

Identifying AI-Driven Learning Analytics Performance Improvement Domains in Higher Education Universities

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Abstract

This study identifies key AI-driven learning analytics domains that support Assessment and Performance Improvement (API) initiatives in U.S. Higher Education Universities (HEUs). Using a qualitative design combining the Delphi Technique and Framework analysis method, data were collected through 20 semi-structured interviews with 24 experts across 13 HEUs. Analysis revealed a set of three key performance domains: 1) Economical value and data Intelligence, 2) AI- driven decision making capabilities and 3) requirements compliance and outcomes projection. The feedback we received from the participants indicates that AI-driven learning analytics implementation is a lot more complicated than simply analyzing and running visualizations for certain tasks. The key learning analytics performance improvement areas identified in this study can help HEUs in their focused and individualized API initiatives. Therefore, The results can be utilized to assist U.S. higher education universities (HEUs) if they decide to become data driven institutions and leverage AI- driven learning analytics. Future quantitative studies, such as large-scale surveys, can be used to collect data from a large number of higher education universities (HEUs). Data collected can then be used to statistically evaluate the characteristics and relationships identified in this study.

Keywords: AI-driven Learning Analytics, Higher Education University, Performance Improvement Domains, Data Driven Institutions, AI in Education.

Introduction

To date, the study of Learning Analytics (LA) has tended to evolve exponentially from the early 2010s in the areas of education and psychology, as well as computing and data science (Prieto et al., 2019). As a result, while the concept of LA is broadly identified in different conceptual variations, including school analytics (Sergis and Sampson, 2016), teacher or teaching analytics (Sergis and Sampson, 2017), academic analytics (Long and Siemens, 2011), assessment analytics (Nouira et al., 2019), social learning analytics (Buckingham Shum and Ferguson, 2012), or multimodal learning analytics (Blikstein and Worsley, 2016). The emergence of AI-driven approaches has further expanded these variations, introducing predictive analytics, adaptive learning systems, and intelligent tutoring systems that can operate in real time (Fan & Ouyang, 2022; Nuangchalerm, 2023). AI-driven LA incorporates predictive and prescriptive capabilities

powered by machine learning algorithms, natural language processing, and deep learning techniques (Ouyang et al., 2023). These advanced capabilities enable institutions to move from reactive to proactive decision-making, identifying at-risk students before they fail, optimizing resource allocation in real time, and personalizing learning pathways at scale (Wang et al., 2023; Sajja et al., 2025).

The role of Higher Education Universities (HEUs) in the United States (US) and across the world is increasingly important in contributing to socio-economic development, particularly in promoting discoveries through various new AI-driven LA methods. The rapid advancement of artificial intelligence has catalyzed a paradigm shift in how educational institutions collect, process, and leverage data for decision-making (Wang et al., 2023; Ouyang et al., 2023). However, HEUs cannot fully play their roles unless proper AI-driven learning analytics performance improvement domains are identified and put in place (Fan & Ouyang, 2022). No doubt AI-driven LA is a promising emerging field, yet higher education stakeholders need to become further familiar with issues related to the use of suitable AI-driven learning analytics performance improvement methods to aid in their individualized Assessment and Performance Improvement initiatives (API).

Accordingly, this paper seeks to achieve two objectives: First, to identify the key AI-driven learning analytics performance improvement domains within U.S. HEUs; and second, to provide guidance that institutions can use to develop and strengthen their individualized API initiatives. The study draws on both the qualitative insights from expert practitioners and the rapidly growing body of research on AI applications in higher education analytics.

Background

Early pioneers like Pistilli and Arnold (2010) identified the potential of Learning Analytics (LA) for supporting study success at HEUs. LA has been playing a vital role in predicting and monitoring students' performance. Based on the same data, other aspects can be analyzed that play an important part in the overall goal alignment of institutions. Recent developments of socio-technical data mining and analytic practice in educational contexts show promise in enhancing study success in higher education, through the collection and analysis of data from learners, learning processes, and learning environments in order to provide meaningful feedback and scaffolds.

The transition from traditional LA to AI-driven analytics represents a fundamental shift in capability and scope. Ouyang et al. (2023) proposed a paradigmatic framework for developing AI-driven learning analytics, establishing a closed loop between AI model development and educational application. Their research demonstrated that integrating AI performance prediction models with learning analytics approaches can significantly improve student learning outcomes in online collaborative learning contexts. This closed-loop approach encompasses four critical steps: AI model development, model and algorithm optimization, AI model educational application, and validation through empirical research.

Furthermore, Alfredo et al. (2024) conducted a systematic literature review on human-centered learning analytics and AI in education, analyzing 108 studies to examine how human-centeredness has been considered in the design of LA and AI in Education (AIED) systems. Their findings revealed important gaps in stakeholder involvement, particularly in the early design and post-evaluation phases, suggesting that even as AI capabilities advance, the human element remains crucial for successful implementation. Topali et al. (2025) similarly emphasized the need for designing human-centered LA and AI solutions, noting that adoption in authentic settings remains limited partly because of insufficient attention to stakeholders' needs and a lack of pedagogical contextualization.

The advancement of technology has provided the opportunity to track and store students' learning activities as big data sets within online environments. Users can leverage big data from different sources including learning management systems (e.g., Blackboard), open source platforms (e.g., Moodle), open social platforms (e.g., LinkedIn), and various web tools (Reyes, 2015). AI-driven analytics can process these vast volumes of data far more effectively than traditional methods, using natural language processing and machine learning to identify meaningful patterns and insights that manual analysis would overlook (Nuangchalerm, 2023).

Wang et al. (2023) explored the potential impact of AI on higher education, examining applications such as personalized learning experiences, adaptive testing, predictive analytics, and AI-powered chatbots. Their research highlighted how AI-driven analytics can improve learning efficiency and provide customized educational support, while also identifying significant risks including privacy concerns and ethical implications that must be addressed. Sajja et al. (2025) further advanced this work by developing an innovative learning analytics tool leveraging large language models to quantify student engagement, map learning progression, and evaluate diverse instructional strategies through real-time data-driven insights.

HEUs are increasingly recognizing the need for individualized API, driven by growing evidence that data-driven, personalized interventions can significantly improve student outcomes (Ouyang et al., 2023; Sajja et al., 2025). LA has been identified as a veritable tool in carrying out this task because it uses predictive models that provide actionable information based on data processing, technology-learning enhancement, educational data mining, and visualization. LA applies techniques from information science, sociology, psychology, statistics, machine learning, and data mining to analyze data collected during education administration and services, teaching, and learning and creates applications that directly influence educational practice. The purpose of identifying AI-driven LA is to tailor educational approaches to respond to each learner's need and ability through actions such as intervening with students at risk or providing feedback and instructional content.

Despite the promise, the systematic and empirical validation of learning analytics' efficacy remains under-explored (Lodge and Corrin, 2017). While numerous research ventures have emerged, from tools to policies, there is a clear challenge for educational stakeholders in developing and implementing the full potential of learning analytics (Gašević et al., 2016). The integration of AI adds both promise and complexity to this challenge. Fan and Ouyang (2022) noted that while AI-driven learning analytics has great potential to advance capabilities for supporting collaboration by offering real-time, adaptive, and detailed feedback, significant gaps remain in understanding how to best integrate these technologies within diverse institutional contexts. Thus, this paper aims to identify the key AI-driven learning analytics performance domains that could empower Higher Education Universities in the U.S. to enhance individual assessments and performance initiatives. The focus is not on prescribing specific AI-driven solutions for each domain, but on clarifying where AI-driven learning analytics may offer the greatest institutional value.

Methods

This qualitative research obtained rich contextual information via semi-structured interviews. The study employed a qualitative research design with the specific aim of understanding the key learning analytics performance improvement domains within Higher Education Universities (HEUs) in the U.S. The research study was reviewed for the protection of human subjects and approved by the Institutional Review Board (IRB) of Bowie State University(BSU). The IRB approval was obtained before any data collection. The unit of observation was individual Higher Education Universities (HEU) in the U.S, maximum variation sampling was adopted as a purposeful sampling (Creswell J.W., 2007). With help from local data analytics

experts and leaders, a representative sample of 13 HEUs located in the United States was recruited to participate in the study. Certain HEUs attributes were used in characterizing HEUs to achieve the greatest diversity in sampling and create a comprehensive understanding of the research topic. Table 1 shows the HEUs attributes used in sampling in its columns.

Table 1. HEUs Attributes Used in Maximum Variation Sampling

Size*	Institution Type	Specialty/Focus	Geographic Location
Large: > 25,000 students (5)	Pubic University (9)	Historically Black Colleges and Universities (HBCUs) (7)	Northeast (5)
Medium: 5,000-25,000 students (5)	Private University (4)	Research Institutions (6)	South (3)
Small: less than 5,000 students (3)			Midwest (3)
			West (2)

* Numbers in parentheses represent the HEUs counts in the sample.

The questions for the semi structured interviews were based on a number of well-established systems analysis concepts and techniques, which included: problem analysis that focuses on understanding the nature and root causes of issues within a system, seeking effective solutions (Lee, Mills, & Neily, 2012), technology analysis which digs into the understanding and assessment of technological components and their fit in a system or process, ensuring optimal integration and functioning (Martinsons, M.G., 1995), and outcome analysis which examines the results or consequences of interventions in a system, ensuring they align with intended goals and objectives (Thyer, B. (Ed.), 2009). The protocol was revised according to feedback received from our colleagues at the HEUs in our state.

20 interviews involving a total of 24 participants, ranging from Directors of data analytics institutes/ centers, Vice principals/Deans of Learning and Teaching, Heads of IT, Directors of E-learning Centers, Assistant of Research and Development to Provost, and Faculty of data analytics who are familiarized with the utilization of learning analytics for pedagogical enhancement, or a single participant serving in both capacities. Participation in the study was voluntary and involved no incentives. The interviews were conducted over the Zoom platform, recorded, and transcribed, verbatim to ensure accuracy. On average, each interview lasted for an hour; the resulting transcripts included more than 250 pages of text. The semi-structured nature of the interviews elicited different views and obtaining clarifications. The main topics covered in the interview included: (1) Understand the interviewee's priorities and challenges (i.e. Emerging challenges and issues with the current state of Learning Analytics adoption in the institution); (2) Understand current solutions and alternatives (i.e. What are the current solutions/methods used to better adopt or develop learning analytics, or use institutional data and learning analytics?); (3) Understand decision-making process and budget (i.e. The current practice or plans for learning analytics adoption? Who are the decision makers?); (4) Define and quantify needs and decision criteria (Measure) (i.e. What are the current learning analytics measures/indicators used by the institution? Suggestions for HEUs aspiring to be more data-driven).

Our primary data collection approach used the Delphi technique (Habibi, Sarafrazi, & Izadyar, 2014), renowned for systematically deriving expert consensus. The process involved three Delphi rounds of semi-structured interviews. In round 1, interviewees were asked open-ended questions about the identified topics, then responses were collected and summarized. In round 2, summaries from the first round were shared with the interviewees, who were then asked to prioritize, expand upon, or refine the previously listed ideas.

In the last round, based on the consolidated feedback from the previous round, interviewees were provided with a more refined list of ideas and asked to rate or rank them based on perceived importance or relevance. In conjunction with the Delphi technique, we employed the Framework method for data analysis (Smith & Firth, 2011), which has been used in many areas. The analysis steps were as follows: (1) constructing an index; (2) labeling data according to the index; (3) sorting, summarizing, and synthesizing the data; (4) creating descriptive accounts; and (5) generating explanatory accounts. As commonly performed, the responses from each Delphi round were analyzed to identify common themes, areas of agreement, and different views. The iterative nature of the Delphi technique allowed for continuous refinement of ideas and insights, culminating in a consolidated set of key domains. The researchers met regularly to discuss the results and insights. Also, the researchers completed all interviews as initially scheduled.

To ensure the validity of our findings after the Delphi rounds were completed, follow-up meetings were scheduled with participants. These meetings served as member-checking sessions, allowing experts to verify, refine, or expand upon the initial analysis results. Before a member-check interview, the transcript of the interview was sent to the interviewee to allow time for review. Additionally, data labeling of interview transcripts was completed by two researchers who first independently labeled their code and achieved 80% consistency before reconciling the labels assigned.

Results

A comprehensive and rigorous analysis of the data gathered from the 20 interviews with 24 domain experts highlighted the depth of understanding and varied perspectives on the AI-driven learning analytics performance improvement domains within the Higher Education Universities (HEUs) in the U.S. From the narratives and insightful discussions, a significant set of learning analytics performance domains identified. These domains were subsequently organized into three main value propositions or 'pain/gain' clusters. Table 2 presents some selected responses for each of the three groups:

Table 2. Selected Representative Quotes from the Interviews

Q1. "There are always issues in resources optimization, eg. many institutions, faced challenges with finite resources and a diverse student population."

Q2. "Every dollar saved through resource optimization is a dollar that can be reinvested in improving the student outcome... Our goal should always be to ensure that our resources are used in the most optimized manner."

Q3. "..... I mean resource optimization is not a one-time task. It demands continuous assessment and reassessment. Our data gives us a view of our campus's needs, and we must be adapted to change".

Q4. "The silos we have, not only in our data but also in our departments, impedes our resource optimization efforts."

Q5. "Coordinating the resources optimization in a sense of making sure that data is accessible and departments are connected is always a challenge"

Q6. " "Sometimes it's just stunning when both departments ended up buying the same expensive e-learning software licenses. Or when one of the departments upgraded their computer labs but used them only three days a week. Another department was unaware of this availability and was renting external spaces... so there is a lot of coordination and reconciliation issues."

Q7. "There is a Data Silos between the Academic and Administrative sides"

Q8. "You know, some sources are better at giving you information than others... The data most often do not count the things administrators want to know"

Q9. "One of the foremost challenges in Higher Education Institutions is the prevalence of ad hoc decision-making.. Most institutions now attempt at stopping ad hoc decisions and backing decisions with data..."

Q10. "The difficulties are... you know when specifically small sized institutions decide to discontinue a particular program simply because it has historically enrolled fewer students..."

Q11. "In academia, program cuts often occur based on historical enrollment numbers and budget constraints..."

Q12. "I think a deeper analysis of program outcomes, graduate employment rates, or projected industry demand could uncover the program's significance and arrived at a more informed choice."

Q13. "Most HEUs may provide instruction-based services without data-backed strategies, e.g. identify students at risk of dropping out or failing as a student support service...Our university offers tutoring services to all students uniformly..."

Q14. "The data related to vaccination rates during the COVID-19 pandemic, was the most crucial challenge for managing the health and safety of Higher Education Institutions (HEUs), it played important roles in various other decisions as Reopening Strategies and resources allocation and re-allocation"

Q15. "We are trying to figure out right now how to improve the students' graduation rates. but a lot of it is what we worked on before... We have different sources of data on declining graduation rates, and we implemented interventions such as academic advising and tutoring... Yet Low graduation rates remain a concern, as we lack the tools to understand the precise factors hindering student success."

Q16. "The big thing I see important is to push the graduation rates... this is a dependent task....Most students, faculty and staff don't know about existing services and tools until they need them, or until they are enforced to use them"

Q17. "We need tools to precisely project graduation rates. However, Sometimes the metrics we have don't really capture the student experience or academic rigor..."

Q18. "Without a solid University-wide Data Governance plan and policy, we often find ourselves incurring redundant costs in gathering and processing data... This is really cause a failure to comply with requirements."

Q19. "Our aim to have a holistic projection gets muddled with issues like Data ethics, privacy, and policies. There's limited awareness and discussions around access and ownership."

Q20. "We have challenges related to understanding 'what data can do', especially in terms of projections, limit our capability to predict future trends effectively."

Economical Value and Data Intelligence Need

Higher Education Universities require AI- driven learning analytics to optimize resource allocation, ensuring that resources are channeled to areas where they can have the most significant impact on student outcomes ((Q1) . Successfully optimizing resources was a core issue expressed by all participants (Q2). The optimization task requires continuous assessment and reassessment by the institution (Q3). To reduce redundant costs, institutional data must be used effectively (Q4). However, many HEUs struggle with silos in data and event departments.

Effective resources optimization requires breaking down data silos and facilitating inter-departmental coordination (Q5). Resources can be utilized inefficiently across the institution because of overlapping expenses, isolated data, and unshared best practices. However, the collected data is often incomplete (Q6-Q8). Also, some mentioned that the data most often do not count the things administrators want to know. This finding aligns with recent research emphasizing the need for integrated data ecosystems in higher education. As Sajja et al. (2025) demonstrated, AI-driven analytics tools that integrate across multiple data sources can provide a more comprehensive view of student engagement and institutional performance than fragmented, siloed systems. These findings represent foundational areas that must be strengthened to realize the full potential of AI-driven learning analytics for integrating multiple data sources and supporting more efficient, evidence-based resource allocation.

AI- Driven Decision-making Capabilities

It was mentioned that HEUs struggle with Ad hoc/ bad decisions such as Instruction-based decisions, and selecting a program to cut resources (Q9). The participants agreed that ad hoc decisions in these areas can result in inefficiencies and missed opportunities. Deciding to cut a particular program is a challenge, especially for smaller HEUs (Q10). Programs can be cut based on historical enrollment data and budget constraints, an approach that HEUs use to decide whether to cut or maintain them (Q11). A couple of participants mentioned that if they had analyzed data on program outcomes, graduate employment rates, or future industry demand, they might have realized the program's importance and made a more informed

decision (Q12). This need for data-driven decision-making is well supported by recent literature. Ouyang et al. (2023) proposed a closed-loop framework for AI-driven learning analytics that moves from model development through optimization to authentic educational application and empirical validation, providing a systematic approach to replacing ad hoc decisions with evidence-based ones. Similarly, Wang et al. (2023) highlighted how AI-powered predictive analytics can support more informed institutional decision-making by analyzing complex patterns across multiple data sources.

Participants from small and mid-size HEUs emphasized that instruction-based decisions made without data-backed strategies is an important challenge (Q13). Traditionally, HEUs provide student support services to all students uniformly, rather than using AI-driven learning analytics to identify students who would benefit most from additional support based on their academic performance and engagement. Fan and Ouyang (2022) noted that AI-driven learning analytics can better analyze the large volume of learning data within educational contexts, promoting more targeted and effective interventions than uniform approaches. Nuangchalerms (2023) further emphasized that AI-driven data analytics can identify specific areas where individual students need additional instruction, enabling teachers to provide personally customized assistance.

Furthermore, some participants mentioned that designing a curriculum for a particular program without considering the current students' enrollments, latest industry trends and job market demands could result in graduates with skills that are less relevant and competitive in the workforce. This represents another institutional area where AI-driven learning analytics holds significant potential value, enabling institutions to align curriculum decisions with real-time labor market data and student enrollment trends.

Requirements Compliance and Outcomes Projection

According to the participants, complying with requirements and outcomes projections would make important contributions for the quality of Higher Education Universities (HEUs). During the COVID-19 pandemic, vaccination rates appeared to be the most challenging problem for many HEUs (Q14). The graduation rates issue remains a persistent matter for both requirements compliance and outcomes projection (Q15-Q17).

To improve the quality of education, the HEUs need accurate, complete and timely data to act quickly and make informed policy decisions. However, the participants agreed that the fragmentation of data sources, the existing IT implementations, and the large number of disruptive tasks for some students, faculty, and staff hinder HEUs from better navigating the complex landscape of compliance requirements and outcomes projections. On the other hand, many participants mentioned the lack of solid university wide data governance plan and policy (Q18-Q20). Poor data governance can result in using different data metrics, inconsistent, outdated, or incomplete data which could lead to failure of requirements compliance and significantly off the mark projections.

The challenge of outcomes projection is one that AI-driven analytics is particularly well-positioned to address. Recent advances in AI performance prediction models have demonstrated promising capabilities for identifying at-risk students and projecting academic outcomes with increasing accuracy (Ouyang et al., 2023). Alfredo et al. (2024) noted that while AI-powered systems can heavily rely on automation for predictive analytics, the most effective approaches balance computer automation with human oversight, ensuring that projections are contextually interpreted and ethically applied. The participants' concerns about data governance echo broader findings in the field; Topali et al. (2025) emphasized that the adoption of AI-driven LA solutions in authentic settings remains limited partly due to insufficient attention to data privacy, trust, and institutional governance frameworks. Addressing these governance and data quality challenges therefore represents a foundational prerequisite for unlocking the potential of AI-driven learning analytics

in requirements compliance and outcomes projection; making this domain a critical area of focus for HEUs pursuing AI-driven LA adoption.

Discussion

This study identified three AI-driven learning analytics performance domains that Higher Education Universities (HEUs) considered vital for improving Assessment and Performance Improvement (API): Economical value and data intelligence, AI-Driven decision making capabilities, and requirements Compliance and outcomes projection. The findings show that HEUs view AI-driven learning analytics as more than a technology solution.

The findings related to the economical value and data intelligence, showed that many HEUs continue to struggle with fragmented data and limited coordination across departments. Participants explained that isolated data sources often lead to duplicated efforts and inefficient use of institutional resources. These findings are consistent with Ouyang et al. (2023) and Sajja et al. (2025), who reported that integrating multiple institutional data sources improves the value of AI-driven learning analytics and supports better institutional planning.

The findings also demonstrate that AI-driven decision making capabilities are essential for replacing ad hoc institutional decisions with evidence-based practices. Participants described challenges in curriculum planning, program evaluation, student support, and resource allocation that frequently relied on historical trends rather than predictive analytics. This finding aligns with Fan and Ouyang (2022), who emphasized that AI-driven learning analytics enables more proactive and personalized institutional interventions, and with Wang et al. (2023), who highlighted AI's potential to support strategic decision-making across higher education.

Finally, the requirements compliance and outcomes projection domain highlights the importance of institutional data governance. Participants consistently reported that inconsistent data quality, fragmented governance structures, and privacy concerns reduce the reliability of compliance reporting and predictive models. These findings reinforce Alfredo et al. (2024) and Topali et al. (2025), who concluded that effective AI-driven learning analytics requires human-centered governance, trustworthy data practices, and institutional oversight in addition to technological capability.

Although the three domains emerged inductively from expert practitioners data, these domains are connected with the Technology-Organization-Environment (TOE) Framework (DePietro et al., 1990), which identifies technological, organizational, and environmental contexts as the primary dimensions shaping organizational technology adoption decisions. Specifically, fragmented data and limited data coordination across departments reflect the technological context; challenges in curriculum planning, program evaluation, student support, and resource allocation reflect the organizational context; and inconsistent data quality, fragmented governance structures, and privacy concerns reflect the environmental context.

The three key performance domains identified in this study pinpoint the main challenges and improvement areas that HEUs should address when pursuing AI-driven learning analytics initiatives. Notably, many of these challenges including data silos, ad hoc decision-making, and governance gaps are persistent institutional issues that predate the emergence of AI-driven LA adoption, yet remain critical considerations for successful AI-driven learning analytics adoption. These domains provide institutions with a focused foundation for their individualized API efforts. The following sections elaborate on specific recommendations emerging from these domains.

Recommendations for Practice

Based on the findings, the following recommendations are offered for HEUs pursuing AI-driven learning analytics initiatives. These recommendations address adoption considerations across institutional perspectives, organizational size, and strategic planning approaches.

AI- Driven Learning Analytics Adoption Recommendations

After a thorough analysis of the data using the Framework method, some descriptive categories emerged through researchers' own higher-level qualitative interpretations of data. Figure 1 summarizes the categories observed by the researchers based on their own interpretations. We note that there is room for improvement, particularly in the areas of data and AI literacy, data connectivity, and analytics types used.

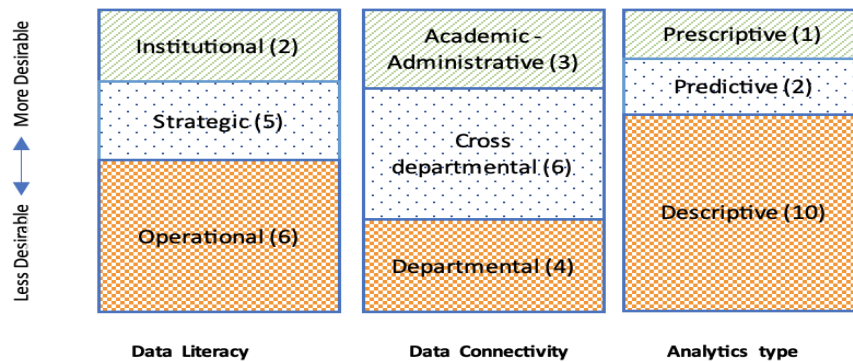


Figure. 1. Descriptive categories for HEUs formed by researchers' high-level interpretations.

A related study was conducted recently by Knobbout et al. (2023), who outlined The Learning Analytics Capability Model (LACM) which provides the essential capabilities and competencies required for effective learning analytics implementation. However, Our study provides specific areas of data literacy, data connectivity, and analytics types used within the broader context of AI-driven learning analytics systems in higher education, suggesting a gap between the potential and actual use of AI- driven LA.

All participants but one reported that their institutions use a learning analytics system. Yet, all institutions mentioned substantial academic, administrative, and data problems. This paradox is consistent with recent findings from Alfredo et al. (2024), who observed that while LA and AI in Education (AIED) systems are increasingly being adopted, their design often lacks adequate stakeholder involvement, leading to tools that are technically functional but pedagogically misaligned. Approaching AI- driven learning analytics projects by considering the important challenges and opportunities is likely to result in a higher return on investment.

Keeping a Holistic Perspective

Out of 24, 15 participants expressed that administrative (eg, course scheduling, requirements compliance, and revenues management) aspects of AI- driven learning analytics play a crucial role in addition to its academic aspects. HEUs would benefit from taking a holistic perspective and consider integration issues well before spending their resources for the acquisition of various separate solutions. This aligns with the closed-loop paradigm proposed by Ouyang et al. (2023), which advocates for AI-driven analytics systems that integrate model development, optimization, application, and validation into a continuous cycle rather than treating them as isolated activities.

Considering Organization Size

Smaller HEUs repeatedly expressed difficulties with data literacy and connectivity, which are necessary to be a data-driven institution, and to perform numerous other administrative and academic functions. While experiencing these difficulties, and due to their limited resources, smaller HEUs cannot afford AI-driven learning analytics solutions to improve their conditions either. Incentive programs such as government grants and contracts could particularly benefit smaller HEUs. Wang et al. (2023) similarly observed that the benefits of AI in education are not uniformly accessible, with smaller institutions facing proportionally greater barriers to adoption despite potentially having the most to gain from personalized analytics solutions.

Using Minimizing Pains and Maximizing Gains Approach

Participants frequently expressed concerns regarding the time and effort invested to make instruction-based decisions, particularly when selecting a program to cut. Modern AI-driven learning analytics tools and methodologies available in the education sector do offer capabilities to facilitate some of these decision-making processes. While traditional learning analytics has provided some relief, it's effective only to a certain degree, as stated by the participants. It is clear that HEUs aim to make data driven policy changes about HEUs institutional population (Instruction based decisions, select a program to cut), maximize revenues and other additions (tuition and fees, government grants and contracts, private gifts), improve the outcomes projection as retention rates, admission rates, graduation rates, enrollment, DWF rates, attendance, demographics, course scheduling, faculty course load,...etc, and comply with requirements as graduation rates, vaccination rates, diversity and inclusion. However, HEUs might also need to weigh the pains and gains of using AI-driven learning analytics along with the requirements and implications, including concerns about data privacy, algorithmic bias, and the need for faculty training and institutional readiness (Nuangchalerm, 2023; Alfredo et al., 2024).

Limitations

The limitations come from the qualitative nature of our study. The study primarily relied on the perspectives and experiences of the Delphi participants. Although efforts were made to ensure diverse and representative participants, individual biases and viewpoints based on personal experiences could potentially influence the findings. Furthermore, the Delphi technique, while iterative, may converge towards prevalent opinions and could potentially miss outlying but valuable insights. The study also focused specifically on United States HEUs, and findings may not be directly transferable to international contexts where institutional structures, regulatory frameworks, and technological infrastructure differ significantly. Future studies using quantitative research methodologies (eg, surveys) can provide quantitative data collected from a large number of HUEs to statistically evaluate certain characteristics and relationships identified in this study.

Conclusion

This qualitative study explored the key AI-driven learning analytics performance domains in HEUs along with their current learning analytics implementations. The analysis of rich contextual data resulted in detailed descriptions of HEUs' important and pressing challenges and opportunities that can be addressed by AI-driven learning analytics. As a result, a number of recommendations were made to guide learning analytics efforts and initiatives in higher education to increase their effectiveness and success. Successfully adopting and leveraging learning analytics for higher education is a sociotechnical problem with many stakeholders. Perhaps, the greatest benefits can be obtained by fostering a continuous dialogue among those stakeholders so that they can work together toward the common higher education goals in the United States, that is, better quality of education, improved outcomes projection, and reduced costs.

In light of these findings, while the landscape of AI-driven learning analytics in HEUs is vast and complex, HEUs in the U.S. aiming to integrate or enhance these capabilities within their institutions can use this study as a foundational reference. We believe that the findings from this research provide preliminary evidence about the areas of importance that are worthy of wider investigation. These findings can serve as a roadmap for U.S. Higher Education Universities aspiring to evolve into data-driven and AI-empowered institutions, empowering them to make informed decisions, optimize resources, and deliver tailored educational experiences that align with individual student needs. Eventually, the results from this study could lead to a framework for developing a set of performance measures. However, future research to assess the impact of these key AI-driven learning analytics performance domains on HEUs' stakeholders would be highly useful before performance measures find common use among HEUs.

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References

- Alfredo, R., Echeverria, V., Jin, Y., Yan, L., Swiecki, Z., Gašević, D., & Martinez-Maldonado, R. (2024). Human-centred learning analytics and AI in education: A systematic literature review. *Computers and Education: Artificial Intelligence*, 6, 100215. <https://doi.org/10.1016/j.caeai.2024.100215>.
- Avella, J. T., Kebritchi, M., Nunn, S., & Kanai, T. (2016). Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review. *Online Learning*, 20(2). <https://doi.org/10.24059/olj.v20i2.790>.
- Banihashem, S. K., Aliabadi, K., Pourroostaei Ardakani, S., Delaver, A., & Nili Ahmadabadi, M. (2018). Learning analytics: A systematic literature review. *Interdisciplinary Journal of Virtual Learning in Medical Sciences*, 9(2), 1–10.
- Bijsmans, P., & Schakel, A. H. (2018). The impact of attendance on first-year study success in problem-based learning. *Higher Education*, 76(5), 867–883.
- Blikstein, P., & Worsley, M. (2016). Multimodal learning analytics and education data mining. In *International Handbook of the Learning Sciences*. Routledge.
- Brown, M. (2012). Learning analytics: Moving from concept to practice. EDUCAUSE Learning Initiative.
- Buckingham Shum, S., & Ferguson, R. (2012). Social learning analytics. *Educational Technology & Society*, 15(3), 3–26.
- Creswell, J. W. (2007). *Qualitative Inquiry and Research Design: Choosing Among Five Approaches* (2nd ed.). SAGE Publications.

- Fan, Y., & Ouyang, F. (2022). AI-driven learning analytics applications and tools in computer-supported collaborative learning: A systematic review. *Educational Research Review*, 43, 100601. <https://doi.org/10.1016/j.edurev.2024.100601>.
- Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all. *Internet and Higher Education*, 28, 68–84.
- Habibi, A., Sarafrazi, A., & Izadyar, S. (2014). Delphi technique theoretical framework in qualitative research. *The International Journal of Engineering and Science*, 3(4), 8–13.
- Herodotou, C., Rienties, B., Boroowa, A., et al. (2019). A large-scale implementation of predictive learning analytics in higher education. *Education Tech Research Dev*, 67, 1273–1306. <https://doi.org/10.1007/s11423-019-09685-0>.
- Ifenthaler, D. (2015). Learning analytics. In *The SAGE Encyclopedia of Educational Technology*. SAGE Publications.
- Knobbout, J., van der Stappen, E., Versendaal, J., & van de Wetering, R. (2023). Supporting learning analytics adoption: Evaluating the learning analytics capability model. *Applied Sciences*, 13(5), 3236.
- Lee, A., Mills, P. D., & Neily, J. (2012). Using root cause analysis to reduce falls with injury. *Jt Comm J Qual Patient Saf*, 38, 366–374.
- Lodge, J., & Corrin, L. (2017). What data and analytics can and do say about effective learning. *npj Science of Learning*, 2(5).
- Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*, 46(5), 30–40.
- Martinsons, M. G. (1995). Radical process innovation using information technology. *Int J Inf Manag*, 15, 253–269.
- Nuangchalermp, P. (2023). AI-driven learning analytics in STEM education. *International Journal of Research in STEM Education*, 5(2), 77–84.
- Nouira, A., Cheniti-Belcadhi, L., & Braham, R. (2019). An ontology-based framework of assessment analytics. *Computer Applications in Engineering Education*.
- Ouyang, F., Wu, M., Zheng, L., Zhang, L., & Jiao, P. (2023). Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering course. *International Journal of Educational Technology in Higher Education*, 20, 4. <https://doi.org/10.1186/s41239-022-00372-4>.
- Picciano, A. G. (2012). The evolution of big data and learning analytics in American higher education. *Journal of Asynchronous Learning Networks*, 16(3), 9–20.
- Pistilli, M. D., & Arnold, K. E. (2010). Purdue Signals: Mining real-time academic data to enhance student success. *About Campus*, 15(3), 22–28.
- Prieto, L. P., Rodríguez-Triana, M. J., Martínez-Maldonado, R., et al. (2019). Orchestrating learning analytics. *Australasian Journal of Educational Technology*, 35(4), 14–33.

- Reyes, J. A. (2015). The skinny on big data in education. *TechTrends*, 59(2), 75–79.
- Sajja, R., Sermet, Y., Cwiertny, D., & Demir, I. (2025). Integrating AI and learning analytics for data-driven pedagogical decisions and personalized interventions in education. *Technology, Knowledge and Learning*. <https://doi.org/10.1007/s10758-025-09897-9>.
- Sarrico, C. S. (2018). Completion and retention in higher education. In *Encyclopedia of International Higher Education Systems and Institutions*. Springer.
- Sengupta, E., Blessinger, P., & Makhanya, M. (2020). *International Perspectives on the Role of Technology in Humanizing Higher Education*. Emerald Publishing.
- Sergis, S., & Sampson, D. G. (2016). School analytics. In *Learning, Design, and Technology*. Springer.
- Sergis, S., & Sampson, D. G. (2017). Teaching and learning analytics dashboards. In *Learning, Design, and Technology*. Springer.
- Siemens, G. (2011). Learning analytics: The emergence of a discipline. *American Behavioral Scientist*, 57(10), 1380–1400.
- Smith, J., & Firth, J. (2011). Qualitative data analysis: The framework approach. *Nurse Res*, 18, 52–62.
- Thyer, B. (Ed.). (2009). *The Handbook of Social Work Research Methods* (2nd ed.). SAGE Publications.
- Tinto, V. (2005). *Taking student retention seriously*. Syracuse University.
- Topali, P., Ortega-Arranz, A., Rodríguez-Triana, M. J., Er, E., Khalil, M., & Akçapınar, G. (2025). Designing human-centered learning analytics and artificial intelligence in education solutions: a systematic literature review. *Behaviour & Information Technology*, 44(5), 1071-1098.
- DePietro, R., Wiarda, E., & Fleischer, M. (1990). The Context for Change: Organization, Technology, and Environmental. In Tornatzky, L. G., & Fleischer, M. (Eds.). *The Process of Technological Innovation*. (pp. 151-175). Lexington, MA: Lexington Books.
- Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the potential impact of artificial intelligence on international students in higher education: Generative AI, chatbots, analytics, and international student success. *Applied Sciences*, 13(11), 6716. <https://doi.org/10.3390/app13116716>.