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A research agenda for studying how AI couples educational functions in broad access higher education

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Perspective

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Abstract

Research on AI in higher education has expanded rapidly, but much of it remains organized around tools and adoption rather than around institutional reorganization. This article proposes a research agenda for studying what it calls **institutional coupling**: the degree to which AI-mediated systems draw together educational functions — authorship, tutoring, advising, assessment, analytics, and governance — that institutions have historically governed as separate domains. The article argues that adoption counts reveal little about how educational work is being reorganized, and that the more consequential research question concerns the redistribution of judgment, the coupling of institutional functions, the visibility of process, the design of contestability, and the uneven effects of optimization across student populations. Drawing on literature on AI in higher education, guided pathways, advising redesign, educational integrity, learning analytics ethics, and governance, the article specifies five research questions, a set of observable indicators grouped into five families, a comparative framework, candidate methods, and the principal threats to inference — including over-attribution, tool fetishism, policy–practice gaps, and sector flattening. It argues that community colleges and other broad-access institutions are especially valuable research sites because advising, scheduling, pathways, student support, and triage are already tightly coordinated there, which makes coupling easier to observe. The contribution is a design for inquiry rather than a finding: a way of specifying what would have to be observed for claims about AI-driven institutional convergence to be tested rather than asserted.

1. Introduction

Conceptual arguments about AI in higher education become more durable when they can be studied systematically. A recurring claim in recent work is that AI-mediated writing, tutoring, advising, assessment, pathway navigation, and support systems increasingly interfere with one another rather than remaining separable educational domains. That argument has conceptual force. It has also, so far, largely escaped empirical test.

This article asks a practical question: how should researchers study institutional convergence in ways that are analytically rigorous, institutionally grounded, and sensitive to sectoral variation? The problem is not to measure AI adoption. Adoption counts reveal little about how educational work is being reorganized. A college may deploy a chatbot without changing much else. Another may integrate AI into advising, scheduling, financial-aid support, writing support, and case management in ways that significantly redistribute authority, attention, and judgment. Both would register identically in a survey asking whether the institution uses AI.

The article argues that research on AI in higher education should move from tool-centered inventories toward studies of **institutional coupling**. Coupling refers to the degree to which educational functions are drawn together through shared AI-mediated workflows such that a change in one propagates to others. Researchers should ask where such coupling is occurring, what new forms of evidence and discretion appear, how governance adapts, and who bears the uneven effects. Community colleges are especially

useful sites for this work because many of the relevant functions are already tightly coordinated through guided pathways, advising redesign, retention infrastructures, and resource triage.

A note on terminology is warranted. Prior conceptual work uses the term *boundary collapse* for the phenomenon at issue (Peck, 2026). That term is retained in the conceptual literature but is deliberately not used as the article's organizing construct, for a methodological reason: *collapse* names an outcome and implies a threshold, and a research design should not embed in its central variable the conclusion it is meant to test. *Coupling* is the more serviceable research object because it is a matter of degree, it can be observed in workflows and documents, and it can in principle be shown to be absent.

2. Relationship to prior work

This article is the empirical counterpart to a conceptual argument advanced elsewhere, and the division of labour between them should be explicit.

Peck (2026) argues that learning, advising, and institutional navigation are now routinely co-produced by learners, educators, institutions, and machines, while institutional policy continues to assign authorship, evidence, and accountability as though each act belonged to a single agent. That work is explicit that it presents no empirical findings; it classifies its own claims as established, emerging, extrapolated, or speculative, and a substantial proportion fall into the latter two categories. Its concluding argument — that community colleges will encounter this reorganization first, because advising, scheduling, pathways, aid, and instruction are already tightly coupled there — is offered as an expectation, not a result.

That expectation is testable, and this article specifies how. Where Peck (2026) argues that convergence is occurring, this article asks what an institution would have to look like for that claim to be true of it, what would count as disconfirming evidence, and what could be mistaken for convergence but is not. The relationship is deliberately asymmetric: nothing in the agenda below depends on that work's conclusions being correct, and the agenda is designed to be capable of undermining them.

A design-based case study currently under review supplies a worked instance at the level of a single system, reporting a community-college pathway-planning prototype and the governance principles derived from building it. That study illustrates what one form of evidence in this agenda — design-artifact analysis at a single institution — can and cannot establish.

3. Method and scope

This is a conceptual research-agenda article. It synthesizes literature on AI in higher education, governance, assessment redesign, advising, guided pathways, postdigital theory, and learning analytics ethics in order to propose a program of inquiry.

The article does not report original data. It identifies research objects, candidate observable indicators, methodological options, threats to inference, and sectoral reasons for prioritizing broad-access

institutions. Its claims are therefore claims about research design, and they should be evaluated as such: not by whether the described convergence is occurring, but by whether the proposed inquiry could determine that it is.

4. What institutional coupling refers to

Coupling refers to the strength of dependency among domains that institutions have often governed independently. The most relevant domains here are authorship and writing support; tutoring and feedback; advising and pathway navigation; assessment and integrity; analytics and intervention; and governance and institutional judgment.

The argument is not that these domains were ever fully separate. It is that AI makes their interdependence more operationally consequential. A single student interaction may involve explanation, advising, drafting support, policy guidance, and triage. A single institutional system may participate in communication, recommendation, classification, and escalation. The result is not merely more technology. It is more coupling.

Three properties make coupling a workable research object rather than a metaphor.

It is a matter of degree. Institutions can be more or less coupled, and the same institution can be tightly coupled in one area and loosely coupled in another. This permits comparison.

It is observable in artifacts. Coupling leaves traces in procurement documents, data-sharing agreements, integration configurations, referral routines, and escalation procedures. It does not require access to model internals.

It predates AI and is partly independent of it. Guided pathways reform deliberately increased coupling among curriculum, advising, and scheduling well before generative AI. This is analytically useful rather than inconvenient: it supplies variation that is not caused by the phenomenon under study, and it is the basis for the over-attribution threat discussed in Section 8.

5. Five research questions

Where is AI being inserted? Researchers should map the actual institutional locations of AI use: writing support, advising platforms, financial-aid chatbots, early-alert systems, course-planning tools, assessment workflows, policy guidance, and student communications. This is the least interesting question and the necessary first one, because without it the remaining four cannot be situated.

What boundaries are becoming less stable? The key issue is role overlap rather than presence. Are advising tools also acting as informational tutors? Are writing supports also functioning as evaluative checkpoints? Are analytics tools shaping triage and academic judgment simultaneously? The unit of analysis is the function, not the product.

How is judgment being redistributed? Who makes recommendations, flags risk, interprets exceptions, or authorizes overrides? Which decisions remain human, which are system-mediated, and which are effectively co-produced? Redistribution is harder to observe than replacement because it usually occurs through configuration and default rather than through decision, and is therefore rarely minuted.

What evidence becomes newly important? Under AI-mediated conditions, institutions may rely more heavily on process traces, logs, disclosures, alerts, revision trails, or escalation records. Assessment scholarship supplies the clearest instance of such a shift: detector-led approaches to authorship have been reported as inconsistent, particularly for hybrid texts and multilingual writers (Hadra et al., 2026), while integrity scholarship argues for redesign around visible judgement rather than artifact policing (Sharma, 2026). Whether institutions actually reweight what they treat as evidence is an empirical question, and a tractable one. Researchers should examine which forms of evidence gain institutional standing, and — equally telling — which lose it.

Who bears the uneven effects? Coupling is unlikely to affect all students, staff, and institutions equally. Researchers should examine differential effects across language background, disability, race, age, enrollment intensity, and institutional resource conditions. This question should not be deferred to a final stage of inquiry, because the sampling and instrumentation decisions that make it answerable have to be made at the beginning.

6. Observable indicators

To make coupling researchable, scholars need indicators observable across cases. Five families are proposed. No single indicator establishes coupling; the construct becomes credible when indicators from several families appear together, and each family below includes at least one indicator whose absence would count against the claim.

Functional overlap. One AI system serving multiple institutional roles; one student workflow crossing formerly separate offices; staff roles combining academic, navigational, and technical mediation. *Disconfirming*: systems that remain confined to a single office with no cross-referral.

Workflow coupling. Shared platforms linking advising, scheduling, progression, and communication; AI-generated alerts triggering both academic and administrative response; institutional reliance on integrated dashboards or recommendation layers. *Disconfirming*: alerts that terminate in a single unit with no downstream routing.

Judgment redistribution. Formal or informal reliance on AI-generated suggestions in consequential decisions; new escalation procedures for AI-mediated cases; measurable change in human discretion within specific workflows. Override rates and whether interfaces record reasons for departure are the most tractable measures here. *Disconfirming*: stable override rates and unchanged decision rights following deployment.

Process visibility. Increased use of revision trails, disclosure statements, decision logs, or interaction histories; new documentation requirements for students or staff; movement away from artifact-only evaluation. *Disconfirming*: assessment and case practice unchanged in what they treat as evidence.

Governance adaptation. New policy documents, training, review protocols, or procurement rules; formal requirements for transparency, oversight, or contestability; cross-unit coordination structures. *Disconfirming*: AI governance remaining wholly within a single committee or office.

7. Methodological approaches

Coupling is unlikely to be captured well by one method. A plural program is preferable, and the methods below are ordered by what each is uniquely positioned to establish.

Comparative case studies. Cross-institution comparison of where AI is inserted, how workflows are organized, and how authority is distributed. Colleges with differing levels of integration are the most informative comparison, and sampling for that variation matters more than sampling for representativeness.

Policy and document analysis. Institutional AI policies, advising protocols, procurement contracts, training materials, and assessment guidelines reveal how colleges define acceptable use, risk, oversight, and responsibility. Procurement documents deserve particular attention because they frequently settle governance questions that no governance body ever debated.

Workflow ethnography. Observation of advising, support, assessment, and escalation practice shows how formal policy differs from actual coordination. This is the only method well positioned to detect redistribution that occurred without a decision.

Interview studies. Interviews with advisors, faculty, IT leaders, student-success staff, and students reveal how AI-mediated judgment is experienced, trusted, resisted, or worked around. Workarounds are especially informative, since they mark where a system's model of the work diverges from the work.

Interface and systems analysis. Researchers should inspect what platforms surface, prioritize, default to, and omit. Interface design is frequently the operative governance instrument, and what a system declines to display is as consequential as what it recommends.

Equity-centered audit work. Where feasible, researchers should examine whether AI-supported systems distribute attention, options, and support unevenly across student populations.

8. Threats to inference

Four threats deserve explicit design attention, because each can generate an apparent finding of convergence where none exists.

Over-attribution. Not every institutional change near AI is caused by AI. Guided pathways, learning analytics, enrollment pressure, and resource restructuring produce convergence independently and generally preceded generative AI. Designs should establish a pre-AI baseline of coupling wherever records permit, and should treat colleges with mature pathways reform and minimal AI deployment as an informative comparison rather than an empty cell.

Tool fetishism. Researchers may attend to the presence of specific products rather than to changes in organizational routine. Vendor turnover is rapid; routines are more durable and more consequential. Instruments keyed to product names will date quickly and will miss coupling accomplished through integration rather than acquisition.

Policy–practice gaps. Official documents may overstate oversight or understate reliance on informal system judgments. Document analysis alone will systematically overestimate governance quality; it should be paired with observation or with records of actual override and escalation behaviour.

Sector flattening. Studies generalizing from well-resourced universities may miss the operational realities of broad-access settings, where caseloads, scheduling constraints, and aid complexity change what a recommendation does. Sector should be treated as a condition of the phenomenon rather than as a control variable.

A fifth risk is specific to this agenda. The construct originates in conceptual work that expects to find convergence, and researchers who adopt it inherit that expectation. Research designs should therefore specify in advance what pattern of indicators would count as evidence of *loose* coupling, and should treat that outcome as a finding rather than a null result.

9. Key variables for future studies

Studies of AI convergence in higher education should consider at least the following: degree of workflow integration; number of institutional functions touched by AI; visibility of AI use to students and staff; level of human override authority; existence of contestability or appeals procedures; reliance on vendor systems versus internally governed systems; class size or advising caseload; sector type and resource capacity; pathway rigidity versus flexibility; and assessment design type.

Caseload deserves particular emphasis. It conditions nearly every other variable — override authority that cannot be exercised in the time available is nominal, and process-visible assessment that exceeds available grading capacity will not be sustained — and it is routinely recorded, which makes it one of the few variables in this list available without new instrumentation.

10. Why broad-access institutions are strong research sites

Community colleges and other broad-access institutions are especially valuable sites for this research for three reasons.

First, many already operate through tightly coupled student-success infrastructures involving guided pathways, case-management advising, course scheduling, onboarding, and intervention systems (American Association of State Colleges and Universities [AASCU], 2021; Advising Success Network, n.d.; Community College Research Center, 2019; Lahr et al., 2023). Coupling is easier to observe where it has already been deliberately built.

Second, student movement through these institutions is consequential and fragile. Course availability, transfer timing, aid status, stop-out risk, work schedules, and caregiving obligations all determine whether a recommendation matters in practice. Where the consequences of guidance are large, the redistribution of judgment is easier to detect.

Third, resource constraints make scalable AI support attractive while simultaneously raising the stakes around fairness, oversight, and staff discretion. The conditions that motivate adoption and the conditions that make adoption risky are present together.

These features make broad-access institutions revealing rather than exceptional. The claim is not that convergence occurs only there, but that it is more legible there — which is a claim about research design rather than about the sector's importance.

11. A comparative framework

A workable comparative framework would ask four questions across institutions: what functions are AI-mediated; how tightly those functions are coupled; where human judgment still enters decisively; and how fairness, contestability, and educational purpose are governed.

Applied consistently, these four questions permit institutions to be compared without reducing the inquiry to adoption counts, and they generate a profile rather than a score. Two colleges with identical AI inventories may differ sharply on the second and third questions, and that difference is the object of study.

13. A phased program

An agenda that specifies everything worth studying and nothing about order is of limited use to a research team with one year and no budget. The following sequence reflects what each phase makes possible for the next, and what each can be done without.

Phase one: descriptive mapping, single institution. Establish where AI has been inserted and how tightly the functions it touches are coupled, using materials an institution already holds: procurement contracts and their configuration schedules, integration documentation, advising protocols, assessment guidance, and committee minutes. This phase requires no new instrumentation and no human-subjects protocol in most jurisdictions, and it can be conducted by an institutional researcher as part of ordinary work. Its output is a coupling profile of the kind sketched in Section 12. Its principal value is that it establishes the

pre-AI baseline that Section 8's over-attribution threat requires, and baselines become harder to reconstruct with every year that passes — which is an argument for conducting this phase soon rather than well.

Phase two: judgment tracing, single institution. Follow a small number of consequential decision types — a probation determination, an aid-eligibility question, a schedule change late in a term — from the point where a system generates a signal to the point where a student is told something. The method is workflow observation supplemented by interviews, and the object is the sequence of hands and interfaces a decision passes through. Override rates are the most tractable quantitative component and are frequently already logged, though whether the interface records a *reason* for departure varies and is itself a finding. This phase is where redistribution becomes visible, because redistribution is precisely what does not appear in the documents examined in phase one.

Phase three: comparison across institutions. Apply the coupling profile and the judgment traces across colleges selected for variation in integration rather than for representativeness. Three to five sites is realistic; the informative contrasts are between institutions similar in mission and student population but different in how far their systems have been connected. This is the phase that can support claims about what coupling does, as distinct from claims that it exists, and it is also the phase most likely to require external funding and multi-site approval.

Phase four: equity audit. Examine whether attention, options, and support are distributed unevenly across student populations under AI-mediated conditions. This is listed last because it depends on the instrumentation the earlier phases build, but the sampling and measurement decisions that make it possible have to be taken in phase one. An agenda that defers equity questions to a final phase without designing for them at the outset will find them unanswerable when it arrives.

Two features of this sequence deserve comment. It is front-loaded with work that does not require external funding, which matters because the institutions where coupling is most legible are frequently those with the least research capacity. And it is designed so that each phase produces a publishable result on its own, since an agenda whose first output arrives in year four will not be executed by the people best positioned to execute it.

14. Discussion

The value of operationalizing this argument is not merely methodological. It changes what researchers notice. Instead of asking only whether AI improves performance or satisfaction, scholars can ask how AI reorganizes institutional work. That shift matters in higher education because academic and administrative functions have often been studied separately even when students experience them together.

A stronger research agenda would connect classroom practice, advising, student support, assessment, and governance rather than treating them as separate literatures. Field reviews have established that AI

in higher education spans these domains (Bond et al., 2024; Coman et al., 2026; Crompton & Burke, 2023), and governance scholarship has begun to treat it as an institution-wide problem (Crompton et al., 2026; City University of New York [CUNY], 2024; National Institute of Standards and Technology [NIST], 2023). What remains largely absent is research that takes the connections themselves as the unit of analysis.

The agenda has limits worth naming. It is demanding: comparative, multi-method institutional research requires access and time that few teams command, and the most informative methods are the least scalable. It risks confirmation, for the reason given in Section 8. And it may be overtaken by events, since the systems it proposes to study are changing faster than institutional research cycles complete. The response to the last of these is to key instruments to functions and routines rather than to products, which is the reasoning behind the indicator families in Section 6.

15. Conclusion

The main claim of this article is that institutional convergence can and should be studied empirically, but only if researchers move beyond tool-centered accounts of AI adoption. The central research task is to examine how AI couples educational functions, redistributes judgment, changes evidentiary practice, and affects students unevenly across institutional contexts.

Broad-access institutions provide strong sites for this inquiry because advising, scheduling, pathway navigation, support, and triage are already tightly integrated there. That makes them analytically important cases for understanding how AI reorganizes educational work across academic and administrative boundaries. A serious next phase of research should focus less on whether AI is present and more on what forms of institutional reorganization its presence makes possible — and should be designed so that it could report finding none.

Abbreviations

AI
Artificial intelligence
APC
Article processing charge
GenAI
Generative artificial intelligence

Declarations

Competing interests:

The author declares no competing interests.

Ethics approval and consent to participate:

Not applicable. This article is a Perspective. It did not involve human participants, their data, or biological material, and it did not involve animals. No ethics committee approval was sought or required, and informed consent is not applicable.

Consent for publication:

Not applicable.

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Not applicable.

Use of generative AI

This manuscript was produced through iterative, human-directed coauthoring with a generative AI system (Claude, Anthropic). The research questions originate in the author's own reading of the primary sources. Each drafting round was directed by the author's written notes, prepared offline between rounds. The AI system drafted prose and proposed syntheses across literatures, which the author evaluated, revised, or rejected. The author selected every source, verified all citation metadata against Crossref or the publishing venue, determined the conceptual framing and the design of the proposed agenda, and approved the final text. The author is accountable for all claims made here, and no generative AI system is listed as an author.

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