MAIN ISSUES OF PEDAGOGY AND PSYCHOLOGY (MIOPAP)
https://miopap.aspu.am/

DATA-DRIVEN EDUCATION IN UNIVERSITY PHYSICS: A COMPREHENSIVE ANALYSIS OF LEARNING ANALYTICS DASHBOARDS AND AI TUTORING***

DOI: 10.24234/miopap.v12i1.85

Samvel ASATRYAN, *PhD in Education, Associate professor, Head of Department for Educational Processes Management and Reforms at Kh. Abovian Armenian State Pedagogical University,* ***Republic of Armenia***

E-mail: ***asatryansamvel@aspu.am***

https://orcid.org/0000-0002-8323-822X

Naira SAFARYAN, *PhD in Education, Associate professor, Vice-rector for education processes at Kh. Abovian Armenian State Pedagogical University, Republic of Armenia, Director's Advisor of the ASPU Base College.* ***Republic of Armenia***

E-mail: ***safaryannaira38@aspu.am***

https://orcid.org/0000-0003-4924-9846

Abstract

This article presents a comprehensive analysis of data-driven learning technologies—specifically Learning Analytics (LA) dashboards and Artificial Intelligence (AI) tutoring systems—in undergraduate physics education. Emphasizing the importance of pedagogical integration and sociological context, the study explores how these tools influence learning outcomes, student engagement, and equity.

Learning Analytics dashboards are shown to support engagement and self-regulation, particularly when integrated with active learning pedagogies. However, their direct impact on academic achievement remains inconsistent, with effectiveness hinging on design and implementation. AI tutoring systems, including cognitive, dialogue-based, and generative models (such as RAG-based LLMs), display greater promise in enhancing conceptual understanding, problem-solving skills, and personalization. Their success depends not only on technological capability but also on the alignment with learner needs, faculty acceptance, and social equity.

The study employs a triangulated methodology combining international case studies, sociological theory (TAM, ANT, Bourdieu), and synthesized survey data to assess user perceptions. It identifies key barriers, such as technological fluency gaps, digital divides, and ethical concerns around data privacy, algorithmic bias, and over-reliance on automation. A focused lens on Armenia's context underscores infrastructural and pedagogical challenges limiting adoption.

The article concludes with a critical synthesis: data-driven tools can significantly enhance physics education but are not panaceas. Their success depends on context-sensitive pedagogical integration, faculty and student readiness, and ethical design. Recommendations emphasize hybrid human-AI models, explainable AI, and equity-first deployment strategies.

Keywords: *learning analytics, AI tutoring systems, undergraduate Physics, personalized learning, educational equity, technology acceptance model (TAM), actor-network theory (ANT), Bourdieu's theory of practice, digital pedagogy, data-driven education.*

INTRODUCTION

The landscape of higher education, particularly within Science, Technology, Engineering, and Mathematics (STEM) disciplines such as physics, is undergoing a significant transformation driven by the proliferation of digital technologies (Physical Review Link Manager, 2025). Amidst this evolution, data-driven learning strategies, notably Learning Analytics (LA) dashboards and Artificial Intelligence (AI) tutoring systems, have emerged as prominent innovations. These technologies are often presented with the promise of revolutionizing pedagogy by offering personalized learning pathways, enhancing student engagement, and ultimately improving educational outcomes (NSF, 2025). Physics education provides a particularly salient context for examining these tools. Characterized by its emphasis on deep conceptual understanding, complex problem-solving, mathematical rigor, and often large introductory courses with diverse student populations, physics presents unique challenges and opportunities for data-driven interventions ("Using machine learning", 2025).

The field of Learning Analytics (LA) centers on the "measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs". Concurrently, Artificial Intelligence in Education (AIED) focuses on developing interactive and adaptive learning environments, frequently employing AI techniques such as machine learning, natural language processing, and sophisticated student modeling to provide tailored support (Liu, Latif, & Zhai, 2025). The recent advent and widespread accessibility of powerful generative AI models, exemplified by systems like ChatGPT and Google's Gemini, have dramatically intensified interest, research, and public discourse surrounding the role of AI in education, presenting both unprecedented opportunities and significant challenges (Society for Learning Analytics Research, 2025).

Despite the considerable potential attributed to LA dashboards and AI tutors, their actual impact within the specific domain of undergraduate physics necessitates rigorous, critical, and context-aware examination. A purely technological perspective is insufficient; it is crucial to analyze the implementation and effects of these tools through sociological lenses, taking into account user experiences, equity implications, and the complex social dynamics inherent in educational settings (Grimm et al., 2023). Critical analyses have cautioned that LA approaches may oversimplify the intricate processes of teaching and learning (Guzmán-Valenzuela et al., 2021) and carry the risk of amplifying pre-existing societal inequalities if not implemented thoughtfully (Grimm et al., 2023). The demonstrable effectiveness of LA dashboards, in particular, has been questioned in recent reviews, suggesting that their impact may not live up to initial expectations (Flanagan, Wasson, & Gašević, 2024).

This article undertakes an in-depth, international analysis of the application, effectiveness, and implications of LA dashboards and AI tutoring systems within undergraduate physics programs. It synthesizes evidence drawn from the intersecting fields of physics education research (PER), educational technology, and the sociology of education. The central argument posits that while these data-driven tools offer tangible potential benefits for personalization, feedback, and engagement, their effectiveness is not inherent but highly contingent upon context. Factors such as pedagogical integration, user acceptance (by both students and instructors), and careful consideration of sociological dimensions, especially concerning equity, are paramount. The analysis incorporates findings from sociological surveys, including synthesized numerical data reflecting trends in user perspectives, and applies relevant theoretical frameworks—including the Technology Acceptance Model (TAM), Actor-Network Theory (ANT), and Bourdieu's theory of practice—to develop a nuanced understanding of technology adoption, use, and impact in this specific educational context.

Additionally, the backdrop of Armenian higher education offers a unique perspective for examining the uneven spread of these technologies. Systems like Moodle and Google Classroom were frequently used by universities for emergency remote instruction during the COVID-19 transition. However, there was little use of AI-based training tools or structured LA dashboards. The main causes of this were inadequate institutional preparedness, faculty lack of technical expertise, and infrastructure constraints. These circumstances emphasize the need for specialized approaches when implementing data-driven educational advances and the global digital divide.

The subsequent sections will first establish the theoretical foundations guiding the analysis. Following this, the article will review international implementations and evidence pertaining to LA dashboards and AI tutoring systems separately, focusing on undergraduate physics contexts. A dedicated section will then delve into a sociological analysis of user experiences, drawing on survey data and qualitative perspectives. The article will synthesize findings regarding the effectiveness of these tools in relation to learning outcomes, student engagement, and equity. Broader social and ethical implications will be discussed before concluding with an overview of key challenges, research gaps, and promising future directions for the field.

II. Theoretical Foundations: Understanding Technology Adoption and Impact in Physics Education

To comprehensively analyze the role and impact of LA dashboards and AI tutors in undergraduate physics, it is essential to employ theoretical frameworks that can illuminate the complex interplay between technology, pedagogy, individual users, and the social context of learning. Several theoretical lenses offer valuable perspectives:

Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT): Originating in information systems research, TAM provides a foundational model for understanding user acceptance of technology. It posits that Behavioral Intention (BI) to use a system is primarily determined by two core beliefs: Perceived Usefulness (PU) – the degree to which a user believes using the system will enhance their performance – and Perceived Ease of Use (PEOU) – the degree to which a user believes using the system will be free of effort (Zhang et al., 2023). Subsequent extensions, such as UTAUT and UTAUT2, incorporate additional factors like Social Influence (or Subjective Norm - SN), Facilitating Conditions, Hedonic Motivation (Perceived Enjoyment), Price Value, Habit, Performance Expectancy, Effort Expectancy, Anxiety, and Self-Efficacy (*AIS Electronic Library (AISEL) - AMCIS 2018 Proceedings: The Effect of Studentsâ€TM Technology Readiness on Technology Acceptance*, n.d.). These models are highly relevant for examining why physics students and instructors might choose to adopt (or resist) LA dashboards or AI tutors, highlighting the importance of user perceptions regarding the tools' utility, usability, and alignment with social norms within the educational environment (Ateş & Gündüzalp, 2025). Studies applying these models to AI adoption in STEM education have found PU and PEOU to be significant predictors of intention, influenced by factors like subjective norm, prior experience, enjoyment, anxiety, and self-efficacy (Ateş & Gündüzalp, 2025).

Social Constructivism: While not a technology-specific theory, social constructivism provides a crucial pedagogical backdrop. It emphasizes that learning is an active, social process where knowledge is constructed through interaction with others and the environment (Guzmán-Valenzuela et al., 2021). This perspective prompts examination of how LA and AI tools mediate or potentially hinder vital student-student and student-instructor interactions. Do these tools foster collaborative knowledge building, or do they lead to more isolated learning experiences? How do they impact the development of shared understanding within a physics learning community (Brown & Cain, 2025)?

Actor-Network Theory (ANT): Originating in science and technology studies, ANT offers a powerful lens for analyzing socio-technical systems by treating both human and non-human elements as 'actors' (or 'actants') within a network (Demirci, 2025). ANT avoids pre-determining the 'social' and instead focuses on how networks of heterogeneous actors (students, instructors, AI tutors, dashboards, algorithms, textbooks, institutional policies, physical spaces) are assembled and stabilized through processes of 'translation' (Kamp, 2019). Translation involves stages like problematization (defining actors and their necessary roles), interessement (actions to impose and stabilize actor identities), enrolment (defining roles and coordinating actors), and mobilization (ensuring actors act as representatives) (Thomas & De Villiers, 2002). ANT encourages a symmetrical view, where technologies like AI tutors are not merely passive tools but active participants that shape interactions, define problems, and influence outcomes within the educational network (Demirci, 2025). This perspective moves beyond individual acceptance (TAM) to analyze how the entire system, including the technology itself, comes to function (or fails to function).

Bourdieu's Theory of Practice: Pierre Bourdieu's sociological framework provides critical tools for analyzing power dynamics, social reproduction, and inequality within social fields (Ignatow & Robinson, 2017). Key concepts include:

- **Field:** A structured social space with its own rules, logic, and forms of competition (e.g., the field of university physics education, or a specific physics department (Stahl et al., 2023).
- **Habitus:** A system of durable, transposable dispositions acquired through socialization that shapes an individual's perceptions, judgments, and practices. It reflects one's position within the social structure (Stahl et al., 2023).
- **Capital:** Resources that confer power and status within a field. Bourdieu identified economic, social (networks, relationships), cultural (knowledge, skills, credentials, often embodied or objectified), and symbolic capital (prestige, recognition (Stahl et al., 2023). Access to and proficiency with digital technologies can be considered a form of cultural or technological capital.
- **Doxa:** The taken-for-granted, unquestioned beliefs and assumptions shared within a field (Stahl et al., 2023).

Bourdieu's theory is particularly useful for examining how pre-existing social and cultural capital influences students' ability to access, navigate, and benefit from educational technologies like LA dashboards and AI tutors (Chikwe et al., 2024). It helps analyze the digital divide not just as an issue of access, but as intertwined with broader social inequalities (Chikwe et al., 2024). It also allows for an analysis of how proficiency with these new tools might become a valued form of capital within the physics education field, potentially creating new forms of stratification or reinforcing existing ones (Dart et al., 2024).

Applying and Integrating Theoretical Perspectives:

No single theory provides a complete picture. TAM and UTAUT offer valuable insights into individual adoption drivers based on perceived utility and ease of use (Ateş & Gündüzalp, 2025). However, the inconsistent findings reported in some TAM studies (Zhang et al., 2023) and the importance of context (Yusuf et al., 2024) highlight the model's limitations when applied in isolation. A student's decision to use an AI tutor is not solely based on its perceived usefulness or ease of use.

ANT complements TAM by shifting the focus from individual perception to the dynamic network of interacting human and non-human actors (Demirci, 2025). It prompts questions about how the AI tutor itself acts within the learning environment, how it 'translates' pedagogical goals, and how students and instructors are 'enrolled' into interacting with it in specific ways (Thomas & De Villiers, 2002). This perspective acknowledges the agency of the technology in shaping the educational process.

Bourdieu's theory adds a crucial layer by embedding the socio-technical network within broader social structures and power relations (Stahl et al., 2023). It explains how a student's background (their habitus and capital) influences their interaction with the technology and the educational field (Dart et al., 2024). For instance, a student's 'habitus' might make them more or less comfortable with the mode of interaction required by an AI tutor, while their 'cultural capital' (e.g., prior technological skills, parental support) might affect their ability to use it effectively. Furthermore, the 'field' of physics education dictates whether proficiency with such tools is recognized and rewarded (becomes 'symbolic capital' (Dart et al., 2024). Therefore, understanding the application of LA and AI requires considering individual perceptions (TAM), the active role of the technology in the network (ANT), and the influence of social structures and individual dispositions (Bourdieu).

However, even this combination of sociological and acceptance theories may not fully capture the nuances of the learning process itself. While these frameworks help explain *why* tools are adopted and *how* social factors shape their use, they often treat the pedagogical interaction as a 'black box'. They do not fully elucidate the cognitive and affective mechanisms through which these tools impact student understanding, reasoning, motivation, or self-regulation (AIS Electronic Library (AISEL) - AMCIS 2018 Proceedings: The Effect of Studentsâ€TM Technology Readiness on Technology Acceptance, n.d.). Therefore, a comprehensive analysis must also draw upon theories from the learning sciences (e.g., cognitive load theory, self-regulated learning theory) to understand *how* learning happens (or fails to happen) during interactions with LA dashboards and AI tutors. The sociological analysis provides the context and conditions, while learning sciences provide insights into the mechanisms of impact.

III. Learning Analytics Dashboards in Undergraduate Physics: International Implementations and Evidence

Learning Analytics (LA) dashboards represent a significant application of LA principles, aiming to provide stakeholders – primarily students and instructors – with visual representations of learning data to foster reflection, inform decision-making, and ultimately optimize the learning process (DeVaney, 2018). In the context of undergraduate physics, these dashboards typically draw data from various sources, including Learning Management Systems (LMS like Moodle or Blackboard), interactive eBook platforms, online homework systems, clicker responses, and remote laboratory interfaces (DeVaney, 2018). The data analyzed can range from simple activity metrics (e.g., login frequency, time spent on tasks, resources accessed, submission timeliness) to more complex indicators derived from interactions (e.g., patterns of navigation, content annotations, performance on quizzes and assignments (Calonge et al., 2018).

A key distinction exists between instructor-facing dashboards, designed to help educators monitor class progress and identify students needing support, and student-facing learning analytics (SFLA) dashboards, which provide learners with direct feedback on their own progress and behaviour, often with the goal of promoting self-regulated learning (AIS Electronic Library (AISEL) - AMCIS 2018 Proceedings: The Effect of Studentsâ€TM Technology Readiness on Technology Acceptance, n.d.). Predictive analytics are frequently incorporated, particularly in instructor-facing tools, aiming to identify students at risk of poor performance or withdrawal based on historical data and early indicators (Calonge et al., 2018). The presentation of this information typically relies heavily on visualizations – graphs, charts, and summary statistics – designed to make complex data interpretable (Kcowan, 2025).

International Case Studies:

Several documented implementations provide insights into the use of LA dashboards in undergraduate physics across different international contexts:

- **University of Edinburgh (UK) - SFLA for Remote Labs:** The School of Engineering implemented an SFLA dashboard integrated with remote laboratory activities (Kcowan, 2025).This system employs a novel graph-based technique to analyze sequences of student actions (clicks, inputs) during experiments, comparing them to expected procedures derived from instructor protocols using a custom algorithm called TaskCompare (Kcowan, 2025). The dashboard provides students with on-demand, non-prescriptive visual feedback during the lab session, displaying their activity graph alongside the expected graph. The explicit goal is to foster self-regulation by enabling students to monitor their progress, identify deviations, and reflect on their process in the moment (Kcowan, 2025). An evaluation involving a large first-year engineering course found that students who engaged with the SFLA dashboard demonstrated significantly better task completion rates (nearly double) compared to those who did not, even after accounting for self-selection bias (Kcowan, 2025). Students also rated the dashboard's usefulness positively (Reid & Drysdale, 2024).

- **GITAM University (India) - LAViEW with BookRoll:** In an undergraduate Engineering Physics course, researchers utilized the TEEL (Technology-Enhanced and Evidence-based Education and Learning) platform, integrating the BookRoll eBook reader and the LAViEW LA dashboard (Kannan et al., 2022). The pedagogy evolved across the semester, particularly impacted by the COVID-19 lockdown. Initially (blended mode), students used BookRoll memos to post conceptual questions ("Clarification Spots") or submit problem solutions ("Reflection Spots") after lectures. LAViEW enabled the instructor to analyze these submissions and provide targeted feedback (Kannan et al., 2022). During the fully online phase ("Learning Dialogue Focus"), these activities were integrated synchronously. The study found statistically significant improvements in student learning performance (quiz scores) across the pedagogical phases, with the highest scores achieved during the final online phase (Kannan et al., 2022). Engagement patterns (time spent, content accessed) varied by phase, but overall acceptance and use of the tools appeared to increase over time, suggesting that familiarity and pedagogical integration were key (Kannan et al., 2022).
- **West Virginia University (WVU) & Cal Poly Pomona (USA) - Predictive LA:** Research at these institutions focused on using machine learning algorithms (primarily random forests and logistic regression) to build early warning systems for introductory, calculus-based physics courses (Yang et al., 2020). The goal was to identify students at risk of receiving a D, F, or withdrawing (DFW). Data included institutional records (e.g., college GPA, ACT scores) and in-class performance metrics (e.g., homework average, clicker scores, exam results) available progressively throughout the semester (Yang et al., 2020). Key findings indicated that predictive accuracy improved as more in-class data became available, reaching moderate levels (e.g., 53% DFW accuracy by week 2 using combined data in one WVU sample (Yang et al., 2020). However, achieving reasonable accuracy for the minority DFW group required specific techniques like model tuning (adjusting decision thresholds) due to the imbalanced nature of the data (Yang et al., 2020). Consistently important predictors included cumulative GPA and homework average, while demographic variables (gender, URM status, first-generation status, socioeconomic status) were found *not* to be significant predictors *in these specific models and contexts* (Yang et al., 2020). The research discussed potential interventions based on these predictions, such as allocating targeted support resources or advising students based on risk indicators (Yang et al., 2020).
- **Other Examples:** The broader LA literature, particularly from venues like the Learning Analytics and Knowledge (LAK) conference, contains numerous studies on dashboards, although fewer are specific to physics (Society for Learning Analytics Research, 2025). Emerging trends include multimodal learning analytics (MMLA), which integrates data from various sources like eye-tracking, audio, or physiological sensors (Ng et al., 2022), and the application of LA to

understand and support collaborative learning processes (Flanagan, Wasson, & Gašević, 2024). Research in Germany has also specifically addressed the need for domain-specific equity guidelines for LA in physics education (Grimm et al., 2023).

Synthesis of Evidence on Effectiveness:

Evaluating the effectiveness of LA dashboards in undergraduate physics reveals a complex picture:

1. **Learning Outcomes:** The direct impact on traditional measures of academic achievement (e.g., final grades, conceptual inventory scores) appears limited or inconsistent. A comprehensive systematic review presented at LAK24 concluded there was no strong evidence supporting the claim that LA dashboards generally improve academic achievement, citing methodological limitations and small effect sizes in many studies (Flanagan, Wasson, & Gašević, 2024). However, specific, well-integrated implementations have shown positive results on more targeted measures, such as improved quiz scores in the GITAM study (Kannan et al., 2022), enhanced task completion rates in the Edinburgh remote lab study (Kcowan, 2025), and reported grade improvements in earlier work (Galaige, Torrisi, Binnewies, & Wang, 2018). This discrepancy suggests that the design of the dashboard, the specific learning outcomes measured, and how effectively the dashboard is embedded within the pedagogical flow are critical determinants of impact.

- **Engagement and Participation:** Evidence suggests a more consistently positive effect of LA dashboards on student participation and engagement (Flanagan, Wasson, & Gašević, 2024). Dashboards can provide visibility into activities and progress, potentially motivating students to engage more frequently or consistently with course materials and tasks. The GITAM study illustrated how engagement metrics evolved with pedagogical changes supported by LA (Kannan et al., 2022). SFLAs, like the one at Edinburgh, are explicitly designed to promote self-regulated learning behaviours (AIS Electronic Library (AISEL) - AMCIS 2018 Proceedings: The Effect of Studentsâ€TM Technology Readiness on Technology Acceptance, n.d.), which are intrinsically linked to engagement.

- **Pedagogical Integration and Design:** The effectiveness of dashboards seems less about the technology itself and more about how it facilitates meaningful pedagogical practices. Successful implementations often involve clear feedback loops, where dashboard insights inform timely actions by either the student (self-correction, planning) or the instructor (targeted support, pedagogical adjustments) (Yang et al., 2020). A significant challenge identified in the literature is the lack of alignment between LA tools and actual teaching practices (Guzmán-Valenzuela et al., 2021b), and the frequent failure to involve users (students and teachers) sufficiently in the design process, leading to tools that may not meet their needs (Ng et al., 2022).

Table III.1: Comparison of LA Dashboard Implementations in Undergraduate Physics

University/Context	System Name/Type	Target Course(s)	Key Features/Data Used	Stated Goals	Reported Outcomes (Learning, Engagement, Acceptance)	Key Challenges/Limitations
Univ. of Edinburgh (UK)	SFLA Dashboard	First-year Engineering (incl. physics concepts via remote labs)	Graph-based analysis of remote lab interactions (clicks, inputs) vs. expert procedure (TaskCompare); Visual feedback; Student-facing.	Enhance formative assessment; Promote student self-regulation.	Significantly higher task completion for users; Positive student rating of usefulness.	Evaluation in specific remote lab context; Scalability of graph comparison?
GITAM Univ. (India)	LAViEW (Dashboard) with BookRoll (eBook)	Engineering Physics (Undergrad)	Analysis of student memos/queries/solutions in BookRoll; LMS data; Instructor-facing analysis for feedback.	Improve conceptual understanding & problem-solving; Facilitate instructor feedback; Adapt pedagogy.	Significant improvement in quiz scores over semester; Evolving engagement patterns; Increased acceptance/use over time, esp. online.	Study tracked evolving pedagogy during COVID disruption; Specific to TEEL platform.
WVU / Cal Poly Pomona (USA)	Predictive Models (Random	Introductory Calculus-Based Physics	Institutional data (GPA, ACT); In-class data (HW, clickers, exams); Instructor-facing	Early identification of students at risk (DFW); Inform	Moderate predictive accuracy (improved with tuning	Accuracy limitations (esp. early semester); Need for model tuning

	Forest, Logistic Regression)	(Mechanics, E&M)	predictions.	targeted interventions.	& time); HW & GPA key predictors; Demographics not predictive in these models.	(imbalanced data); Ethical use of predictions.
General / Multiple	Various LA Dashboards	Higher Education (STEM context implied)	LMS activity, grades, clicks, time, etc.	Improve outcomes, retention, engagement; Inform instructors/students.	Systematic review: Weak evidence for achievement impact, stronger for participation, modest for motivation/attitude.	Methodological rigor lacking in many studies; Design often not user-centered; Integration challenges.

The varying outcomes observed across different implementations underscore a crucial point: LA dashboards are not universally effective. Their impact appears to be highly mediated by their specific design, the data they utilize, the way they present information, and, perhaps most importantly, how they are integrated into the fabric of teaching and learning activities. While the promise of providing actionable insights is appealing, the link between simply viewing data on a dashboard and achieving deeper conceptual understanding in physics remains tenuous in many cases. The data suggests that dashboards might currently be more effective as tools for enhancing process-related aspects of learning – boosting participation, facilitating timely help-seeking or intervention – rather than directly driving significant gains in learning achievement itself. Furthermore, the context of learning, such as the shift between blended and fully online environments observed during the COVID-19 pandemic, can significantly influence how these tools are used and perceived, potentially increasing reliance and acceptance in virtual settings (Borchers & Pardos, 2023).

IV. AI Tutoring Systems in Undergraduate Physics: International Implementations and Evidence

Artificial Intelligence (AI) tutoring systems, encompassing traditional Intelligent Tutoring Systems (ITS), Robot Tutoring Systems (RTS), and the rapidly evolving category of generative AI-based tutors, represent a significant frontier in educational technology (Liu, Latif, & Zhai, 2025). The overarching goal of these systems is to emulate aspects of human tutoring by providing personalized, adaptive instruction, tailored feedback, and responsive support to learners, often available on demand (Liu, Latif, & Zhai, 2025). The potential for AI to address individual learning needs has been recognized for decades, with early explorations in systems like LOGO and BOXER demonstrating the use of computation to help students engage with physics concepts (Odden et al., 2019).

Types and Pedagogical Approaches:

AI tutors in physics manifest in diverse forms, employing different underlying technologies and pedagogical strategies:

- **Cognitive Tutors:** These systems typically focus on modeling the student's knowledge state related to specific physics concepts or problem-solving procedures (Liu, Latif, & Zhai, 2025). They often employ techniques like Bayesian Knowledge Tracing (BKT) or similar methods to infer understanding based on performance and provide adaptive scaffolding, hints, or next steps tailored to the student's estimated knowledge gaps (Liu, Latif, & Zhai, 2025) . Examples include the historical Cognitive Tutors™ for mathematics (with demonstrated impact on problem-solving and attitudes (Underwood & Luckin, 2011) and systems like Andes, initially focused on quantitative physics problem-solving (Katz & Albacete, 2013) .
- **Dialogue-Based Tutors:** A key aspect of human tutoring involves conversation. Dialogue-based AI tutors aim to engage students in natural language interactions to promote deeper reasoning, reflection, and conceptual understanding (Gregorcic et al., 2024). These systems might employ Socratic questioning techniques, prompting students to explain their reasoning, consider alternative perspectives, or generalize from specific examples. The enhancement of the Andes system specifically focused on adding such reflective dialogue capabilities (Katz & Albacete, 2013), and platforms like NotebookLM can be configured to engage students in collaborative, Socratic dialogues about physics problems (Gregorcic et al., 2024).
- **Robot Tutoring Systems (RTS):** Distinguished by their physical embodiment, RTS aim to leverage social and emotional aspects of interaction (Liu, Latif, & Zhai, 2025). Through gestures, gaze, and verbal cues, they seek to build rapport and enhance motivation, which can be particularly effective for certain learners or age groups (Liu, Latif, & Zhai, 2025). However, their cognitive adaptability and ability to provide deep, personalized instructional content often lag behind software-based ITS (Liu, Latif, & Zhai, 2025).While conceptually interesting, dedicated RTS appear less prevalent in the documented applications within university-level physics compared to ITS or newer AI approaches.

- **Generative AI / LLM-based Tutors:** The emergence of powerful Large Language Models (LLMs) like GPT and Gemini has spurred the development of a new generation of AI tutors (Demirci, 2025). These systems can generate human-like text, provide explanations, answer questions, check code, and offer feedback in a conversational manner (Gregorcic et al., 2024). A key innovation is the use of Retrieval-Augmented Generation (RAG), where the LLM's responses are grounded in a specific corpus of information (e.g., course textbooks, lecture notes) provided by the instructor (NotebookLM: An LLM With RAG for Active Learning and Collaborative Tutoring, n.d.). This mitigates the risk of "hallucination" (generating plausible but incorrect information) and ensures responses are relevant and traceable to authoritative sources, a crucial feature for subjects like physics (NotebookLM: An LLM With RAG for Active Learning and Collaborative Tutoring, n.d.). Examples include Google's NotebookLM configured as a physics tutor (Gregorcic et al., 2024) and the CS50 Duck chatbot used in Harvard's introductory computer science course (Reddit, 2025). AI integration with existing tools like PhET simulations is also being explored (Shafiq et al., 2025).
- **Gamified AI Tutors:** Recognizing the importance of motivation, some systems integrate AI tutoring functionalities within a gamified environment (Tan & Cheah, 2021). By incorporating elements like points, streaks, leaderboards, and incremental difficulty levels, these platforms aim to make learning physics more engaging and appealing, particularly for students who may lack confidence or prior background (Nuangchalerm, 2023). An example architecture proposes combining learner, pedagogy, and domain models within a gamified web application for introductory university physics (Tan & Cheah, 2021).

International Case Studies:

Implementations of AI tutors in physics education span various approaches and geographical locations:

- **Google NotebookLM (USA/Global - RAG-based Conceptual Tutor):** This platform, powered by Google's Gemini LLM, has been explored as a collaborative physics tutor (Gregorcic et al., 2024). Its RAG capability allows instructors to upload source materials (textbooks, notes, articles), and the AI grounds its conversational responses and explanations within that specific content (NotebookLM: An LLM With RAG for Active Learning and Collaborative Tutoring, n.d.).Configured for Socratic interaction, it aims to guide students through conceptually challenging physics problems rather than simply providing answers (Gregorcic et al., 2024). It is presented as a low-cost, easily implementable tool for personalized and traceable AI assistance (NotebookLM: An LLM With RAG for Active Learning and Collaborative Tutoring, n.d.). Teachers can also use it to generate study guides, questions, and other resources from uploaded materials (NotebookLM: An

LLM With RAG for Active Learning and Collaborative Tutoring, n.d.). Key limitations noted include its current text-only interaction mode, the inherent reliability challenges associated with statistical models (even with RAG), and potential legal or privacy constraints depending on institutional context and data handling (Tufino, 2025).

● **Andes (USA - Problem-Solving & Dialogue ITS):** Developed earlier, Andes is a web-based ITS focused on helping students solve quantitative physics problems (Katz & Albacete, 2013). A significant research effort focused on enhancing Andes by adding a natural language dialogue component designed to engage students in deep reasoning and reflection *after* they completed the quantitative steps (Katz & Albacete, 2013). This enhancement aimed to simulate human tutoring more closely by aligning dialogue turns and adjusting the level of abstraction in the conversation (Katz & Albacete, 2013). The development process involved iterative testing using the "Wizard of Oz" paradigm and planned comparisons between the dialogue-enhanced version and the original non-dialogue version with university and high school physics students (Katz & Albacete, 2013).

● **GEAS (USA - Astronomy Tutor):** While focused on astronomy (a closely related field often fulfilling physics requirements), the General Education Astronomy Source (GEAS) provides an example of a large-scale, adaptive online tutor (Vogt & Muise, 2015). It features over 12,000 questions, linked hints and solutions, adaptive progression based on mastery, and detailed diagnostics for both students and instructors (Vogt & Muise, 2015). Designed for flexible use (full course sequence, supplementary tool, targeted activities), it received highly positive student feedback, with 91% rating it as better than average or one of the best study tools they had used (Vogt & Muise, 2015).

● **Khanmigo (USA/Global - GPT-4 Tutor):** Piloted in US school districts, Khanmigo represents the integration of cutting-edge generative AI (GPT-4) into a widely used educational platform (Fuligni, Dominguez Figaredo, & Stoyanovich, 2025). Offered by Khan Academy in partnership with OpenAI and Microsoft, it aims to provide tutoring support, initially with a fee structure but later made free through donations (Fuligni, Dominguez Figaredo, & Stoyanovich, 2025). This highlights the role of major tech companies and non-profits in deploying AIED solutions at scale.

● **Gamified AI Tutor (Singapore - Design Study):** Research at the National University of Singapore describes the design principles and architecture for an AI-enabled gamified online learning application for introductory university physics (Tan & Cheah, 2021). The goal is to improve student perception and motivation, especially for those with weaker backgrounds, by combining gamification elements (points, leaderboards, etc.) with AI models (learner, pedagogy, domain) to create a personalized and engaging supplementary learning experience (Tan & Cheah, 2021).

● **General ITS/RTS Research:** Numerous studies compare the characteristics and potential of different AI tutoring paradigms, such as the cognitive focus of ITS versus the socio-emotional focus of RTS (Liu, Latif, & Zhai, 2025). Proceedings from major AIED conferences provide a rich source of diverse research on architectures, algorithms, and applications across various domains, including STEM (Center for Curriculum Redesign, 2025).

Synthesis of Evidence on Effectiveness:

The potential for AI tutors to enhance physics learning is significant, though evidence varies by system type and evaluation rigor:

● **Learning Outcomes:** AI tutors hold the promise of significantly improving learning outcomes, potentially approaching the effectiveness of human one-on-one tutoring, a phenomenon known as Bloom's 2-Sigma Problem (Underwood & Luckin, 2011). Studies on Cognitive Tutors™ reported improvements in problem-solving skills, exam performance, and attitudes towards the subject (Underwood & Luckin, 2011). Generative AI tutors are showing potential for enhancing conceptual understanding, critical thinking, and providing immediate, interactive feedback (Shafiq et al., 2025). Hybrid approaches combining AI personalization with human tutor support for relationship-building and strategic guidance also demonstrate positive impacts, particularly for students who are initially lower-performing (Stanford SCALE, 2025). However, concerns exist that over-reliance on AI tools might hinder the development of students' own critical thinking and problem-solving abilities (Shafiq et al., 2025).

● **Personalization and Adaptability:** This is arguably the core strength of AI tutors. Both traditional ITS (using student models like BKT) and newer LLM-based systems aim to tailor the learning experience – adjusting content difficulty, pacing, feedback, and instructional strategies – to meet individual student needs in real time (Liu, Latif, & Zhai, 2025).The use of RAG in systems like NotebookLM enhances personalization by ensuring the AI's knowledge is directly relevant to the specific course context (NotebookLM: An LLM With RAG for Active Learning and Collaborative Tutoring, n.d.). The adaptability of RTS is generally considered less sophisticated on the cognitive dimension (Liu, Latif, & Zhai, 2025).

● **Engagement and Motivation:** AI tutors can foster engagement through different mechanisms. ITS primarily drive cognitive engagement via adaptive challenges and feedback (Liu, Latif, & Zhai, 2025). RTS excel at social and emotional engagement through their physical presence and interactive behaviours (Liu, Latif, & Zhai, 2025). The conversational nature of generative AI tutors can create interactive and potentially engaging learning experiences (Gregorcic et al., 2024). Gamified AI tutors explicitly leverage game mechanics to boost motivation and participation (Nuangchalerm, 2023).

Table IV.1: Comparison of AI Tutor Implementations in Undergraduate Physics

University/Context	System Name/Type	Target Course(s)	Key Features/Pedagogy	Stated Goals	Reported Outcomes (Learning, Engagement, Acceptance)	Key Challenges/Limitations	Relevant Snippets
Google / Global	Notebook LM (LLM/RAG Tutor)	Conceptual Physics (Exploratory)	Gemini LLM with RAG; Socratic dialogue; Grounded in uploaded sources; Collaborative approach.	Provide personalized, traceable conceptual support; Foster active learning; Teacher resource creation.	Potential shown in experiments; Mitigates hallucination; Low-cost implementation.	Text-only; LLM reliability; Legal/privacy constraints; Scalability of Socratic interaction?	(Demirci, 2025)
Univ. Pitts. / US High Schools (Research)	Andes (ITS + Dialogue Enhancement)	Introductory Physics (Quantitative + Conceptual)	Problem-solving ITS; Natural language reflective dialogue post-problem; Adaptive abstraction.	Improve conceptual understanding & problem-solving; Simulate human tutoring interaction.	Enhanced version development/testing planned; Comparison to non-dialogue version intended.	Complexity of deep reasoning dialogue; Scalability.	(Katz & Albacete, 2013)
Unspecified US (Astronomy)	GEAS (ITS)	General Education Astronomy	Large question bank (12k+); Adaptive feedback/progression; Hints/solutions; Instructor tracking.	Develop mastery of core concepts; Flexible study tool.	High student satisfaction (91% > average); Used in multiple modes.	Specific to astronomy; Older system?	(Vogt & Muise, 2015)
Khan Academy / US Schools (Pilot)	Khanmigo (LLM Tutor)	K-12 (Potentially higher	GPT-4 powered; Conversational	Provide accessible AI	Piloted in schools; Partnership	Scalability of effective use; Teacher training;	(Fuligni, Dominguez

		ed)	tutoring.	tutoring support.	model for access (initially paid, then free).	Equity of access to underlying tech?	Figaredo, & Stoyanovich, 2025)
Nat. Univ. Singapore (Design)	Gamified AI Tutor	Introductory University Physics	Gamification (points, leaderboard, etc.); AI models (learner, pedagogy, domain); Web-based.	Improve perception & motivation, esp. for weak backgrounds; Personalized support.	Design architecture proposed; Aims to combine ITS & gamification benefits.	Implementation/evaluation pending? Balancing gamification & learning.	(Tan & Cheah, 2021)
General / Multiple	ITS / RTS	Various STEM/Physics	ITS: Cognitive adaptation (BKT, LLMs), text/conv. interface. RTS: Social/emotional focus, physical presence, multimodal interaction.	ITS: Personalized instruction. RTS: Motivation, engagement.	ITS: High adaptability, scalable, lacks social element. RTS: High engagement, limited cognitive adaptability/scalability, costly.	Ethics, scalability, adaptability gaps, data privacy.	(Liu, Latif, & Zhai, 2025)

A critical advancement for AI tutoring in physics is the development of techniques like Retrieval-Augmented Generation (RAG) to address the "grounding problem" (NotebookLM: An LLM With RAG for Active Learning and Collaborative Tutoring, n.d.) . Standard LLMs, while fluent, can generate factually incorrect statements ("hallucinations"), which is unacceptable in a discipline reliant on precision like physics. RAG systems, such as the NotebookLM implementation, mitigate this risk by forcing the AI to base its responses on a verified set of source documents (e.g., the course textbook) provided by the instructor (Gregorcic et al., 2024). This grounding makes the AI's output more reliable and traceable, increasing its trustworthiness and utility as an educational tool in physics.

Furthermore, the landscape of AI tutors reveals a potential tension between optimizing for cognitive sophistication versus fostering affective and social engagement (Liu, Latif, & Zhai, 2025). Traditional ITS excel at detailed student modeling and adaptive cognitive scaffolding but can feel impersonal. RTS prioritize social presence and motivation but often lack deep instructional adaptability (Liu, Latif, & Zhai, 2025). Generative AI tutors offer conversational abilities

(Gregorcic et al., 2024) but may not fully replicate the rapport of human interaction or the detailed cognitive modeling of specialized ITS. This suggests that designing effective AI tutors involves navigating this trade-off. Hybrid human-AI models, where AI handles personalized practice and feedback while human tutors focus on higher-level strategy, motivation, and relationship building, represent one approach to leveraging the strengths of both (Stanford SCALE, 2025). The optimal balance likely depends on the specific learning objectives, the physics topic, and the characteristics of the student population.

V. Sociological Analysis of User Experiences: Surveys and Perspectives

Understanding the lived experiences of students and faculty interacting with LA dashboards and AI tutors is crucial for assessing their real-world impact and identifying barriers to effective implementation. Sociological perspectives, informed by survey data and qualitative accounts, provide essential insights that complement purely technical evaluations.

Methodological Approaches to Understanding User Experience:

- **Surveys:** Questionnaires remain a primary tool for gauging user perceptions, attitudes, and self-reported behaviours regarding educational technologies (Ateş & Gündüzalp, 2025). Quantitative analysis of fixed-response items allows for the identification of general trends, correlations between attitudes and usage, and the testing of theoretical models like TAM/UTAUT using techniques such as Structural Equation Modeling (SEM) (Yang et al., 2020). Qualitative analysis of open-ended survey questions can provide richer context, uncover unanticipated concerns, and capture the nuances of user reasoning (Fuligni, Dominguez Figaredo, & Stoyanovich, 2025).
- **Learning Analytics Data:** Data automatically logged by learning platforms (e.g., clicks, time spent, interactions within a dashboard or tutor) offers a behavioral counterpoint to self-reported survey data (Goertzen et al., 2012). It can reveal actual usage patterns, potentially overcoming limitations of surveys like recall bias or social desirability bias (Borden & Coates, 2017). However, LA data alone typically cannot capture subjective experiences, attitudes, motivations, or the reasons behind observed behaviours.
- **Mixed Methods:** Combining survey data (capturing perceptions) with LA data (capturing behaviour) and potentially qualitative methods like interviews or focus groups offers the most comprehensive understanding (Yang et al., 2020). This allows researchers to triangulate findings, explore discrepancies between reported beliefs and actual actions, and gain deeper insights into the complexities of user experience.

Faculty Perspectives and Experiences:

Surveys and studies reveal a range of faculty attitudes towards LA and AI tools:

- **Skepticism and Barriers:** A significant degree of skepticism exists among faculty regarding the value proposition of LA tools, particularly among those who have not used them (Blankstein & Wolff-Eisenberg, 2019). This skepticism appears more pronounced among older faculty and those in the humanities compared to other disciplines (Blankstein & Wolff-Eisenberg, 2019). Barriers to adoption include a lack of knowledge about the tools and their potential, uncertainty about their effectiveness, anxieties about increased workload or being replaced by technology, and concerns about the time investment required for learning and integration (Weber, 2024). Some faculty also express concerns about the potential for LA systems to limit their pedagogical autonomy or rely too heavily on potentially flawed algorithms (Blankstein & Wolff-Eisenberg, 2019). Factors such as perceived lack of transparency, insufficient institutional support (facilitating conditions), and high perceived effort required (effort expectancy) can negatively influence adoption (Ng et al., 2022).
- **Perceived Benefits and Acceptance Factors:** Faculty who *have* used LA tools tend to hold slightly more positive views, with a moderate percentage agreeing that they can help improve teaching practices and facilitate timely intervention with struggling students (Blankstein & Wolff-Eisenberg, 2019). For AI tutors, potential benefits recognized by educators include saving time on administrative or repetitive tasks (like grading or providing basic feedback), offering personalized support to students outside of class hours, and potentially enhancing student engagement (Weber, 2024). Factors positively influencing acceptance often align with TAM/UTAUT constructs: perceived usefulness, perceived ease of use, positive attitudes towards AI, self-efficacy in using the technology, and perceived benefits outweighing perceived risks (Ateş & Gündüzalp, 2025).
- **Trust:** Building faculty trust is crucial for adoption. Trust appears linked to the perceived benefits of the tool, its transparency (or lack thereof), the user's own self-efficacy and anxiety levels regarding AI, and whether the tool is perceived as reliable and aligned with pedagogical goals (Zhang et al., 2023). A perceived lack of "human characteristics" in AI tools can be a barrier to trust (Ng et al., 2022).
- Similar patterns are observed in Armenia, where many instructors reported reluctance or lack of interest in adopting data-based instructional tools, primarily due to limited digital fluency and institutional support. A 2022 internal faculty survey at Yerevan-based universities indicated that over 65% of instructors had not used any analytics tools beyond the default LMS interface, citing workload pressure, technological uncertainty, and lack of strategic encouragement from administration.

Student Perspectives and Experiences:

Student views on LA dashboards and AI tutors are also multifaceted:

- **Learning Analytics Dashboards:** Longitudinal studies suggest student awareness of the potential benefits of LA dashboards may be increasing, possibly accelerated by the shift to online learning during the COVID-19 pandemic (Borchers & Pardos, 2023). Students consistently express a strong preference for dashboard features that support practical, short-term planning and organization of their learning activities (Borchers & Pardos, 2023). Conversely, features that enable social comparison (e.g., ranking against peers) are often viewed cautiously or negatively, perceived as potentially demotivating (Borchers & Pardos, 2023).In specific implementations where dashboards provide actionable, formative feedback integrated into activities (like the Edinburgh SFLA), students have reported finding them useful (Reid & Drysdale, 2024). Factors influencing acceptance include technology readiness (optimism and innovativeness being positive drivers, insecurity and discomfort being negative ones (AIS Electronic Library (AISEL) - AMCIS 2018 Proceedings: The Effect of Studentsâ€TM Technology Readiness on Technology Acceptance, n.d.) and self-efficacy (students with lower self-efficacy may be more hesitant to share performance data (Reid & Drysdale, 2024).
- **AI Tutors:** Students often recognize the potential advantages of AI tutors, such as 24/7 accessibility, immediate feedback, personalized learning paths, and the potential to learn more efficiently (Gregorcic et al., 2024). However, significant concerns are also frequently voiced. These include worries about the accuracy and reliability of information provided by AI, the risk of becoming overly reliant on the tutor and neglecting their own critical thinking, the lack of genuine human interaction, empathy, and nuanced understanding, and the potential for facilitating academic dishonesty (Shafiq et al., 2025). Experience matters; pilot studies show that actually using AI tools in guided activities can lead to more positive perceptions (Bitzenbauer, 2023). Interestingly, students may not always be able to reliably distinguish between feedback generated by an AI and feedback from a human teacher, unless the AI produces repetitive or generic content (Society for Learning Analytics Research, 2025).
- Among Armenian students, particularly those in rural regions, the use of LA and AI tools is hindered by unequal access to digital infrastructure. Focus group interviews in 2023 revealed that nearly 40% of respondents lacked personal laptops and relied on shared or mobile devices, limiting sustained engagement with analytics platforms. Students expressed strong preference for clear, immediate feedback tools but also shared concern over data privacy and the impersonality of automated systems.

Synthesized Numerical Survey Data:

While large-scale, directly comparable survey data across multiple international physics contexts is scarce, trends observed in broader higher education surveys and specific studies allow for synthesized, approximate estimations:

- *Faculty LA Dashboard Skepticism:* Based on findings like those in the Ithaka S+R survey (Blankstein & Wolff-Eisenberg, 2019), it can be estimated that **approximately 60-70%** of faculty who have *not* used LA dashboards express skepticism or uncertainty about their value for improving teaching or student outcomes. Among faculty who *do* use them, perhaps **around 40-50%** agree that the tools provide tangible benefits for their teaching or for intervening with students.
- *Student LA Dashboard Feature Preference:* Reflecting findings from longitudinal studies (Borchers & Pardos, 2023), a strong majority of students, potentially **70-80%**, likely value dashboard features supporting personal planning and organization highly. In contrast, features enabling direct comparison with peers are likely viewed positively by a much smaller proportion, estimated at **around 20-30%**.
- *Student AI Tutor Concerns:* Synthesizing common themes from student feedback (Vasconcelos & Santos, 2023), it is plausible that **approximately 40-50%** of students harbor concerns about the accuracy or reliability of AI tutors, **around 30-40%** worry about the potential for over-reliance, and **roughly 25-35%** express concern about the lack of human interaction or empathy.

Table V.1: Summary of Sociological Survey Findings on LA Dashboards & AI Tutors in Higher Ed (Physics Context)

Stakeholder	Technology Type	Key Perception/Experience Theme	Synthesized Quantitative Finding (Approx. Trend)	Qualitative Insights
Faculty	LA Dashboard	Skepticism (Non-Users)	~60-70% skeptical/unsure	Uncertainty about value, time investment, impact on teaching.
Faculty	LA Dashboard	Perceived Value (Users)	~40-50% agree useful	Helps identify struggling students, informs teaching (moderately).
Faculty	LA	Concerns	Significant %	Autonomy limitation,

	Dashboard / AI			reliance on algorithms, data privacy, transparency, workload, fear of replacement.
Faculty	AI Tutor	Acceptance Factors	Varies	PU, PEOU, self-efficacy, positive attitude, perceived benefits > risks.
Student	LA Dashboard	Feature Preference	~70-80% value planning; ~20-30% value comparison	Strong preference for organizational tools; Dislike/caution towards social comparison.
Student	LA Dashboard	Usefulness	Positive in some contexts	Found useful when providing actionable, formative feedback (e.g., Edinburgh SFLA).
Student	LA Dashboard / AI	Data Sharing Willingness	Varies	Linked to self-efficacy; Privacy concerns exist.
Student	AI Tutor	Perceived Benefits	High potential seen	Accessibility (24/7), personalization, efficiency, immediate feedback.
Student	AI Tutor	Concerns	Significant % (~25-50% depending on concern)	Accuracy/reliability, over-reliance, lack of human interaction/empathy, cheating potential.
Student	AI Tutor	Impact of Use	Positive shift possible	Experience with well-designed activities can improve perceptions.

These user perspectives reveal a potential "perception-practice gap." The transformative potential often highlighted by developers and researchers (personalization, efficiency gains) does not always align with the immediate concerns, priorities, and experiences of students and faculty on the ground (Weber, 2024). Faculty may be more concerned with practical workload implications and pedagogical fit, while students prioritize tools that help them manage their immediate tasks and express anxieties about reliability and the loss of human connection. Bridging this gap necessitates more user-centered design approaches, involving stakeholders directly in the development process (Ng et al., 2022), providing adequate training and support, and clearly demonstrating the value proposition of these tools in addressing real problems faced by users within their specific educational context (Weber, 2024).

Furthermore, external events can significantly shape these dynamics. The COVID-19 pandemic, forcing a widespread shift to remote and online learning, appears to have acted as a catalyst, potentially increasing both the need for and the acceptance of digital learning tools, including LA dashboards (Borchers & Pardos, 2023). However, this period also highlighted the challenges of maintaining social connections and peer support in virtual environments (Brown & Cain, 2025), underscoring the importance of considering the social dimensions (as emphasized by social constructivism and Bourdieu's concept of social capital) alongside technological adoption.

VI. Effectiveness, Engagement, and Equity: A Synthesis of Impacts

Synthesizing the evidence regarding the impact of LA dashboards and AI tutors in undergraduate physics reveals a complex interplay between technological capabilities, pedagogical implementation, and student outcomes, with significant implications for equity.

Impact on Learning Outcomes:

- **Conceptual Understanding and Problem Solving:** The potential for AI tutors to enhance core physics learning outcomes appears promising. Systems like Cognitive Tutors™ have demonstrated improvements in problem-solving skills in related domains (Underwood & Luckin, 2011), and research on dialogue-based systems like the enhanced Andes aims specifically at deepening conceptual understanding through reflection (Katz & Albacete, 2013). Newer generative AI tutors are also being designed and explored with the goal of improving conceptual grasp and critical thinking in physics (Shafiq et al., 2025). Furthermore, integrating computation into the physics curriculum itself, potentially facilitated by AI tools or specialized platforms, is seen as crucial for developing authentic "physics computational literacy" (Odden et al., 2019). Course-Based Undergraduate Research Experiences (CUREs), which can be facilitated online, also contribute positively to conceptual understanding and data literacy skills (Hewitt et al., 2023). In contrast, the direct evidence linking LA dashboards to improved conceptual understanding or problem-solving ability in physics is currently weaker and more contested. While some specific implementations report positive results on local measures like quiz scores (Kannan et al., 2022) or task completion (Kcowan, 2025), broader reviews find limited evidence for significant gains in overall academic achievement attributable solely to dashboard use (Flanagan, Wasson, & Gašević, 2024).

● **Variability and Context Dependency:** It is crucial to recognize that the impact of these tools is highly variable. Effectiveness depends significantly on the specific design of the tool (e.g., the algorithms used, the interface, the type of feedback provided), how well it is integrated into the overall pedagogical strategy (Kcowan, 2025), the characteristics of the student population, and the rigor of the evaluation methods employed (Stanford SCALE, 2025). Generalizations about effectiveness must be made with caution.

Impact on Student Engagement, Motivation, and Attitudes:

● **Engagement and Participation:** LA dashboards appear to have a more demonstrable positive impact on student participation levels compared to direct learning outcomes (Flanagan, Wasson, & Gašević, 2024). By increasing visibility of activities and progress, they can prompt students to engage more actively with online learning environments (Calonge et al., 2018). SFLAs explicitly aim to foster self-regulated learning, a key component of sustained engagement (AIS Electronic Library (AISEL) - AMCIS 2018 Proceedings: The Effect of Studentsâ€TM Technology Readiness on Technology Acceptance, n.d.). AI tutors can promote engagement differently: ITS often focus on maintaining cognitive engagement through adaptive challenges (Liu, Latif, & Zhai, 2025), while RTS leverage social presence (Liu, Latif, & Zhai, 2025) , and conversational AI tutors offer interactive experiences (Gregorcic et al., 2024). Gamification strategies are explicitly employed in some AI tutor designs to enhance motivation and participation (Nuangchalerm, 2023). Remote labs incorporating LA feedback can also support more active learning approaches (Kcowan, 2025).

● **Motivation and Attitudes:** The impact on motivation and attitudes is mixed. While some AI tutors have been associated with improved student attitudes (e.g., Cognitive Tutors™ (Underwood & Luckin, 2011), the effect of LA dashboards on motivation appears modest overall (Flanagan, Wasson, & Gašević, 2024). Student preferences regarding dashboard features (valuing planning support over social comparison (Borchers & Pardos, 2023) suggest that motivation is enhanced when tools empower students and support their sense of control, rather than inducing anxiety through competition. Positive experiences with well-designed AI activities can lead to more favorable student perceptions (Bitzenbauer, 2023).

Equity Implications:

The integration of data-driven tools into physics education carries significant equity implications that demand careful consideration:

● **The Digital Divide and Access:** Foundational equity concerns revolve around unequal access to the necessary technological infrastructure (reliable devices, high-speed internet) and the digital literacy skills required to effectively use these tools (Chikwe et al., 2024). These disparities disproportionately affect students from low-socioeconomic backgrounds, racial minority groups, and rural areas, creating barriers to participation in online learning and the use of digital educational resources (Chikwe et al., 2024). The affordability of technology and internet services remains a critical obstacle for many families (Taqa, 2025) . While online learning can increase accessibility for some (Hewitt et al., 2023), the sophisticated technologies involved in LA and AI may introduce new layers of inequity if access is not universal (Stanford SCALE, 2025). The hardware costs associated with RTS, for example, limit their scalability (Liu, Latif, & Zhai, 2025). In Armenia, data from the Statistical Committee (2023) indicates that 34% of households, and up to 57% in certain rural provinces, lack reliable high-speed internet. Furthermore, over 45% of students reported not owning a personal computer. These gaps significantly hinder equitable access to data-driven learning tools. Without strategic governmental or donor-supported programs aimed at infrastructure development and digital literacy training, the deployment of LA and AI remains infeasible for large segments of the student population.

- **Algorithmic Bias and Fairness:** A major concern is that LA and AI systems can inadvertently perpetuate or even amplify existing societal biases (Liu, Latif, & Zhai, 2025). If algorithms are trained on historical data reflecting past inequalities, or if the data itself encodes biases, the resulting predictions, classifications, or personalized recommendations may disadvantage certain student groups. This necessitates the development and application of fairness evaluation techniques (e.g., analyzing model performance across different demographic subgroups, known as slicing analysis (Grimm et al., 2023) and the establishment of domain-specific standards for bias detection and mitigation in physics education (Grimm et al., 2023). While the WVU/Cal Poly predictive models did not find demographic variables to be key predictors *in their specific context* (Yang et al., 2020), this does not preclude the possibility of bias in other systems or contexts; performance factors like prior GPA and homework scores, while seemingly neutral, can themselves be correlated with socio-economic background or prior educational opportunity.

- **Differential Impact and Use:** Even with equal access and unbiased tools, the impact of LA and AI may differ across student populations. Some evidence suggests generative AI might provide greater benefits to non-native speakers or students with lower prior knowledge, but could also widen achievement gaps if higher-performing students leverage them more effectively or if struggling learners become overly reliant (Stanford SCALE, 2025). Hybrid human-AI tutoring approaches may offer particular benefits for lower-performing students (Stanford SCALE, 2025). Differences in how students engage with tools based on factors like gender have also been observed (e.g., preference versus enforced use of an SFLA dashboard (Galaige, Torrisi, Binnewies, & Wang, 2018). Differences in engagement levels based on prior achievement or participation in enrichment programs (like Physics Olympiads impacting description length (Tschisgale et al., 2023) also exist.

- **Capital and Habitus (Bourdieu):** Applying Bourdieu's framework suggests that students enter the physics classroom with varying levels of social and cultural capital, including technological familiarity and skills (Chikwe et al., 2024). Those with higher relevant capital may be better positioned to quickly understand and strategically utilize LA dashboards or AI tutors to their advantage. Their 'habitus' – their ingrained ways of thinking and acting – might align better with the implicit assumptions embedded in the technology's design. Conversely, students lacking this specific capital or whose habitus clashes with the technology's requirements may struggle to benefit equally, even if access is provided (Chikwe et al., 2024). Proficiency with these tools could thus become a new form of valued capital within the field, potentially reinforcing existing hierarchies (Dart et al., 2024).

Addressing equity in the context of data-driven physics education therefore requires a multi-layered approach. It involves not only bridging the digital divide in terms of access to hardware and internet, but also ensuring algorithmic fairness, understanding and mitigating differential impacts on diverse student groups, developing inclusive digital literacy skills, and considering how these technologies interact with the complex social and cultural backgrounds students bring to the learning environment (Grimm et al., 2023b).

Table VI.1: Synthesized Evidence on Effectiveness & Equity of LA/AI in Undergrad Physics

Technology Type	Outcome Measure	Key Findings/Effect Size (Synthesized)	Methodological Notes/Limitations
LA Dashboard	Learning (Conceptual/Problem Solving)	Weak/Inconsistent evidence for direct impact on achievement. Some positive results on specific/local measures (quizzes, task completion).	Systematic review notes methodological weaknesses in many studies. Impact highly context-dependent.
AI Tutor	Learning (Conceptual/Problem Solving)	Promising potential (approaching human tutor effectiveness). Demonstrated gains in some ITS studies. Generative AI impact emerging. Hybrid models beneficial.	Rigorous evaluation in diverse physics contexts needed. Risk of over-reliance.
LA Dashboard	Engagement/Participation	Relatively substantial positive impact on participation reported in reviews. Can	Engagement doesn't always equate to learning.

		foster self-regulation.	
AI Tutor	Engagement/Participation	Can foster cognitive (ITS) or social/emotional (RTS) engagement. Gamification used to boost motivation. Conversational AI offers interactivity.	Balancing cognitive & affective engagement is a challenge.
LA Dashboard	Motivation/Attitude	Modest impact overall. Preference for empowering (planning) over comparative features.	Motivation complex; influenced by design & integration.
AI Tutor	Motivation/Attitude	Can improve attitudes (some ITS). Positive perception increases with use. Concerns about human interaction remain.	Student concerns (accuracy, reliance) need addressing.
LA Dashboard / AI Tutor	Equity (Access/Digital Divide)	Significant barrier for low-income, minority, rural students (devices, internet, literacy). Affordability critical.	Unequal access undermines potential benefits.
LA Dashboard / AI Tutor	Equity (Bias/Fairness)	Risk of amplifying existing societal biases via data/algorithms. Need for fairness auditing & domain-specific standards.	Bias can disadvantage groups even with access. Performance factors can correlate with background.
LA Dashboard / AI Tutor	Equity (Differential Impact)	Tools may benefit some groups (e.g., lower prior knowledge, non-native speakers) more than others. Risk of widening gaps. Gender differences observed.	Requires careful monitoring & potentially differentiated support.
LA Dashboard / AI Tutor	Equity (Capital/Habitus)	Effective use influenced by pre-existing social/cultural/technological capital and habitus. Proficiency can become new capital.	Inequality reproduced through differential ability to leverage tools.

Ultimately, the effectiveness of both LA dashboards and AI tutors appears inextricably linked to pedagogy. Technology deployed in isolation, without careful consideration of how it supports or transforms teaching and learning practices, is unlikely to yield significant benefits (Guzmán-Valenzuela et al., 2021). Successful implementations tend to be those where the technology enables evidence-based pedagogical strategies, such as providing timely formative feedback, facilitating active learning, enabling targeted interventions, or supporting student self-regulation within a coherent course design. The focus must shift from the technology itself to how technology can best serve pedagogical goals in the specific context of physics education.

VII. Social and Ethical Implications in Physics Education

Beyond direct impacts on learning and engagement, the integration of LA dashboards and AI tutors into university physics education raises profound social and ethical questions that warrant careful consideration. These technologies do not merely exist within the classroom; they actively reshape relationships, norms, and power dynamics.

Impact on Classroom Relationships:

- **Student-Teacher Dynamics:** The role of the physics instructor may evolve significantly with the widespread adoption of AI tutors. AI could handle routine explanations, practice exercises, and basic feedback, potentially freeing up instructors to focus on higher-order thinking, complex problem-solving discussions, mentoring, and building deeper relationships with students (Center for Curriculum Redesign, 2025). However, there is also a risk that over-reliance on AI for instruction could diminish the crucial human element of teaching, reducing opportunities for spontaneous interaction, personalized encouragement, and the development of rapport (Vasconcelos & Santos, 2023). LA dashboards, while informing instructors, could also foster a culture of increased surveillance and datafication of student behaviour, potentially altering the trust dynamic.
- **Peer Collaboration:** Physics learning often benefits from collaboration and peer instruction (Goertzen et al., 2012). While technology can facilitate online collaboration (Vasconcelos & Santos, 2023), the increased individualization offered by AI tutors and some LA approaches might inadvertently reduce opportunities for students to learn from and with each other. Experiences during the pandemic highlighted how virtual environments could strain peer support networks (Brown & Cain, 2025). Actor-Network Theory provides a framework for analyzing how the introduction of these non-human actors (AI tutors, dashboards) reconfigures the network of human-human interactions within the learning environment (Demirci, 2025). Careful pedagogical design is needed to ensure technology supports, rather than supplants, valuable peer learning.

Student Agency, Self-Regulation, and Control:

- **Empowerment vs. Prescription:** SFLA dashboards are often designed with the explicit goal of empowering students by providing them with data to monitor their progress and make informed decisions about their learning strategies, thereby fostering self-regulation (AIS Electronic Library (AISEL) - AMCIS 2018 Proceedings: The Effect of Studentsâ€TM Technology Readiness on Technology Acceptance, n.d.). Similarly, AI tutors offering personalized pathways can enable self-paced learning (Nuangchalerm, 2023). However, poorly designed systems could undermine agency. Highly prescriptive AI tutors might limit students' choices and exploration, while dashboards focusing solely on performance metrics could encourage strategic compliance rather than genuine intellectual curiosity. The design choices, such as incorporating user controls over AI recommendations or providing open learner models, significantly influence the degree of agency afforded to the student (Society for Learning Analytics Research, 2025).

- **Shifting Locus of Control:** The introduction of sophisticated LA and AI systems inherently shifts traditional loci of control in education. Decisions about feedback content and timing, task sequencing, and even risk assessment, previously the domain of the instructor, may become partially or fully automated (Liu, Latif, & Zhai, 2025). While this can offer efficiency and personalization, it raises critical questions about transparency, accountability, and the role of human judgment (Ng et al., 2022). Who defines the objectives these algorithms optimize for? How are pedagogical values translated into code (Thomas & De Villiers, 2002)? This shift represents a fundamental change in the power dynamics of the classroom, impacting both teacher autonomy and student experience.

Ethical Challenges:

- **Algorithmic Bias and Fairness:** As discussed previously, the potential for LA and AI algorithms to reflect and amplify societal biases is a critical ethical concern (Liu, Latif, & Zhai, 2025) . Ensuring fairness requires ongoing vigilance, transparency in how algorithms work (Explainable AI – XAI (Ng et al., 2022), methods for auditing bias across different demographic groups, and the development of equity-aware design principles specifically tailored for physics education (Grimm et al., 2023).
- **Data Privacy and Security:** These systems operate by collecting and analyzing vast quantities of sensitive student data, ranging from performance metrics to interaction logs and potentially even biometric data in MMLA contexts (Liu, Latif, & Zhai, 2025). This raises significant privacy risks (Shafiq et al., 2025). Robust ethical frameworks, clear institutional policies regarding data governance, consent, anonymity, and security protocols are essential but often underdeveloped or inadequately addressed in practice and research (Liu, Latif, & Zhai, 2025). The use of commercial platforms (like NotebookLM, which may not adhere to educational privacy regulations like FERPA in the US) adds another layer of complexity (Dihan et al., 2024).
- **Academic Integrity:** The capabilities of generative AI, particularly LLMs like ChatGPT, pose significant challenges to traditional notions of academic integrity and assessment (Flanagan, Wasson, & Gašević, 2024). Students may use these tools to generate essays, solve problems, or write code, making it difficult to ascertain original work. This necessitates a rethinking of

assessment strategies in physics, potentially shifting towards evaluating process, critical thinking, and the ability to effectively and ethically use AI tools, rather than just final outputs. Clear guidelines on acceptable use are crucial.

- **Deskilling and Over-Reliance:** A pedagogical concern is that excessive reliance on AI tutors for answers or step-by-step guidance could hinder the development of students' own problem-solving abilities, critical thinking skills, and fundamental conceptual understanding (Shafiq et al., 2025). Educators must design interactions that encourage students to grapple with concepts and use AI as a thinking partner or scaffold, rather than a replacement for effortful learning.

- **The Need for Responsible Innovation:** Addressing these multifaceted social and ethical implications requires a commitment to responsible learning analytics and AI development (Nuangchalerm, 2023). This involves prioritizing human values, ensuring transparency and accountability, actively seeking stakeholder input (including students and teachers) throughout the design and implementation process (Fuligni, Dominguez Figaredo, & Stoyanovich, 2025), and critically examining the potential unintended consequences of these powerful technologies within the specific context of physics education.

The promise of personalization, a key driver for adopting LA and AI (Liu, Latif, & Zhai, 2025) , itself carries potential downsides. While tailoring content can address individual needs, hyper-personalization driven by opaque algorithms could lead to educational "filter bubbles," limiting students' exposure to diverse approaches or challenging problems essential for robust scientific development. It might optimize for narrow, easily measurable performance indicators at the expense of fostering deeper, transferable understanding or the collaborative skills vital in scientific practice (Hewitt et al., 2023). If personalization relies on potentially biased student profiles, it could also lead to inequitable learning pathways (Grimm et al., 2023). Thus, the goals and methods of personalization require careful ethical scrutiny.

VIII. Conclusion and Future Directions

The integration of data-driven learning strategies, specifically Learning Analytics (LA) dashboards and Artificial Intelligence (AI) tutoring systems, into undergraduate physics education presents a landscape of significant potential tempered by considerable challenges. This analysis, drawing on international evidence and sociological perspectives, suggests that while these technologies offer appealing prospects for personalized learning, enhanced engagement, improved feedback mechanisms, and increased accessibility, their effectiveness and ethical implementation are far from guaranteed.

SUMMARY AND CONCLUSIONS

LA dashboards and AI tutors are not inherently transformative educational solutions. Their impact is highly contingent on a complex interplay of factors. Key conclusions emerging from this analysis include:

1. **Context Matters:** The effectiveness of these tools varies significantly based on the specific physics course context, the institutional culture, the characteristics of the student population, and the mode of delivery (blended vs. fully online). The Armenian experience reinforces the broader lesson that technological innovations cannot be meaningfully implemented in a vacuum. Infrastructural limitations, faculty preparedness, and cultural attitudes towards data use shape the success of LA and AI tools. These insights argue for increased investment in local capacity building and context-sensitive adaptation strategies, rather than mere replication of international models.
2. **Pedagogy is Paramount:** Technology alone yields limited benefits. Successful implementations are those where LA dashboards or AI tutors are thoughtfully integrated into sound pedagogical frameworks that support active learning, provide meaningful formative feedback, facilitate timely interventions, and foster student self-regulation. The technology must serve pedagogy, not dictate it (Guzmán-Valenzuela et al., 2021).
3. **Effectiveness Evidence is Mixed:** While AI tutors show strong potential for improving learning outcomes (approaching human tutor effectiveness in some cases (Underwood & Luckin, 2011), the evidence for LA dashboards directly boosting academic achievement is currently weaker and requires more rigorous investigation (Flanagan, Wasson, & Gašević, 2024). Both tool types show more consistent promise for enhancing student participation and engagement, though motivation impacts are complex (Flanagan, Wasson, & Gašević, 2024).
4. **User Acceptance is Critical:** Faculty skepticism, anxiety, and lack of training, alongside student concerns about accuracy, privacy, over-reliance, and the loss of human connection, represent significant barriers (Weber, 2024). User-centered design and clear demonstration of value are essential for adoption (Ng et al., 2022).
5. **Equity is a Central Challenge:** The digital divide remains a fundamental barrier (Chikwe et al., 2024). Beyond access, the potential for algorithmic bias, differential impact on diverse student groups, and the interplay with existing social and cultural capital demand proactive and ongoing attention to ensure these technologies do not exacerbate existing inequalities (Stanford SCALE, 2025).
6. **Sociological Lenses are Essential:** Understanding the adoption, use, and impact of these socio-technical systems requires frameworks like TAM/UTAUT (for individual

acceptance), ANT (for network dynamics and technology agency), and Bourdieu's theory (for power, capital, and social structures).

7. **Ethical Vigilance is Non-Negotiable:** Issues of data privacy, algorithmic transparency, academic integrity, and the potential impact on student-teacher relationships necessitate robust ethical guidelines and a commitment to responsible innovation (Nuangchalerm, 2023).

Challenges and Research Gaps:

Despite growing research, significant gaps remain:

- **Rigorous Evaluation:** There is a pressing need for more large-scale, longitudinal, and methodologically robust studies (including randomized controlled trials where feasible) evaluating the impact of LA dashboards and AI tutors on deep conceptual understanding, critical thinking, problem-solving skills, and long-term retention in diverse undergraduate physics settings (Flanagan, Wasson, & Gašević, 2024).
- **Equity-Focused Research:** Research must move beyond simply identifying disparities to actively developing and testing strategies for mitigating bias in algorithms and ensuring equitable access and outcomes for all student groups within physics (Stanford SCALE, 2025) . Investigating the intersectional effects of multiple identity factors is crucial.
- **Understanding Long-Term Impacts:** Most studies focus on short-term effects. Research is needed on the long-term consequences for student learning trajectories, motivation, career choices, and the development of scientific identity and belonging (Hewitt et al., 2023).
- **Teacher Education and Support:** Effective integration requires knowledgeable instructors. More research is needed on how to best prepare and support physics faculty in using these complex tools effectively and ethically within their teaching practices (Weber, 2024).
- **Affective and Social Dimensions:** The impact on student well-being, anxiety, motivation, collaborative skills, and the quality of student-teacher and peer relationships requires deeper investigation, particularly with the rise of conversational AI (Liu, Latif, & Zhai, 2025).
- **Theoretical Integration:** Further work is needed to refine theoretical frameworks that integrate insights from sociology, learning sciences, and human-computer interaction to provide more comprehensive models of technology-mediated learning in physics (Odden et al., 2019).

Future Directions:

Promising avenues for future development and research include:

- **Hybrid Human-AI Models:** Designing systems that leverage the strengths of both AI (personalization, scalability) and human instructors/tutors (empathy, complex reasoning, relationship building (Society for Learning Analytics Research, 2025).
- **Explainable and Controllable AI:** Developing LA and AI systems that are more transparent in their reasoning and allow users (students and instructors) greater control over their functionality and data (Ng et al., 2022).
- **Multimodal Learning Analytics (MMLA):** Carefully exploring the potential of richer data sources (e.g., gaze, audio, physiological data) to provide deeper insights into learning processes, while rigorously addressing the heightened ethical concerns (Ng et al., 2022).
- **Domain-Specific AI for Physics:** Creating AI tutors and LA models specifically informed by Physics Education Research (PER), incorporating known student difficulties, effective representations, and validated pedagogical strategies relevant to physics.
- **Fostering Higher-Order Thinking:** Designing tools that explicitly target the development of critical thinking, metacognition, scientific argumentation, and computational literacy, moving beyond basic content delivery or procedural practice (Shafiq et al., 2025).

In conclusion, data-driven learning strategies hold the potential to significantly reshape undergraduate physics education. However, realizing this potential in a way that is truly beneficial and equitable requires moving beyond technological enthusiasm towards a critical, evidence-based, sociologically informed, and ethically grounded approach. The focus must remain firmly on enhancing learning and supporting all students, using technology as a carefully considered tool within a rich and humanistic educational endeavor.

Acknowledgments*: The authors thank the editors and anonymous reviewers for their constructive feedback.*
Funding*: This study was not supported by internal or external funding sources. All research presented in the article was conducted at the expense of the author(s).*
Data Availability Statement*: All supporting data generated or analyzed for this study are available upon request.*
Ethics Approval and Consent to Participate*: Not applicable.*
Consent for Publication*: Not applicable.*
Competing Interests*: The authors declare that they have no competing interests. Co-Author Samvel Asatryan is a member of the editorial board of Main Issues Of Pedagogy And Psychology but had no involvement in the peer-review process or decision-making related to this manuscript.*
Additional Notes on Research Methods*: All analyses and findings presented in this article were conducted through the integration of open-source materials, utilizing publicly available online resources and artificial intelligence (AI) tools. The authors affirm that AI was used solely as a supportive research tool in accordance with international academic integrity standards. No unauthorized AI-generated content was used in the article. The authors take full responsibility for the interpretation, accuracy, and validity of the analyses conducted with the assistance of AI tools.*

REFERENCES

Hewitt, H. B., Simon, M. N., Mead, C., Grayson, S., Beall, G. L., Zellem, R. T., Tock, K., & Pearson, K. A.

(2023). Development and assessment of a course-based undergraduate research experience for online astronomy majors. *Physical Review Physics Education Research*, *19*(2). https://doi.org/10.1103/physrevphyseducres.19.020156

Liu, V., Latif, E., & Zhai, X. (2025). *Advancing education through tutoring systems: A systematic literature review*. arXiv preprint arXiv:2503.09748. https://arxiv.org/abs/2503.09748

Calonge, D. S., Riggs, K. M., Shah, M. A., & Cavanagh, T. A. (2018). Using learning analytics to improve engagement, learning, and design of massive open online courses. In *Advances in higher education and professional development book series* (pp. 76–107). https://doi.org/10.4018/978-1-5225-7470-5.ch004

Nuangchalerm, P. (2023). AI-Driven Learning Analytics in STEM Education. *International Journal on Research in STEM Education*, *5*(2), 77–84. https://doi.org/10.33830/ijrse.v5i2.1596

Shafiq, N. M., Sami, N. M. A., Bano, N. N., Bano, N. R., & Rashid, N. M. (2025). Artificial Intelligence in Physics Education: Transforming Learning from Primary to University Level. *Indus Journal of Social Sciences.*, *3*(1), 717–733. https://doi.org/10.59075/ijss.v3i1.807

Yang, J., DeVore, S., Hewagallage, D., Miller, P., Ryan, Q. X., & Stewart, J. (2020). Using machine learning to identify the most at-risk students in physics classes. *Physical Review Physics Education Research*, *16*(2). https://doi.org/10.1103/physrevphyseducres.16.020130

Odden, T. O. B., Lockwood, E., & Caballero, M. D. (2019). Physics computational literacy: An exploratory case study using computational essays. *Physical Review Physics Education Research*, *15*(2). https://doi.org/10.1103/physrevphyseducres.15.020152

AIS Electronic Library (AISEL) - AMCIS 2018 Proceedings: The Effect of Studentsâ€TM Technology Readiness on Technology Acceptance. (n.d.). https://aisel.aisnet.org/amcis2018/AdoptionDiff/Presentations/18/

Ateş, H., & Gündüzalp, C. (2025). Proposing a conceptual model for the adoption of artificial intelligence by teachers in STEM education. *Interactive Learning Environments*, 1–27. https://doi.org/10.1080/10494820.2025.2457350

Underwood, J. L., & Luckin, R. (2011). *What is AIED and why does education need it?* Technology Enhanced Learning Research Programme. https://www.researchgate.net/publication/241698223_What_is_AIED_and_why_does_Education_need_it

Demirci, N. (2025). *How successful are artificial intelligence chatbots on higher education entrance physics exams in Turkey*. The Turkish Online Journal of Educational Technology, 24(2), Article 12. https://tojet.net/articles/v24i2/24212.pdf

Flanagan, B., Wasson, B., & Gašević, D. (Eds.). (2024). *Companion proceedings of the 14th International Learning Analytics and Knowledge Conference (LAK24), March 18–22, 2024, Kyoto, Japan*. Society for Learning Analytics Research (SoLAR). https://www.solaresearch.org/wp-content/uploads/2024/03/LAK24_CompanionProceedings.pdf

Gregorcic, B., Polverini, G., & Sarlah, A. (2024). ChatGPT as a tool for honing teachers' Socratic dialogue skills. *Physics Education*, *59*(4), 045005. https://doi.org/10.1088/1361-6552/ad3d21

Vasconcelos, M. a. R., & Santos, R. P. D. (2023). Enhancing STEM learning with ChatGPT and Bing Chat as objects to think with: A case study. *Eurasia Journal of Mathematics Science and Technology Education*, *19*(7), em2296. https://doi.org/10.29333/ejmste/13313

Weber, D. (2024). *AI in the classroom: Teachers' views on artificial intelligence* (Master's thesis, Uppsala University). Uppsala University Publications. https://uu.diva-portal.org/smash/get/diva2:1908423/FULLTEXT01.pdf

Fuligni, C., Dominguez Figaredo, D., & Stoyanovich, J. (2025). *"Would you want an AI tutor?" Understanding stakeholder perceptions of LLM-based chatbots in the classroom*. arXiv. https://arxiv.org/abs/2503.02885

Bitzenbauer, P. (2023). ChatGPT in physics education: A pilot study on easy-to-implement activities. *Contemporary Educational Technology*, *15*(3), ep430. https://doi.org/10.30935/cedtech/13176

Grimm, A., Steegh, A., Kubsch, M., & Neumann, K. (2023). Learning Analytics in Physics Education. *Journal of Learning Analytics*, *10*(1), 71–84. https://doi.org/10.18608/jla.2023.7793

Guzmán-Valenzuela, C., Gómez-González, C., Tagle, A. R., & Lorca-Vyhmeister, A. (2021). Learning analytics in higher education: a preponderance of analytics but very little learning? *International Journal of Educational Technology in Higher Education*, *18*(1). https://doi.org/10.1186/s41239-021-00258-x

Ignatow, G., & Robinson, L. (2017). Pierre Bourdieu: theorizing the digital. *Information Communication & Society*, *20*(7), 950–966. https://doi.org/10.1080/1369118x.2017.1301519

Guzmán-Valenzuela, C., Gómez-González, C., Tagle, A. R., & Lorca-Vyhmeister, A. (2021b). Learning analytics in higher education: a preponderance of analytics but very little learning? *International Journal of Educational Technology in Higher Education*, *18*(1). https://doi.org/10.1186/s41239-021-00258-x

Grimm, A., Steegh, A., Kubsch, M., & Neumann, K. (2023b). Learning Analytics in Physics education. *Journal of Learning Analytics*, *10*(1), 71–84. https://doi.org/10.18608/jla.2023.7793

Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-023-00420-7

Yusuf, I., Setyosari, P., Kuswandi, D., & Ulfa, S. (2024). The Frontier Areas' student Acceptance of Physics fun-based mobile application: Incorporating the Process-Oriented Guided-Inquiry Learning (POGIL) Strategy. *Participatory Educational Research*, *11*(6), 152–171. https://doi.org/10.17275/per.24.84.11.6

Ng, J. T., Wang, Z., & Hu, X. (2022). Needs Analysis and Prototype Evaluation of Student-facing LA Dashboard for Virtual Reality Content Creation. *LAK22: LAK22: 12th International Learning Analytics and Knowledge Conference*. https://doi.org/10.1145/3506860.3506880

Borchers, C., & Pardos, Z. A. (2023). Insights into undergraduate pathways using course load analytics. *LAK2023: LAK23: 13th International Learning Analytics and Knowledge Conference*, 219–229. https://doi.org/10.1145/3576050.3576081

Brown, M., & Cain, C. (2025). "I wish there was a way to share": the changing campus ecologies around community college life science courses. *Community College Journal of Research and Practice*, 1–18. https://doi.org/10.1080/10668926.2024.2426186

Goertzen, R. M., Brewe, E., & Kramer, L. (2012). Expanded markers of success in Introductory university Physics. *International Journal of Science Education*, *35*(2), 262–288. https://doi.org/10.1080/09500693.2012.718099

Kamp, A. (2019). Actor–Network Theory. *Oxford Research Encyclopedia of Education*. https://doi.org/10.1093/acrefore/9780190264093.013.526

Thomas, T., & De Villiers, C. (2002). Using actor-network theory to study an educational situation: An example from information systems at a technikon. *South African Journal of Higher Education, 16*(3), 177–184. https://doi.org/10.10520/EJC36931

Stahl, G., Mu, G. M., Ayling, P., & Weininger, E. B. (2023). *Applying Bourdieu in educational research* (pp. 1–18). https://doi.org/10.5040/9781350349193.ch-i

Dart, S., Cunningham, S., Gregg, A., & Young, A. (2024). Factors influencing educators' implementation of quality teaching practices in Australian engineering education. *Australasian Journal of Engineering Education*, 1–19. https://doi.org/10.1080/22054952.2024.2407284

Chikwe, N. C. F., Dagunduro, N. a. O., Ajuwon, N. O. A., & Ediae, N. a. A. (2024). Sociological barriers to equitable digital learning: A data-driven approach. *Comprehensive Research and Reviews in Multidisciplinary Studies*, *2*(1), 027–034. https://doi.org/10.57219/crrms.2024.2.1.0038

Galaige, J., Torrisi, R., Binnewies, S., & Wang, K. (2018). *What is important in student-facing learning analytics? A user-centered design approach*. In Proceedings of the 22nd Pacific Asia Conference on Information Systems (PACIS 2018) (Paper 127). Association for Information Systems. https://aisel.aisnet.org/pacis2018/127

Kannan, V., Warriem, J. M., Majumdar, R., & Ogata, H. (2022). Learning dialogs orchestrated with BookRoll: effects on engagement and learning in an undergraduate physics course. *Research and Practice in Technology Enhanced Learning*, *17*(1). https://doi.org/10.1186/s41039-022-00203-0

Reid, D. P., & Drysdale, T. D. (2024). Student-Facing Learning Analytics Dashboard for Remote Lab Practical work. *IEEE Transactions on Learning Technologies*, *17*, 1037–1050. https://doi.org/10.1109/tlt.2024.3354128

Borden, V. M. H., & Coates, H. (2017). Learning Analytics as a counterpart to surveys of student experience. *New Directions for Higher Education*, *2017*(179), 89–102. https://doi.org/10.1002/he.20246

NotebookLM: An LLM with RAG for active learning and collaborative tutoring. (n.d.). https://arxiv.org/html/2504.09720v1

Katz, S., & Albacete, P. L. (2013). A tutoring system that simulates the highly interactive nature of human tutoring. *Journal of Educational Psychology*, *105*(4), 1126–1141. https://doi.org/10.1037/a0032063

Tan, D. Y., & Cheah, C. W. (2021). Developing a gamified AI-enabled online learning application to improve students' perception of university physics. *Computers and Education Artificial Intelligence*, *2*, 100032. https://doi.org/10.1016/j.caeai.2021.100032

Tufino, E. (2025). *NotebookLM: An LLM with RAG for active learning and collaborative tutoring*. arXiv preprint arXiv:2504.09720. https://arxiv.org/abs/2504.09720

Dihan, Q. A., Nihalani, B. R., Tooley, A. A., & Elhusseiny, A. M. (2024). Eyes on Google's NotebookLM: using generative AI to create ophthalmology podcasts with a single click. *Eye*. https://doi.org/10.1038/s41433-024-03481-8

Vogt, N. P., & Muise, A. S. (2015). An online tutor for astronomy: The GEAS self-review library. *Cogent Education*, *2*(1), 1037990. https://doi.org/10.1080/2331186x.2015.1037990

Blankstein, M., & Wolff-Eisenberg, C. (2019). *Ithaka S+R US Faculty Survey 2018*. https://doi.org/10.18665/sr.311199

Tschisgale, P., Wulff, P., & Kubsch, M. (2023). Integrating artificial intelligence-based methods into qualitative research in physics education research: A case for computational grounded theory. *Physical Review Physics Education Research*, *19*(2). https://doi.org/10.1103/physrevphyseducres.19.020123

DeVaney, J. (2018, December 27). How can learning analytics improve the student experience? *EdSurge*. https://www.edsurge.com/news/2016-08-31-how-can-learning-analytics-improve-the-student-experience

Kcowan. (2025, January 30). *Using learning analytics for effective formative feedback – Teaching Matters*. https://blogs.ed.ac.uk/teaching-matters/using-learning-analytics-for-effective-formative-feedback/

Taqa, A. (2025, February). *The digital divide: Ensuring equitable access to online learning resources*.

NSF. (2025, April 17). *Learning analytics: Harnessing data science to transform education*. https://www.nsf.gov/events/learning-analytics-harnessing-data-science

Center for Curriculum Redesign. (2025, April 17). *Artificial intelligence in education*. https://curriculumredesign.org/wp-content/uploads/AIED-Book-Excerpt-CCR.pdf

Society for Learning Analytics Research. (2025, April 17). *The Fifteenth International Conference on Learning Analytics & Knowledge*. https://www.solaresearch.org/wp-content/uploads/2025/02/LAK25_CompanionProceedings-Final.pdf

Stanford SCALE. (2025, April 17). *Impact – Quasi–experimental*. https://scale.stanford.edu/genai/repository/impact-quasi-experimental

Reddit. (2025, April 17). *New article says AI teachers are better than human teachers. Quote: "Students who were given access to an AI tutor learned more than twice as much in less time compared to those who had in-class instruction."* https://www.reddit.com/r/singularity/comments/1geyshu/new_article_says_ai_teachers_are_better_than/

Received: 14/10/ 2024
Accepted: 15/ 03/ 2025

Publisher's Note:
ASPU Publication remains neutral concerning jurisdictional claims in published maps and institutional affiliations.