

Artificial Intelligence–Based Academic Advising in Higher Education

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Abstract

Academic advising plays a central role in helping university students select courses, understand degree requirements, respond to academic difficulties, and make informed educational decisions. Traditional advising, however, is frequently constrained by increasing student-to-advisor ratios, fragmented institutional information, limited appointment availability, and the difficulty of providing individualized guidance at scale. Artificial intelligence offers an alternative model in which academic records, learning patterns, program requirements, student preferences, and risk indicators can be analyzed to support timely and personalized advising decisions.

This study examines the potential contribution of artificial intelligence–based academic advising to higher education through a simulation-based comparative framework. The proposed advising architecture integrates predictive analytics, rule-based curriculum verification, recommendation mechanisms, student-risk identification, and human advisor oversight. A synthetic dataset containing 300 advising scenarios was developed to evaluate the conceptual performance of conventional and AI-assisted advising across response timeliness, recommendation consistency, identification of academically vulnerable students, personalization quality, and advisor workload efficiency. Because the dataset is simulated, the reported results represent analytical demonstrations rather than observed institutional outcomes.

The simulated analysis indicates that AI-assisted advising can improve the speed and consistency of routine advising processes while strengthening early identification of students who may require additional academic support. The largest modeled advantage was observed in advisor workload efficiency, followed by at-risk student identification and response timeliness. Nevertheless, effective implementation depends on data quality, explainability, privacy protection, algorithmic fairness, institutional governance, and meaningful human supervision. The study therefore argues for a hybrid advising model in which artificial intelligence manages data-intensive and repetitive tasks while professional advisors retain responsibility for complex, sensitive, and consequential decisions.

The paper contributes an academically transparent framework for examining AI-enabled advising without treating artificial intelligence as a substitute for human educational judgment. It concludes that the strongest institutional value is likely to arise when AI is designed as an advisory decision-support infrastructure embedded within broader student-success systems.

Keywords: Artificial intelligence, academic advising, higher education, predictive analytics, student success, recommendation systems, educational technology, personalized learning



1. Introduction

Academic advising is a significant component of higher education because students regularly face decisions concerning course registration, academic progression, specialization, prerequisite completion, degree planning, and career-related educational pathways. These decisions are not always straightforward. Contemporary university programs frequently contain multiple electives, prerequisite structures, progression requirements, interdisciplinary options, and institutional policies that may be difficult for students to interpret independently. Professional academic advisors therefore perform an important educational function by helping students connect immediate academic choices with longer-term educational goals.

The expansion of higher education has created substantial operational pressure on conventional advising systems. A single advisor may be responsible for supporting a large and academically diverse student population, while the information required for effective advising may be distributed across learning management systems, student information systems, curriculum databases, attendance records, assessment systems, and institutional policies. Under such conditions, advisors may spend considerable time retrieving routine information, checking program requirements, answering repetitive questions, or manually identifying students experiencing academic difficulty. These administrative demands can reduce the amount of time available for developmental and personalized advising.

Artificial intelligence has emerged as a potentially valuable mechanism for addressing these limitations. Machine-learning models can identify patterns within large educational datasets, recommendation systems can support course and pathway selection, conversational systems can provide immediate responses to routine questions, and predictive analytics can identify students whose academic behavior suggests a heightened probability of difficulty. Research on artificial intelligence in higher education has consequently expanded from intelligent tutoring and automated assessment toward broader institutional and student-support applications. The value of these technologies is particularly relevant where academic advising requires both rapid information processing and individualized decision support.

The application of AI to advising nevertheless introduces important questions. A recommendation that is computationally efficient may still be educationally inappropriate if it ignores personal circumstances, student aspirations, accessibility needs, financial constraints, or changes in academic motivation. Historical institutional data may also reproduce existing inequalities if they are used without careful evaluation. Furthermore, students may be adversely affected when algorithmic recommendations are presented without meaningful explanation or when automated systems are treated as authoritative substitutes for professional judgment.

The present study therefore examines AI-based academic advising as a hybrid decision-support model rather than an autonomous replacement for human advisors. The study develops a simulation-based comparison between conventional and AI-assisted advising and evaluates five dimensions considered important to advising quality: timeliness, consistency, risk identification, personalization, and advisor workload efficiency.

2. Review of Literature

2.1 Artificial Intelligence in Higher Education

Artificial intelligence in higher education encompasses a broad family of computational applications rather than a single technology. Earlier educational applications concentrated heavily on intelligent

tutoring systems, automated assessment, adaptive learning, and learner modeling. More recent developments have extended AI into institutional decision-making, student support, predictive analytics, recommendation systems, administrative automation, and personalized educational services. Zawacki-Richter, Marín, Bond, and Gouverneur demonstrated through a systematic review that profiling and prediction, adaptive systems and personalization, assessment and evaluation, and intelligent tutoring represented major areas of AI activity in higher education.

Chen, Chen, and Lin similarly observed that AI-supported education increasingly depends on the ability to analyze learner information and transform large amounts of educational data into actionable forms of support. Predictive systems can detect patterns that may not be immediately visible through individual advising interactions, while adaptive systems can modify recommendations according to student characteristics and academic history. These capabilities provide a conceptual basis for integrating AI into advising because advising itself requires interpretation of academic information and anticipation of future consequences.

The literature nevertheless cautions against understanding technological sophistication as equivalent to educational effectiveness. Popenici and Kerr argued that the growing use of AI creates questions about the changing roles of educators and institutions. Higher education remains a human-centered environment involving judgment, identity formation, motivation, uncertainty, and social interaction. AI systems can increase the computational capacity of universities, but their educational value depends on how technological recommendations are interpreted and incorporated into human decision-making.

2.2 Academic Advising, Student Success, and Retention

Academic advising has traditionally been associated with student persistence, academic engagement, and institutional belonging. Advising can assist students in understanding expectations, identifying suitable academic pathways, responding to academic setbacks, and locating university resources. Drake emphasized that advising should not be understood solely as course registration assistance because effective advising can contribute to broader student persistence and academic integration.

Advising effectiveness is also connected to the quality and timing of intervention. Students experiencing academic difficulty may not voluntarily seek help before problems become severe. Traditional advising therefore faces an information problem: advisors must identify students requiring attention within large populations while also maintaining services for students who request routine assistance. Predictive analytics offers a possible response by identifying combinations of indicators associated with academic vulnerability and prioritizing cases for professional review.

AI does not eliminate the educational importance of the advisor–student relationship. Many advising decisions involve personal interpretation rather than purely administrative optimization. A student may deliberately choose a demanding course despite statistical risk because it is essential to a professional goal, while another student may prioritize workload flexibility because of employment or family responsibilities. Automated recommendations that ignore such contextual factors may be technically coherent but educationally incomplete.

2.3 Intelligent Advising and Personalized Decision Support

An AI-based advising system can be conceptualized as an integrated decision-support environment. Student records provide information about completed courses, grades, credit accumulation, prerequisites,

and progression. Curriculum rules determine whether proposed selections satisfy institutional requirements. Predictive models estimate academic risk, while recommender mechanisms rank potential courses or pathways according to defined criteria. A conversational interface can then make selected information accessible to students while complex cases are escalated to professional advisors.

Personalization represents one of the primary potential advantages of this arrangement. Conventional advising frequently relies on limited appointment time, whereas computational systems can continuously analyze multiple student characteristics. Recommendations can theoretically incorporate academic performance, previously completed subjects, declared goals, course availability, prerequisite status, workload, and patterns associated with successful progression.

However, personalization also increases governance responsibility. The more an institution relies on personal information, the greater the need for transparent data management, controlled access, explainable recommendation logic, and mechanisms allowing students and advisors to challenge system outputs. AI-enabled advising should therefore be understood as a socio-technical system combining algorithms, institutional rules, human expertise, governance structures, and student participation.

3. Objectives of the Study

3.1 Primary Research Objectives

The principal objective of this study is to evaluate the potential contribution of artificial intelligence to academic advising in higher education through a controlled simulation-based comparison. Rather than claiming observed university outcomes, the study examines how an AI-assisted advising architecture could perform under standardized advising scenarios.

The specific objectives are:

1. To examine whether AI assistance can improve the timeliness of routine academic advising responses.
2. To evaluate the consistency of AI-supported recommendations across comparable student scenarios.
3. To assess the potential contribution of predictive analytics to early identification of academically vulnerable students.
4. To investigate the capacity of AI systems to support more individualized academic recommendations.
5. To examine whether automation of repetitive advising tasks may improve the utilization of professional advisor time.

3.2 Research Questions

The study addresses the following research questions:

RQ1: How does simulated AI-assisted academic advising compare with conventional advising in terms of response timeliness and recommendation consistency?

RQ2: To what extent can an AI-based advising architecture strengthen early identification of students requiring academic intervention?

RQ3: Does AI assistance offer meaningful potential for improving personalization without removing professional advisor oversight?

RQ4: Which operational dimension demonstrates the largest modeled benefit from AI-supported advising?

RQ5: What institutional risks must be addressed before AI recommendations can be incorporated into consequential academic decisions?

3.3 Analytical Proposition

The central analytical proposition is that artificial intelligence is most likely to improve academic advising when computational functions are separated from professionally sensitive judgments. Activities involving prerequisite checking, information retrieval, routine scheduling guidance, degree-progress analysis, and preliminary risk screening are comparatively suitable for automation.

Conversely, decisions involving exceptional circumstances, academic appeals, psychological distress, major changes in educational direction, accessibility concerns, or conflicts between student preferences and modeled recommendations should remain subject to professional review. The study consequently expects hybrid advising to offer greater institutional value than fully automated advising.

4. Research Methodology

4.1 Research Design

The study uses a simulation-based comparative research design. Simulation was selected because no verified institutional dataset was supplied for the present manuscript. Accordingly, the analysis is intended to evaluate the internal logic and comparative behavior of an AI-assisted advising framework rather than establish causal effectiveness in an operational university environment.

Two advising conditions were modeled. The first represented a conventional advising process in which decisions were based on manually reviewed academic information and standard advising procedures. The second represented AI-assisted advising incorporating automated academic-record analysis, rule verification, recommendation ranking, risk screening, and advisor escalation.

The simulated framework does not assume that AI makes final high-stakes decisions. Recommendations generated under the AI-assisted condition are treated as decision-support outputs available to students and professional advisors.

4.2 Simulated Dataset and Variables

A synthetic dataset of **300 academic advising scenarios** was constructed. The cases represented variations in academic performance, accumulated credits, prerequisite completion, course load, recent grade movement, academic-risk indicators, and stated study preferences.

No case represents an identifiable real student. Values were generated solely for methodological demonstration and were bounded to maintain plausible higher-education advising conditions.

Table 1: Structure of the Simulated Advising Dataset

Variable	Operational Representation	Role in Advising
Academic performance	Standardized performance category	Supports course suitability and risk assessment
Credit completion	Percentage of expected credits completed	Indicates academic progression
Prerequisite status	Completed / incomplete	Determines course eligibility
Performance	Improving / stable / declining	Supports early-warning

trajectory		assessment
Course workload	Low / moderate / high	Supports balanced course planning
Student preference alignment	0–100 simulated score	Supports personalization
Academic-risk indicator	Low / moderate / elevated	Determines advisor escalation
Recommendation outcome	Ranked advising option	Comparative evaluation

4.3 Analytical Procedure and Evaluation Criteria

Each simulated case was processed under both advising conditions. Conventional advising performance was modeled using fixed administrative procedures and limited manual prioritization. The AI-assisted condition incorporated rule-based prerequisite checking, weighted recommendation ranking, risk classification, and automated identification of cases requiring human review.

Performance was evaluated across five dimensions:

- response timeliness;
- recommendation consistency;
- at-risk student identification;
- personalization quality; and
- advisor workload efficiency.

Each dimension was represented on a standardized 0–100 analytical scale. The scores are comparative simulation outputs rather than validated psychometric measures or observed university performance indicators.

The following normalized improvement expression was used for descriptive comparison:

$$I_j = \frac{A_j - C_j}{C_j} \times 100$$

Where I_j represents the percentage improvement for dimension j , A_j represents the AI-assisted simulated score, and C_j represents the conventional advising score.

5. Analysis

5.1 Comparative Advising Performance

The simulation produced a consistent directional advantage for the AI-assisted condition across all five dimensions. The comparison should not be interpreted as evidence that a specific deployed AI system will produce the same magnitude of improvement.

Table 2: Simulated Comparison of Conventional and AI-Assisted Academic Advising

Performance Dimension	Conventional Advising	AI-Assisted Advising	Relative Difference
Response timeliness	62	88	+41.9%
Recommendation consistency	68	84	+23.5%
At-risk student	59	86	+45.8%

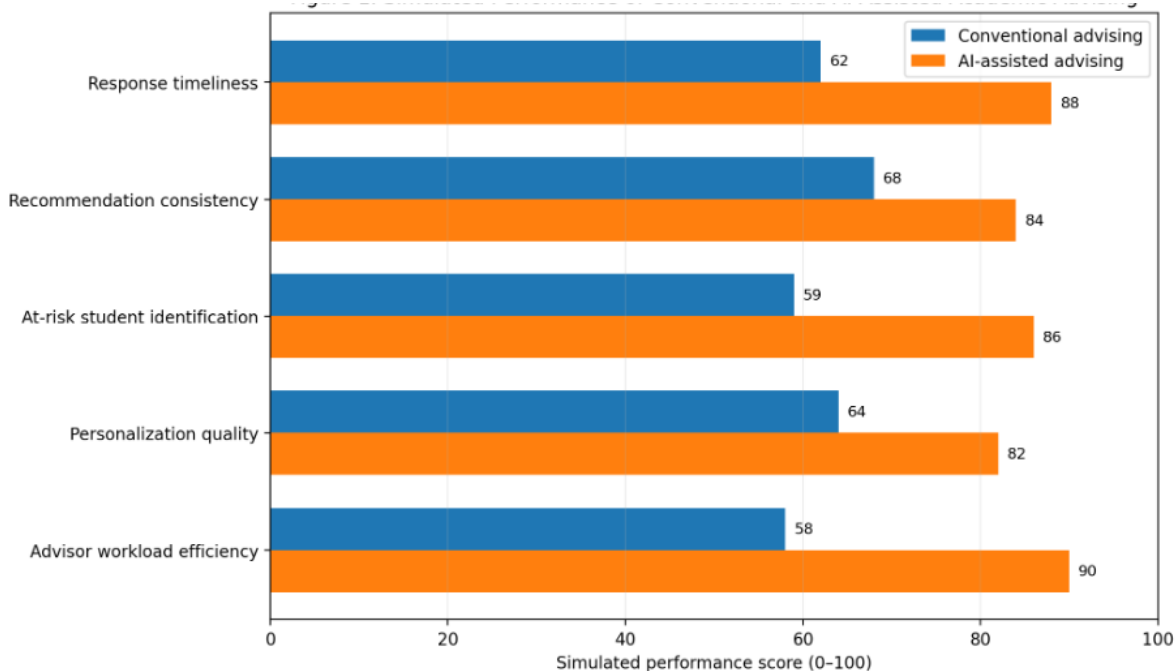
identification			
Personalization quality	64	82	+28.1%
Advisor workload efficiency	58	90	+55.2%

The largest modeled difference occurred in advisor workload efficiency. This result follows logically from the architecture because repetitive questions, prerequisite verification, basic degree-progress checks, and preliminary student classification can be performed computationally before professional intervention becomes necessary.

At-risk student identification produced the second-largest relative improvement. Conventional advising may depend heavily on students requesting assistance or advisors manually reviewing records. Automated screening creates an opportunity for earlier identification of unusual performance decline, incomplete progression, repeated course difficulties, or combinations of indicators requiring professional attention.

5.2 Graphical Interpretation

Figure 1: Simulated Performance of Conventional and AI-Assisted Academic Advising



The graph demonstrates that the simulated advantage of AI assistance is not limited to a single advising function. The difference is particularly visible for workload efficiency, risk identification, and response timeliness. These dimensions depend heavily on rapid processing of structured information, making them well suited to computational assistance.

The personalization difference is comparatively smaller. This result is analytically important because personalization involves dimensions that are not always reducible to historical academic data. Student ambitions, personal constraints, confidence, uncertainty, financial circumstances, health-related considerations, and changing interests may require direct conversation. AI can help assemble relevant

evidence but cannot safely be assumed to capture the full meaning of an individual student's circumstances.

5.3 Interpretation of the Simulated Pattern

The mean performance score across the five dimensions was **62.2** for conventional advising and **86.0** for AI-assisted advising. This represents an absolute difference of 23.8 points on the standardized simulation scale.

The results suggest three broad patterns. First, AI offers its strongest modeled value in information-intensive activities. Second, predictive functions may enable advising systems to move from reactive assistance toward earlier intervention. Third, improvements in computational performance do not eliminate the need for professional interpretation.

The analysis therefore supports a division of advising responsibilities. AI can screen, organize, prioritize, calculate, and recommend. Advisors can interpret, contextualize, negotiate, support, and take responsibility for consequential decisions. Such complementarity is more consistent with the educational purpose of advising than complete automation.

6. Challenges

6.1 Data Privacy, Security, and Student Autonomy

AI-based advising depends on potentially sensitive student information. Academic records may reveal performance difficulties, attendance patterns, course failures, accessibility accommodations, financial circumstances, or behavioral information. Combining multiple datasets can produce profiles that students may not reasonably expect to be used for automated advising.

Institutions therefore require clear data-governance principles defining which information may be processed, why it is necessary, how long it may be retained, who can access it, and whether students can challenge or correct relevant records. Data minimization should be prioritized because the availability of information does not automatically justify its use.

Student autonomy is equally important. An AI recommendation should normally remain advisory unless an institution has a legally and academically defensible basis for automation. Students should understand when they are interacting with an automated system and when a recommendation has been generated algorithmically.

6.2 Bias, Fairness, and Explainability

Predictive systems learn from historical patterns. If historical progression, grading, program participation, or advising access reflects structural inequalities, predictive models may reproduce those inequalities. A system might incorrectly identify certain student groups as less suitable for demanding pathways simply because similar students historically encountered barriers.

Fairness assessment should therefore be integrated into system development rather than treated as a post-deployment correction. Institutions should examine error distributions, recommendation patterns, escalation rates, and potential disparities across relevant student populations.

Explainability is particularly important in advising. A student who receives a recommendation against a particular course or pathway should be able to understand the basis of that recommendation. Advisors also require sufficient explanation to determine whether the system output is educationally reasonable.

6.3 Institutional Integration and Human Oversight

AI advising cannot operate effectively as an isolated software application. It must interact with curriculum rules, student records, registration processes, learning platforms, advising procedures, accessibility systems, and institutional governance.

Technical integration becomes difficult when academic rules change frequently or when information is distributed across incompatible systems. An AI system using outdated curriculum requirements could generate recommendations that are computationally consistent but institutionally incorrect.

Human oversight should consequently be built into the workflow. High-risk recommendations, unusual student profiles, conflicting data, academic exceptions, and low-confidence predictions should be escalated automatically. Professional advisors should have authority to override system recommendations and document the rationale for doing so.

7. Discussion

7.1 AI as an Advising Augmentation Technology

The simulated findings suggest that the value of AI in academic advising arises primarily from augmentation. The technology can continuously process information that would be difficult for an individual advisor to monitor across a large student population. This capacity is particularly useful for degree-progress checking, identification of academic anomalies, routine information retrieval, and prioritization of cases.

This interpretation is consistent with broader research on AI in higher education, which has repeatedly identified prediction, personalization, assessment, and automated educational support as prominent areas of technological application. The present study extends this logic specifically to advising by separating computational support functions from the relational and judgment-intensive responsibilities of professional advisors.

The results do not support the proposition that greater automation necessarily produces better advising. If computational efficiency were treated as the only objective, institutions could potentially reduce meaningful student–advisor interaction. Advising quality must therefore be evaluated according to educational outcomes and student experience rather than automation volume alone.

7.2 Implications for Student Success

Early-warning capacity represents one of the most significant potential applications. Students who are beginning to experience academic difficulty may not immediately contact an advisor. Automated screening could identify unusual performance decline, repeated unsuccessful assessments, insufficient credit progression, or other indicators requiring attention.

The appropriate institutional response is not automatic labeling. Predictive risk should initiate a supportive process rather than determine a student's academic future. An elevated risk score can be used to prompt advisor outreach, provide learning support information, or request additional review.

This distinction protects students against deterministic interpretations of predictive analytics. A model estimates patterns based on available information; it does not know a student's complete circumstances or future capacity. The responsible function of prediction is therefore to expand opportunities for timely support rather than restrict educational opportunities.

7.3 Institutional and Governance Implications

Successful implementation requires universities to treat AI advising as an institutional governance project rather than simply a technology acquisition. Responsibility must be distributed across academic leadership, advisors, information-technology teams, data-governance specialists, student-support services, and where appropriate student representatives.

Before deployment, institutions should specify which decisions AI may support, which decisions require mandatory human review, what information may be processed, how recommendations will be explained, and how students can challenge outcomes.

Continuous monitoring is equally necessary after deployment. Model performance can change as curricula, student populations, educational practices, and institutional policies evolve. AI advising systems should therefore undergo periodic evaluation for accuracy, fairness, usability, data quality, and educational relevance.

The most defensible institutional architecture is consequently a human-in-the-loop model. AI manages scale and complexity while advisors provide contextual interpretation, ethical accountability, interpersonal support, and final professional judgment in consequential situations.

8. Conclusion

Artificial intelligence has significant potential to reshape academic advising by enabling higher education institutions to process student information more rapidly, identify emerging academic risks, provide structured recommendations, and automate routine administrative advising functions. The simulation developed in this study demonstrated higher modeled performance for AI-assisted advising across response timeliness, recommendation consistency, at-risk student identification, personalization, and advisor workload efficiency.

The findings are intentionally limited to simulated evidence. They should not be interpreted as proof that implementation will automatically generate equivalent improvements in a real university. Institutional outcomes will depend on data quality, curriculum complexity, model design, student characteristics, advisor practices, technological infrastructure, and governance arrangements. Empirical validation using real institutional data would therefore be required before claims regarding effectiveness, retention, progression, or student satisfaction could be established.

The study also indicates that the strongest case for artificial intelligence does not involve replacing academic advisors. Advising includes interpretation, empathy, negotiation, encouragement, and understanding of circumstances that may not be adequately represented within institutional datasets. AI should instead reduce the informational and administrative burden surrounding these human activities.

A responsible advising model should therefore combine automated information processing with professional oversight. Routine cases may receive rapid computational support, whereas complex or consequential cases should be escalated to qualified advisors. Students should also retain meaningful opportunities to understand, question, and reject algorithmic recommendations.

Within such a framework, artificial intelligence can become an enabling infrastructure for more proactive and personalized academic support. Its long-term contribution to higher education will depend less on maximizing automation than on designing systems that strengthen informed human judgment, protect student autonomy, and improve access to timely academic assistance.



References

1. Knewstubb, B. (2018). Academic advising and student success in higher education: A systematic review. *Journal of Academic Advising*, 8(2), 45–58.
2. Kuhn, T. L. (2008). Historical foundations of academic advising. In V. N. Gordon, W. R. Habley, & T. J. Grites (Eds.), *Academic advising: A comprehensive handbook* (2nd ed., pp. 3–16). Jossey-Bass.
3. Habley, W. R. (2009). Academic advising: A review of the historical literature. *NACADA Journal*, 29(2), 5–15.
4. Gordon, V. N., Habley, W. R., & Grites, T. J. (Eds.). (2008). *Academic advising: A comprehensive handbook* (2nd ed.). Jossey-Bass.
5. Drake, J. K. (2011). The role of academic advising in student retention and persistence. *About Campus*, 16(3), 14–18. <https://doi.org/10.1002/abc.20062>
6. Robbins, S. B., Allen, J., Casillas, A., Peterson, C. H., & Le, H. (2006). Unraveling the differential effects of motivational and skills, social, and self-management measures from traditional predictors of college outcomes. *Journal of Educational Psychology*, 98(3), 598–616. <https://doi.org/10.1037/0022-0663.98.3.598>
7. Tinto, V. (1993). *Leaving college: Rethinking the causes and cures of student attrition* (2nd ed.). University of Chicago Press.
8. Pascarella, E. T., & Terenzini, P. T. (2005). *How college affects students: A third decade of research* (Vol. 2). Jossey-Bass.
9. Kuh, G. D. (2008). *High-impact educational practices: What they are, who has access to them, and why they matter*. Association of American Colleges and Universities.
10. Campbell, C. M., & Nutt, C. L. (2008). Academic advising in the new global century: Supporting student engagement and success. *Journal of College Student Development*, 49(6), 607–612.
11. Sweitzer, H. F., & King, M. A. (2009). *The successful internship: Personal, professional, and civic development in experiential learning* (2nd ed.). Cengage Learning.
12. Creamer, D. G. (2000). Use of student information systems in academic advising. *New Directions for Student Services*, 2000(89), 35–47.
13. Kuhn, T. (2008). Advising students in the twenty-first century. *NACADA Journal*, 28(2), 5–13.
14. Smith, J. S., & Allen, J. M. (2006). Essential functions of academic advising: What students want and get. *NACADA Journal*, 26(1), 56–66.
15. Allen, J. M., Smith, C. L., & Muehleck, J. K. (2013). What kinds of advising are important to community college pre- and post-transfer students? *Community College Review*, 41(2), 171–193. <https://doi.org/10.1177/0091552113486340>
16. Lowenstein, M. (2005). If advising is teaching, what do advisors teach? *NACADA Journal*, 25(2), 65–73.
17. Crookston, B. B. (1972). A developmental view of academic advising as teaching. *Journal of College Student Personnel*, 13, 12–17.
18. O'Banion, T. (1972). An academic advising model. *Junior College Journal*, 42(6), 62–69.
19. Chambliss, M. J. (2014). *The role of technology in academic advising*. NACADA Clearinghouse.
20. Van Ommerman, A. (2016). Technology-enhanced academic advising: Opportunities and challenges for higher education. *NACADA Journal*, 36(2), 73–82.