollment) Course GPA

(Enrollment) # of Prerequisites



Study Design

Part 1 - CLA predictive validation

Workload Survey

LMS & Enrollments

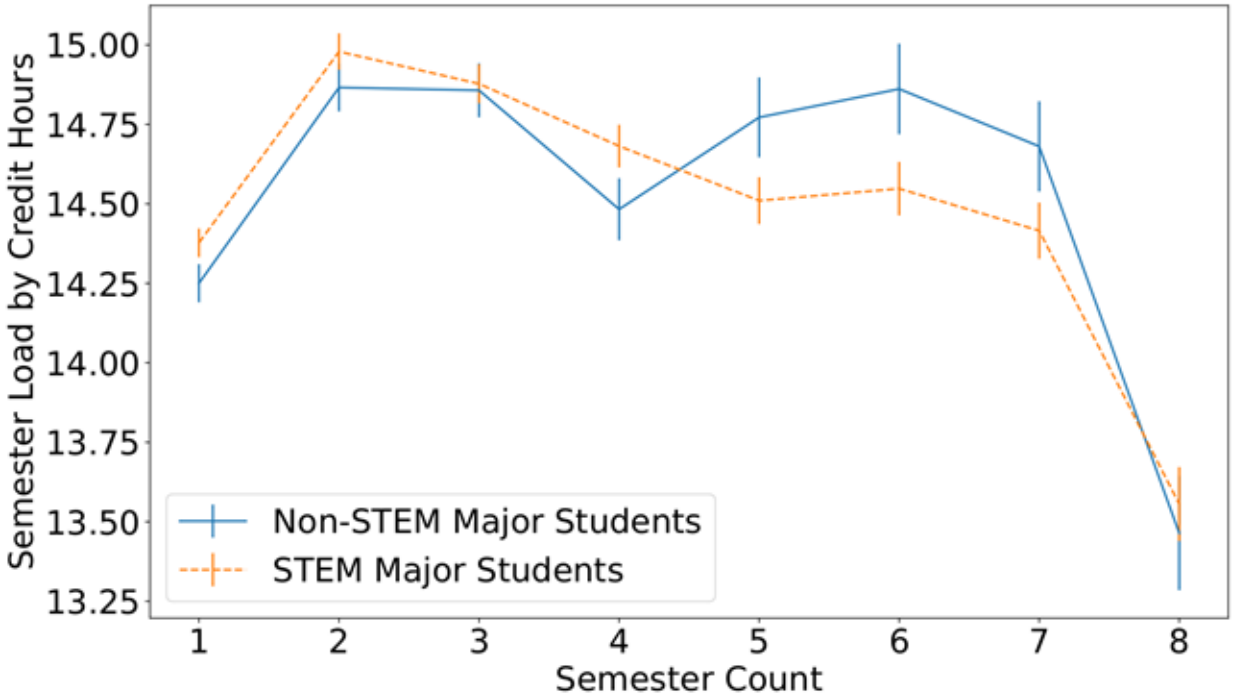
Machine Learning

Part 2 - **Longitudinal analysis of CLA applied to over 10,000 courses**

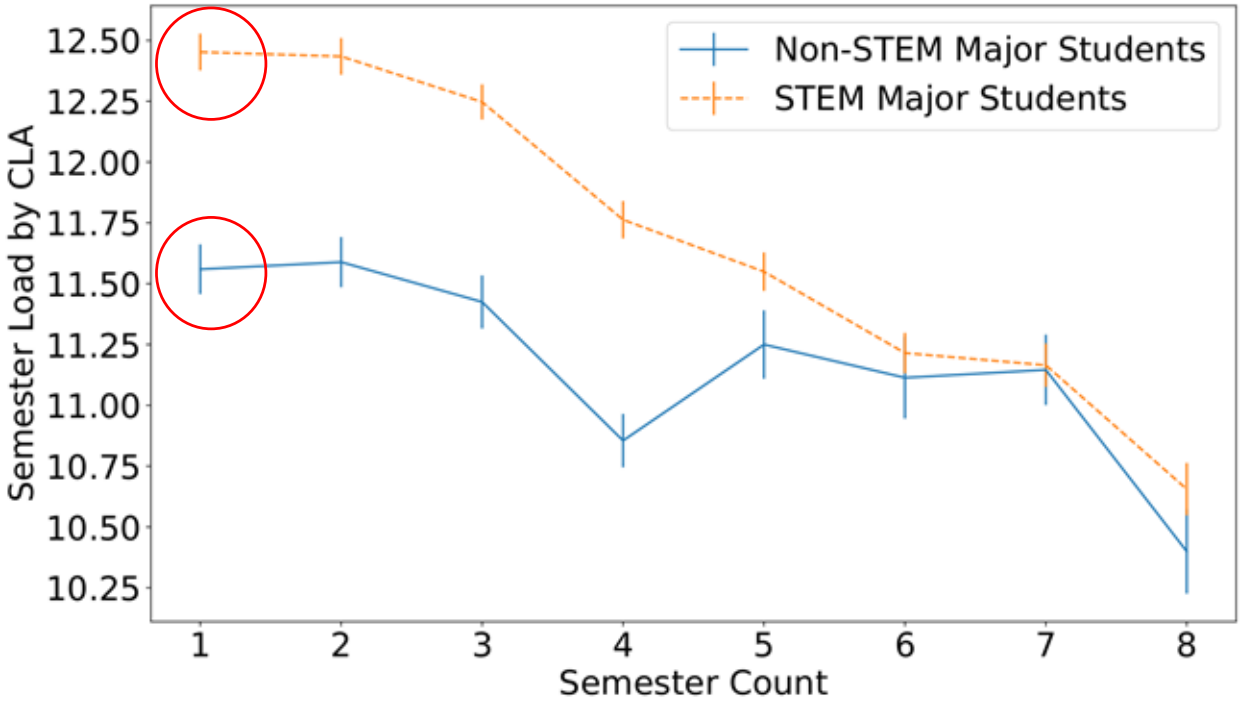
2017 Student Cohort (N = 9,160)

New Insights

Credit Hours: First Semesters are Lighter



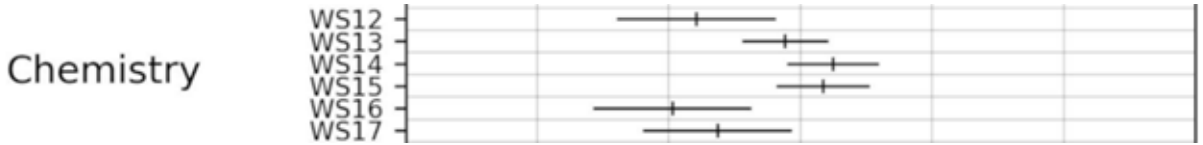
Course Load Analytics: Overload in First Semester + STEM



Other Examples of Workload Analytics

- Is the same course harder for students from non-traditional backgrounds?
  - Baucks et al., 2024a

- Is the same course equally difficult over the years?
  - Baucks et al., 2024b



Outlook: Emerging Areas of Work for Practitioners

Institutional Efficiency	**Student Mobility**	**Decision-Making**
90%+ accuracy in transcript/course data extraction (Bhaskaran & Pardos, 2025)	Automated course transfer equivalencies (Pardos et al., 2019)	Supporting expert course articulation decisions (Xu et al., 2023)
20x faster assessment & learning content creation (Reza et al., 2025)	Reduced credit loss in transfer pathways (Monaghan & Attewell, 2015)	Personalized workload advising (Borchers et al., 2025)

Translational Challenges and Opportunities

Challenges	**Opportunities**
Faculty and advisor buy-in	Value-sensitive design (Borchers et al., 2025)
Data access and governance	Generalizable, low-cost course workload models (Borchers & Pardos, 2025)
Overcoming uniform overload discouragement (McKinney et al., 2024)	Student personalization and context sensitivity

Take-Home Message

Policy priority: invest in AI for institutional workflows (not just AI for teaching and learning) to improve student credit mobility, program design, and degree completion.

Generative AI to Streamline Institutional and System Workflows

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March 23rd, 2026

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