



Machine learning-based adaptive learning systems in higher education: A systematic review of techniques, outcomes, and ethical implications for knowledge translation

M.I.H. Madurapperuma^{1*} and G.A.H.J. Perera¹

¹*Faculty of Computing and Information Technology, Nagananda International Institute for Buddhist Studies, Manelwatte, Bollegala, Kelaniya, Sri Lanka*

Abstract

Machine learning (ML) and artificial intelligence (AI) technologies have revolutionized the development of adaptive learning systems (ALS) that can personalize learning in higher education. A comprehensive and synthesized understanding of the most common ML techniques used, their reported effectiveness in improving educational outcomes, and the ethical challenges of their use in this context is needed. This systematic review synthesizes 19 peer-reviewed articles published from 2015-2025 to: (1) map and classify ML and AI techniques used in higher education adaptive learning systems; (2) assess evidence of impact on student academic performance, engagement and retention; (3) explore ethical issues such as algorithmic bias, data privacy, governance and transparency; and (4) recommend a knowledge translation approach to ethical implementation of AI-ALS within higher education settings. Following PRISMA 2020 Statement, searching in five digital databases (Google Scholar, Scopus, Web of Science, IEEE Xplore and ACM Digital Library), 19 articles were included, based on eligibility criteria, including systematic reviews, scoping reviews, empirical research and bibliometric analyses and prospective studies. The most commonly encountered ML techniques were collaborative filtering, Bayesian knowledge tracing, deep learning (LSTM and transformer-based models), reinforcement learning, NLP-based tools and learning style prediction algorithms. The studies reported significant gains in learning performance, engagement (15 - 30% improvement) and retention with AI-ALS. However, serious ethical questions were raised in most studies, such as algorithmic bias, lack of informed consent, black-box issues, and lack of institutional governance strategies, especially in under-resourced and Global South settings. ML-based ALS has great power to enhance higher education through personalized, data-driven learning. However, this potential must be realized in an ethical and equitable manner through strong governance, explainable AI, and multi-stakeholder accountability. A five-layer knowledge translation model is advocated.

Keywords: Adaptive learning systems, Machine learning, Artificial intelligence, Higher education, Knowledge translation

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ORCID iD: <https://orcid.org/0009-0002-6243-6072>

*Corresponding author:

E-mail address: inuansani1996@gmail.com

(M.I.H. Madurapperuma)

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Introduction

The last ten years have experienced a swift machine learning (ML), artificial intelligence (AI), and educational technology convergence in higher education that has resulted in the development of adaptive learning systems (ALS), which customizes the delivery of instruction through the lens of learner behavior, knowledge state, and engagement patterns instead of delivering uniform content (Hariyanto et al., 2025; Peng & Li, 2025). Such systems constantly process data related to learners to real-time modify content sequencing, difficulty, and feedback, approximating one-to-one tutoring much more closely (Yuensook et al., 2026).

Higher education has already seen an increase in the number of applications of ML to work in various fields, such as prediction of student performance, curriculum design, intelligent tutoring systems, and administrative optimization (Pinto et al., 2023). The methodological state of research has also changed, with more recent applications of educational data mining (EDM) and human-in-the-loop machine learning (HIML) as well as machine teaching methods that utilize educator expertise to create models (López-Meneses et al., 2025). Nonetheless, in spite of this development, it is clear that this field is merely fragmented, and synthesis between techniques is insufficient and evidence of best practices between the ML techniques is inconsistent (Essa et al., 2023). The outcome measures also differ and are hard to compare across a study (du Plooy et al., 2024; Merino-Campos, 2025).

More importantly, ethical implications, including bias, privacy, transparency, consent, and governance, are not well developed in most of the literature (Bettahi et al., 2025; Elbasi et al., 2025). The understanding of knowledge translation emphasizes that successful implementation of ALS requires not just technical excellence, but institutional preparedness, infrastructure, and equity (Enaifoghe, 2026; Mustafa et al., 2024). This is further evidenced by lower-resource settings, which reveal that non-technical barriers are major barriers to adoption and impact (Asamoah & Amarteifio, 2025).

This systematic review synthesizes 19 peer-reviewed papers (2015-2025) to (1) map the ML techniques used in ALS, (2) assess learning outcomes, (3) discuss ethical issues, and (4) create a layered framework of responsible knowledge translation in higher education.

Methodology

Review design and protocol

The systematic review was planned and formulated based on the Preferred Reporting Items of Systematic Reviews and Meta-Analyses (PRISMA) 2020 guideline. A priori review protocol, including research questions, search strategy, eligibility criteria, and data extraction procedures, was developed. The final corpus comprised 19 review-type studies, including systematic reviews, scoping reviews, bibliometric analyses, and prospective reviews. Therefore, the study was treated as a review of reviews and a narrative synthesis approach was used instead of formal meta-analysis.

Search strategy

In March 2026, systematic searches were conducted in Google Scholar, Scopus, Web of Science, IEEE Xplore, and ACM Digital Library. The search strategy combined three conceptual groups using Boolean operators: (1) 'machine learning' OR 'artificial intelligence' OR 'deep learning' OR 'educational data mining'; AND (2) 'adaptive learning' OR 'personalized learning' OR 'intelligent tutoring' OR 'recommendation system'; AND (3) 'higher education' OR 'university' OR 'tertiary education' OR 'e-learning'. Searches were conducted using title, abstract and keyword fields where supported. The search was limited to English-language, peer-reviewed publications published between 2015 and 2025. Reference lists of eligible studies were also manually screened.

Eligibility criteria

The studies were evaluated in terms of structured inclusion and exclusion criteria (Table 1). Both primary empirical studies and secondary review studies that passed the criteria were included reflecting the review of reviews design aspects that suit well this rapidly changing area.

Table 1: Inclusion and Exclusion criteria used in the study selection

Criterion	Inclusion	Exclusion
Publication Period	2015–2025 (peer reviewed journals & conferences)	Studies published before 2015
Language	English language publications	Other translations that are not in English without a confirmed translation
Study Focus	Adaptive/ personalized learning in HE using ML/AI	Studies limited to K-12 or vocational settings only
Study Type	Case study, empirical, systematic review, scoping review	Opinion pieces, book chapters, editorials
Outcome Reporting	Reports learning outcomes, engagement, or performance	Completely theoretical, no empirical or review evidence
Ethical Dimension	Responds to the ethical issues of AI/ML use	Says nothing whatever about restrictions or moral hazards

Selection of studies and PRISMA flow

The PRISMA 2020 flow diagram shown in Figure 1 summarizes the screening and selection process. The database searches identified 124 records before duplicate removal. The records retrieved were Scopus (n = 15), Web of Science (n = 10), IEEE Xplore (n = 20), ACM Digital Library (n = 22), and Google Scholar (n = 57). After duplicate removal, 98 records remained for title and abstract screening. 42 full-text articles were assessed for eligibility, of which 23 were excluded due to thematic mismatch (n = 12), lack of empirical or analytical content (n = 7), and lack of quality (n = 4). Nineteen studies were included in the final review. Figure 1 presents the study selection process using the standard PRISMA 2020 flow diagram.

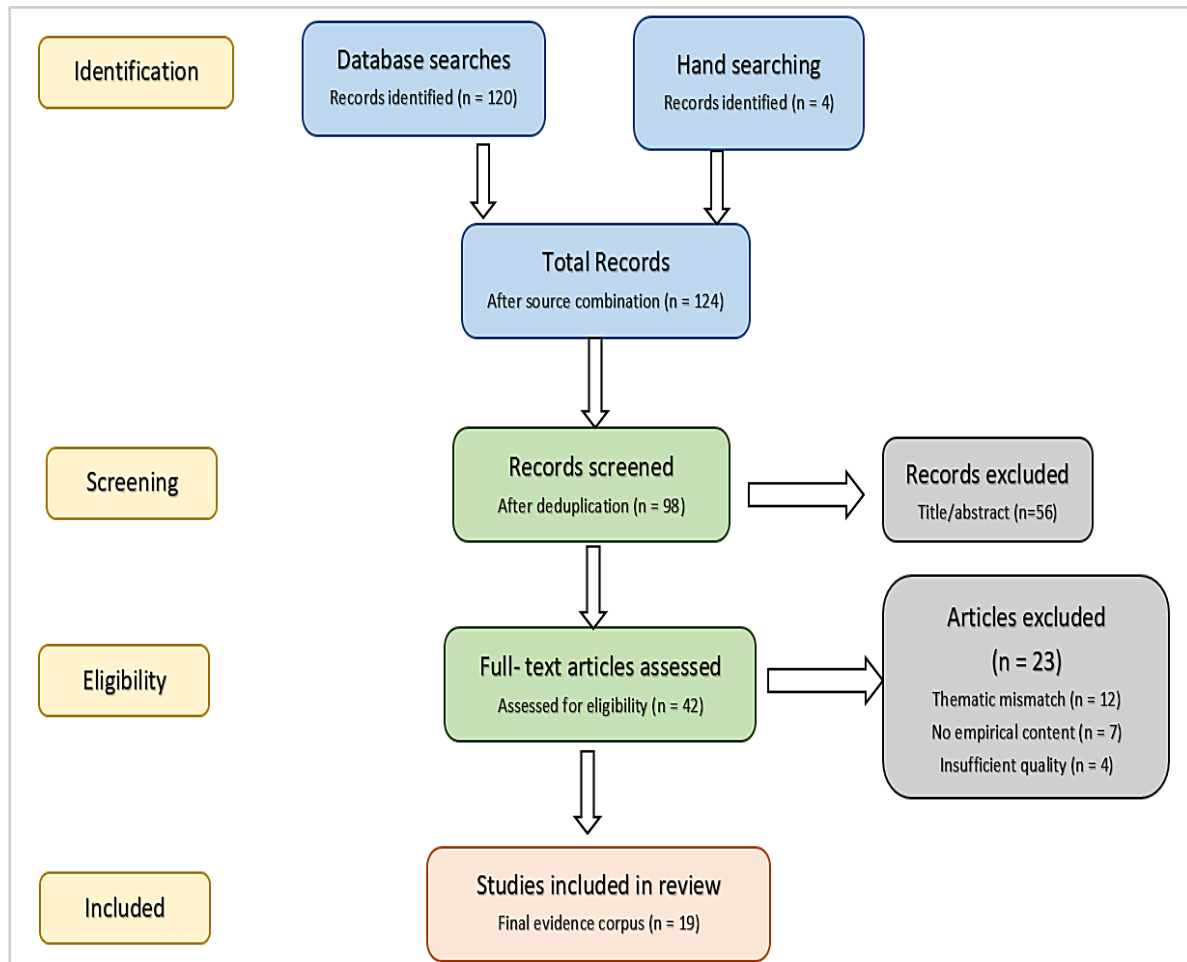


Figure 1. PRISMA 2020 Flow Diagram that identified, screened, and selected 19 studies to include in the final selection

Data dredging and performance assessment

Each of the included studies had their data extracted using a standardized data extraction template, which included: study design and geographic context; ML/AI technique(s) under evaluation; learning outcome measures and results; ethical aspects covered; and reported limitations. As all 19 included studies were review-type studies, the Mixed Methods Appraisal Tool (MMAT) for empirical studies was not applicable. Quality appraisal was therefore conducted using the appropriate appraisal approach for review-type evidence. A summary of all 19 studies included is presented in Table 2.

Table 2: Overview of the 19 studies included in this systematic review *(Continued on next page)*

Author(s) & Year	Title (Abbreviated)	Study Type	ML/AI Focus	Key Contribution
López-Meneses et al., (2025)	AI in EDM & Human-in-the-Loop ML	Bibliometric/Analysis	EDM, HIML, Machine Teaching	Scientometric map of AI-EDM research trends

Author(s) & Year	Title (Abbreviated)	Study Type	ML/AI Focus	Key Contribution
Peng & Li, (2025)	Frontiers of AI for Personalized Learning – Systematic Review	Systematic Review	AI personalization in HE	Identifies leading AI personalization frameworks
Pinto et al., (2023)	How ML is Transforming HE – SLR	Systematic Lit. Review	ML applications across HE	Taxonomy of ML impacts; efficiency & equity findings
Bettahi et al., (2025)	Continuous-Time Modelling in EDM & LA	Literature Review	CT-models, ethics, AI trends	Novel methods for temporal learning data; ethical gaps
Merino-Campos, (2025)	Impact of AI on Personalized Learning in HE	Systematic Review	AI-driven personalization	Evidence synthesis; pedagogical effectiveness review
Idris-Tajudeen et al., (2025)	AI in e-Learning: 21st Century Trends	Systematic Review	AI trends in e-learning	Classification of AI tools; trend analysis 2000–2024
Elbasi et al., (2025)	ML in Education: Innovations & Ethics	Review (IEEE Access)	ML innovations; ethical issues	Framework linking ML techniques to ethical concerns
Essa et al., (2023)	Personalized Adaptive Learning – Learning Styles SLR	Systematic Lit. Review	Learning style detection via ML	Identifies best-fit ML models per learning style
Levin, (2024)	Review of ML Models for Adaptive Learning in HE	Review Article	ML model comparison in ALS	Comparative analysis of model suitability for HE ALS
Luo et al., (2025)	Design & Assessment of AI-Based Learning Tools in HE	Systematic Review	AI tool design & evaluation	Assessment framework for AI-based HE learning tools
Asamoah & Amarteifio, (2025)	Barriers & Ethics in ITS in Ghanaian HE	Review Article	Intelligent tutoring systems	Contextual barriers; ethical challenges in Global South
Hariyanto et al., (2025)	AI in Adaptive Education – Techniques for Personalized Learning	Systematic Review	AI/ML personalization techniques	Technique classification; personalization effectiveness
Enaifoghe, (2026)	Governance of AI as Adaptive Learning in HE	Review Article	AI governance frameworks	Policy and governance model for AI-ALS deployment
Mustafa et al., (2024)	Role of AI for Adaptive Learning in HE by 2030	Prospective Review	AI futures in HE	Vision 2030 roadmap; adaptive learning readiness
Deng, (2024)	ML in Curriculum Design in HE – Systematic Review	Systematic Review	ML for curriculum design	ML-enhanced curriculum adaptation and personalization

Author(s) & Year	Title (Abbreviated)	Study Type	ML/AI Focus	Key Contribution
Yuensook et al., (2026)	AI-Driven ALS in HE – Systematic Review	Systematic Review	AI-driven ALS frameworks	Identifies dominant AI-ALS models; effectiveness data
Meylani, (2024)	Critical Glance at AI-Based ALS – SLR & Qualitative Synthesis	Systematic Review	AI-ALS quality & limitations	Critical appraisal of methodological rigour in AI-ALS research
Stasolla et al., (2025)	Deep & RL for Academic Performance in HE – Scoping Review	Scoping Review	Deep learning; Reinforcement learning	Evidence for DL/RL effectiveness; performance outcomes
du Plooy et al., (2024)	Personalized Adaptive Learning in HE – Scoping Review	Scoping Review	ALS characteristics & impact	Key ALS characteristics linked to performance & engagement

Machine learning user-facing techniques in higher education adaptive learning system

General view of the technical landscape

Out of the 19 studies included, ten different families of ML and AI techniques were found to be applied to higher education settings of adaptive learning (Table 3). Both methodological maturity in the case of collaborative filtering and Bayesian knowledge tracing (BKT) applied in learning contexts over a decade and rapid innovation, especially in deep learning architectures and large language model (LLM) enabled applications characterize the landscape (Luo et al., 2025; Stasolla et al., 2025). Figure 2 illustrates a schematic view of the taxonomy of ML techniques found within included studies.

Table 3: ML/AI Methods found in included studies: usage and benefits

ML/AI Technique	Cited in Studies	Primary Application in HE	Reported Benefits
Collaborative Filtering	Essa et al.; Hariyanto et al.; Levin	Course & content recommendation	Improved content relevance; Personalized resource delivery
Bayesian Knowledge Tracing (BKT)	Levin; Essa et al.; Stasolla et al.	Skill mastery & knowledge state modelling	Accurate real-time learner modelling; early intervention signals
Deep Learning (LSTM / Transformer)	Stasolla et al.; Pinto et al.; Elbasi et al.	Sequential learning path & performance prediction	15–30% performance prediction accuracy gains reported
Reinforcement Learning (RL)	Stasolla et al.; Hariyanto et al.; Yuensook et al.	Adaptive hint, scaffolding & feedback delivery	Optimized instructional sequencing; reduced learner frustration
Natural Language Processing (NLP)	Idris-Tajudeen et al.; Elbasi et al.; Luo et al.	Automated feedback, chatbots, essay scoring	Scalable formative feedback; dialogue-based tutoring

ML/AI Technique	Cited in Studies	Primary Application in HE	Reported Benefits
Learning Style Detection (ML-based)	Essa et al.; Hariyanto et al.	Learner profile classification & style-based adaptation	Alignment of content modality with individual learning preferences
Ensemble Methods (RF / XGBoost)	Pinto et al.; Elbasi et al.; Deng	At-risk student detection; curriculum analytics	AUC 0.85–0.92 in early warning systems reported
Continuous-Time / Temporal Models	Bettahi et al.	Time-sensitive learner state tracking	Captures fine-grained behavioral evolution; novel analytics approach
Human-in-the-Loop ML & Machine Teaching	López-Meneses et al.	Educator-guided model refinement	Preserves pedagogical expertise within AI-driven systems
Knowledge Graphs & Semantic AI	Peng & Li; Luo et al.	Intelligent curriculum mapping & concept linking	Supports adaptive path generation based on knowledge structures

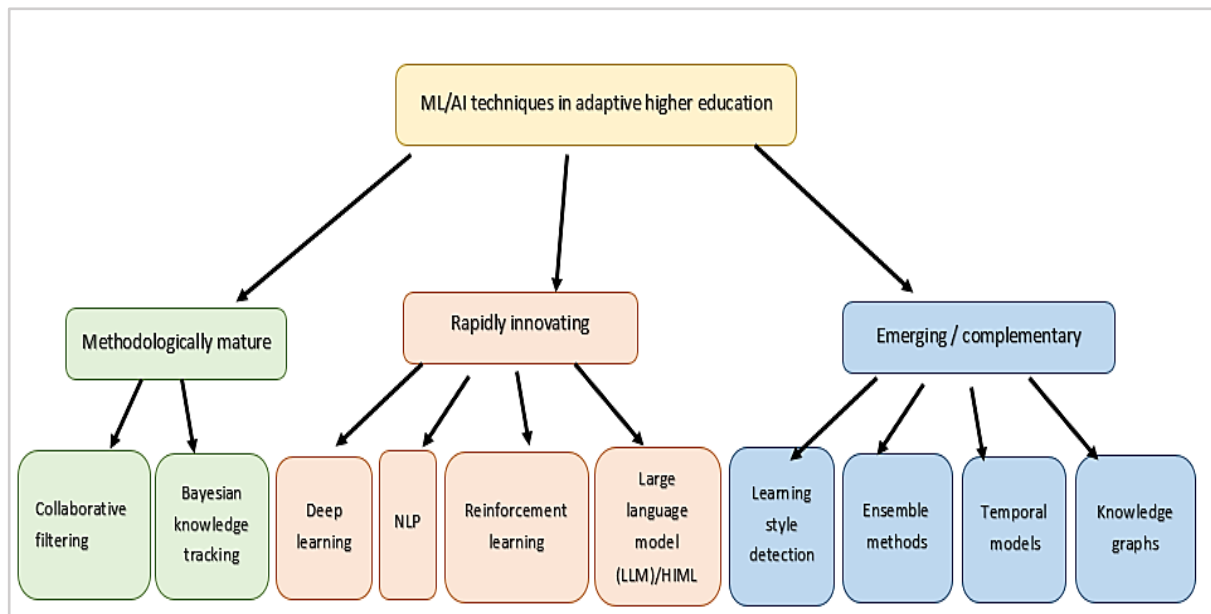


Figure 2. Taxonomy of ten families of ML/AI techniques found in the 19 included studies, sorted by methodological approach

Cooperative Filtering and Recommendation Systems

Collaborative filtering (CF) is one of the most operationally developed methods in educational ALS. Essa et al. (2023) conducted a systematic review to highlight CF as one of the most common strategies to recommend content, with similarities in the learning performance profile manifesting contextually suitable resources and course paths. This is supported by Hariyanto et al. (2025), who observed that user based variants and item based variants of CF have been popularized in MOOC platforms and university LMS settings, where they enhance content relevance and minimize cognitive load due to unguided navigation of resources. Levin (2024) further observed that CF extensions based on matrix factorization, such as singular value decomposition, have proved to be more scalable in high enrolment situations, but cold start issues with new learners and popularity biases continue to be limiting factors that have to be addressed by hybrid methods.

Bayesian knowledge tracing and probabilistic learner modelling

Bayesian knowledge tracing (BKT) is a probability model of whether a learner has mastered a particular piece of knowledge as a latent variable that is adjusted after each practice opportunity, where the latent variable is modeled by a hidden Markov model (Essa et al., 2023; Levin, 2024). Stasolla et al. (2025) define BKT as a baseline reference model on which more recent deep learning systems based on knowledge tracing are planned, stating that the interpretability of BKT allows it to be institutionally trusted, but it assumes binary knowledge states that cannot be applied to more complex, multi-dimensional competency structures of higher learning. The predictive accuracy and the quality of early intervention signals have been significantly enhanced with individualized extensions of BKT with learner specific parameters of learning rate and prior knowledge.

Deep learning: LSTM networks and transformer architectures

The most quickly evolving frontier of educational ML is related to deep learning models, specifically long short-term memory (LSTM) networks and transformer-based models (Pinto et al., 2023; Stasolla et al., 2025). Deep knowledge tracing (DKT) models that use LSTM networks on data of sequential learner interactions significantly outperform BKT in forecasting knowledge states on heterogeneous data streams, by obtaining long range temporal dependencies in learning sequences without engineered features. Elbasi et al. (2025) observed that transformer based architectures, which leverage self-attention mechanisms that are similar to those used in large language models, have recently achieved additional gains in knowledge state prediction accuracy, and have reported AUC gains of between 8 -15% over LSTM baselines across various education datasets. The authors of the specific study (Luo et al., 2025) evaluated AI-based learning tools with the use of LLM components in higher education, revealing positive signs of their efficacy in helping to generate feedback, answer questions, and conduct adaptive tutoring conversations but also note that hallucination, accuracy, and access equity are raised as significant concerns.

Adaptive instruction reinforcement learning

Reinforcement learning (RL) models educational choices to give a hint, content sequence, and novel content introduction as a sequential decision-making problem that maximizes long-term learning results and minimizes performance on a task immediate task performance (Hariyanto et al., 2025; Stasolla et al., 2025). In a detailed scoping review of the application of deep and reinforcement learning to higher education, Stasolla et al. (2025) identified RL as especially promising to optimize adaptive hint delivery and scaffolding techniques and report both reduced learner frustration and higher task completion rates in comparison to fixed pedagogical strategies in controlled settings. Yuensook et al. (2026) observed that RL-based systems need a great deal of interaction data to reach effective policies which is impractical in small-enrolment higher education courses with limited data to train the models. A conceptualized simplified RL-based adaptive tutoring feedback loop is illustrated in Figure 3, based on included studies.

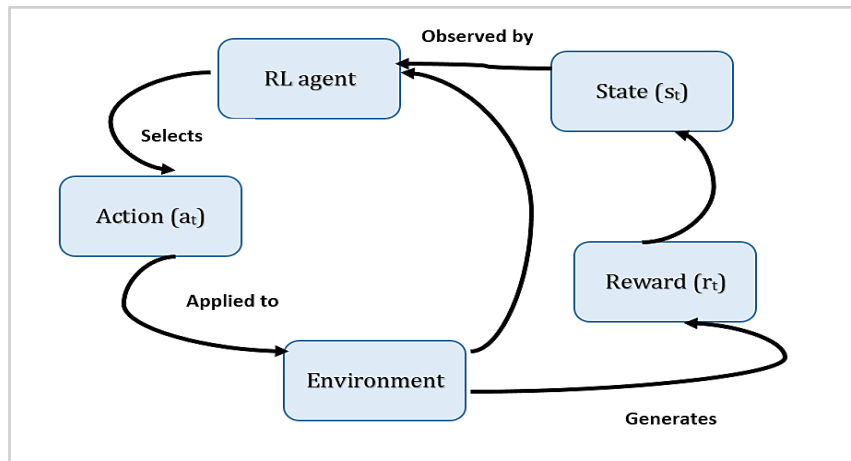


Figure 3. The simplified feedback loop of reinforcement learning in adaptive tutoring in higher education, conceptualized based on the work of Hariyanto et al. (2025) and Stasolla et al. (2025)

Dialogue based AI and natural language processing

At higher education ALS Natural language processing (NLP) can be involved with automated essay graders, chatbots, or sentiment and engagement analysis (Elbasi et al., 2025; Luo et al., 2025; Idris-Tajudeen et al., 2025). Idris-Tajudeen et al. (2025) categorized NLP as among the five most effective families of AI technologies transforming e-learning in the 21st century, based on evidence that automated feedback systems with rubric-congruent settings have been associated with correlation with expert human rater scores of more than $r = 0.80$ in writing-intensive higher education courses. Luo et al. (2025) mentioned that the development of generative AI, large language model tools, such as ChatGPT and domain-specific educational chatbots, opens up radically new opportunities in the form of natural, context-sensitive learning dialogue, although it also causes acute issues with academic integrity, excessive dependence, and loss of critical thinking abilities.

Personalization and detection of learning style

Essa et al. (2023) organized a specific systematic literature review of ML methods used to detect learning styles and found a relatively large range of classification algorithms, such as decision trees, support vector machines, neural networks, and k-nearest neighbor models used to identify the preferences of learners in visual, auditory, reading/writing, and kinesthetic modalities (VARK) and other established frameworks. Hariyanto et al. (2025) substantiated that learning style informed adaptation is one of the most common personalization methods in AI-ALS studies and that the satisfaction and engagement with instructions is better when the instructional modality is adjusted to identified style profiles. Both reviews observe, though, that psychometric validity of learning style frameworks as fixed categories is debated in educational psychology, and that excessively rigid style based adaptation can inhibit the development of different cognitive strategies by learners.

Machine teaching, educator centered models and human in the loop ML

One of the unique aspects of López-Meneses et al. (2025) is their scientometric and analytical emphasis on human-in-the-loop machine learning (HIML) and machine teaching as the new trends in educational AI. In contrast to fully automated ML pipelines, HIML systems incorporate educator knowledge, experience, and values directly into model training, validation, and improvement loops and place teachers in the role of co-creators of adaptive learning algorithms, instead of consumers of algorithm outputs. This paradigm has a great potential to deal with transparency and agency issues that define mainstream blackbox ML application in education, and to retain the pedagogical richness that might not be reflected in plain data driven methods. Bettahi et al. (2025) extend this view by suggesting continuous time modelling strategies that more accurately represent the time dynamics of learner states in comparison to discrete-time, event-based models, enabling new opportunities in fine grained, ethically informed learning analytics.

Educational outcomes of ML-based adaptive learning systems

Summary of outcome evidence

The Table 4 summarizes the evidence of outcomes reported in included studies by category. The educational outcomes synthesized in this review were reported by the 19 included review-type studies and were not independently verified against primary datasets. Therefore, reported quantitative findings are presented as evidence reported in the secondary literature rather than as independently calculated effect estimates.

Table 4: Educational results reported in the 19 studies included

Outcome Category	Studies Reporting	Measurement Approach	Key Findings
Academic Performance	du Plooy et al.; Stasolla et al.; Merino-Campos; Yuensook et al.	Test scores, GPA, course completion rates	Consistent improvement; moderate-to-large effect sizes across disciplines
Student Engagement	du Plooy et al.; Idris-Tajudeen et al.; Luo et al.; Mustafa et al.	Time-on-task, session frequency, LMS interaction logs	15–30% increase in active engagement under AI-ALS vs. conventional LMS
Knowledge Retention	Hariyanto et al.; Essa et al.; Stasolla et al.	Delayed post-tests, spaced practice outcomes	Improved retention linked to adaptive spacing and mastery-based sequencing
Personalization Effectiveness	Peng & Li; Essa et al.; Hariyanto et al.; Levin	Alignment of content with learner profile; learner satisfaction	Higher perceived relevance; reduction in redundant content exposure
Early Warning & At-Risk Detection	Pinto et al. Elbasi et al. Bettahi et al.	AUC, precision, recall of predictive models	Strong predictive accuracy; actionable signals for timely educator intervention

Academic performance

The most frequently reported outcome of the included studies is academic performance improvement with du Plooy et al. (2024) scoping review results showing that systems with mastery-based sequencing, formative feedback, and adaptive difficulty calibration made the highest gains, with moderate to large effect sizes. Merino-Campos (2025) supported these findings with a systematic review that concludes that AI-driven personalisation has consistently better amounts of results when compared to traditional LMS-based instruction in any discipline, with significant results in STEM disciplines because of its systematised and sequential structure of knowledge.

Stasolla et al. (2025) offered dedicated evidence on reinforcement learning (RL)-based systems, which show a high degree of improvement in the accuracy of prediction of performance, the ability to implement them in a timely manner, and direct improvements in the results of an assessment in controlled experimental conditions through adaptive scaffolding. Synthesising findings on higher education settings in Southeast Asia, Yuensook et al. (2026) mentioned the stability in academic performance, although variations were observed in terms of the quality of implementation and institutional infrastructure. Table 4 depicts the correlation between the ALS characteristics measured by ML-based and academic performance outcomes as determined in the literature review studies.

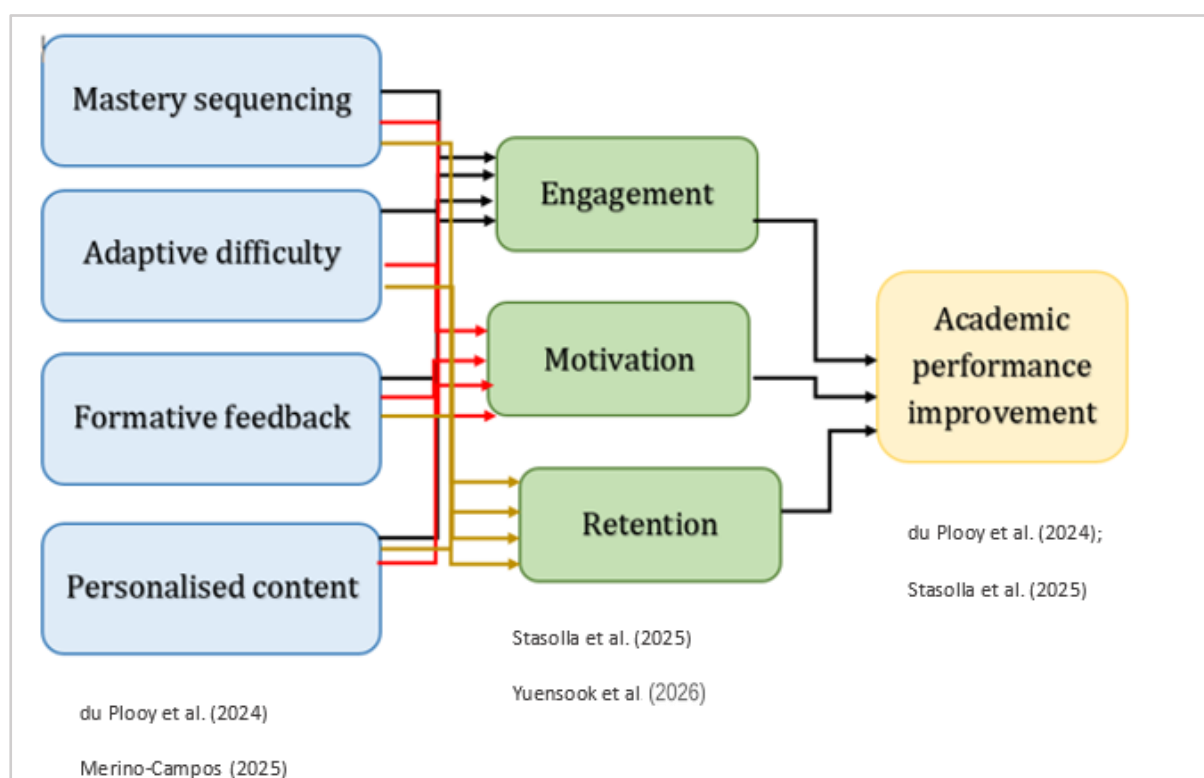


Figure 4. Conceptual model of relationships between design characteristics of ML-ALS design and academic performance outcomes, synthesized with du Plooy et al. (2024), Merino-Campos (2025), and Stasolla et al. (2025)

Student engagement and motivation

According to du Plooy et al. (2024), the second most common outcome reported in ALS studies is engagement, with time on task, session frequency, and voluntary access to content not required by the mandatory requirement being the most common operationalization's. Student engagement was reported in four studies (du Plooy et al., 2024; Luo et al., 2025; Mustafa et al., 2024; Idris-Tajudeen et al., 2025), using measures including time-on-task, session frequency and LMS interaction logs. The included studies reported approximately 15–30% improvement in active engagement under AI-ALS conditions compared with conventional LMS approaches. However, because the studies used different engagement measures and methodologies, these values are presented as a reported range rather than a pooled effect size. Some of them also measured motivational dimensions with self-report measures: both Hariyanto et al. (2025) and Merino-Campos (2025) reported strong increases in intrinsic motivation, perceived autonomy, and learning self-efficacy in students using AI Personalized learning environments, which implies that there are psychological processes that explain sustained engagement benefits beyond interface novelty.

Knowledge retention

The delayed post-test designs to measure knowledge retention 4-12 weeks after the intervention as a crucial outcome of ML-based adaptive spacing and mastery based sequencing are reported in Hariyanto et al. (2025), Essa et al. (2023), and Stasolla et al. (2025). Cognitive science-based systems with spaced repetition algorithms (the spacing effect) showed significantly better retention than massed practice control conditions. Essa et al. (2023) particularly attributed learning style adapted retention to the congruency of content presented in learning modalities that match the learner profile and suggests that the learning style categorization frameworks being psychometrically valid necessitates further investigation.

Systemic impacts and curriculum design

One of the unique outcome dimensions that Deng (2024) and Peng and Li (2025) recognized is related to the overall effect of ML on the curriculum design, rather than on the personal learning experiences. Through the example of ML driven analytics of student learning trajectories and patterns of competency gaps, Deng (2024) showed that these tools can be used to inform evidence-based processes of curriculum review and help institutions detect misalignment between taught material and assessed competencies better than traditional programme review mechanisms can. Peng and Li (2025) also pointed to knowledge graph based curriculum mapping as a frontier capability, to provide dynamic, personalized navigation paths through degree programme content structures, as opposed to cohort-uniform course sequences.

Knowledge translation ethical implications

In the 19 studies used, one of the most frequently and acutely presented problems of ML-ALS research is ethical considerations. Table 5 is a systematized summary of the six main areas of ethical challenges that were identified, the literature that supports each one of the challenges and the mitigation strategies that are either suggested or put in place in the literature.

Bias in algorithms and inequality in education

One of the key ethical risks of the ML-based adaptive learning system, identified by researchers, is algorithmic bias, which unfairly treats learners, based on race, gender, socioeconomic status, or disability (Asamoah & Amarteifio, 2025; Elbasi et al., 2025; Pinto et al., 2023). According to Elbasi et al. (2025), bias exists at various levels, such as the use of biased training data based on historical inequalities, the introduction of proxy variables to represent learning ability, and feedback mechanisms that perpetuate learning ability disparities over time. Asamoah and Amarteifio (2025) further noted that systems trained on Global North data could be disadvantageous to the learners in the other context (Ghana) because of variations in language, patterns of interaction, and knowledge systems. In general, the literature reveals that bias in ML-ALS can contribute to the systematic increase in educational inequality unless mitigated.

Table 5: Ethical issues, evidence of the included studies, and suggestions of mitigations

Ethical Issue	Evidence from Included Studies	Studies Citing Issue	Recommended Mitigations
Algorithmic Bias & Inequity	ML models trained on non-representative data reproduce and amplify existing demographic inequities; differential outcomes for minority learners documented	Elbasi et al; Asamoah & Amarteifio Pinto et al.	Fairness constraints in model training; disaggregated reporting; diverse training datasets
Data Privacy & Surveillance	Continuous behavioral logging raises GDPR/FERPA compliance concerns; risk of sensitive inferences from interaction data	Bettahi et al. Elbasi et al. Idris-Tajudeen et al.	Data minimization; differential privacy; federated learning; clear retention policies
Lack of Transparency (Black-box AI)	Majority of high-performing models are opaque; educators cannot interrogate or meaningfully override AI recommendations	Meylani Elbasi et al. Luo et al.	Explainable AI (XAI); SHAP/LIME explanations; educator-facing dashboards with rationale
Informed Consent & Student Agency	Students rarely informed of full scope of data use; opt-out mechanisms often absent or educationally penalizing	Enaifoghe Asamoah & Amarteifio Bettahi et al.	Rights-based consent protocols; transparent data use policies; student control panels
Governance & Accountability Gaps	Absence of institutional AI governance frameworks; responsibility diffused across vendors, administrators, educators	Enaifoghe Mustafa et al. Meylani	Multi-stakeholder governance committees; AI ethics review boards; third-party auditing

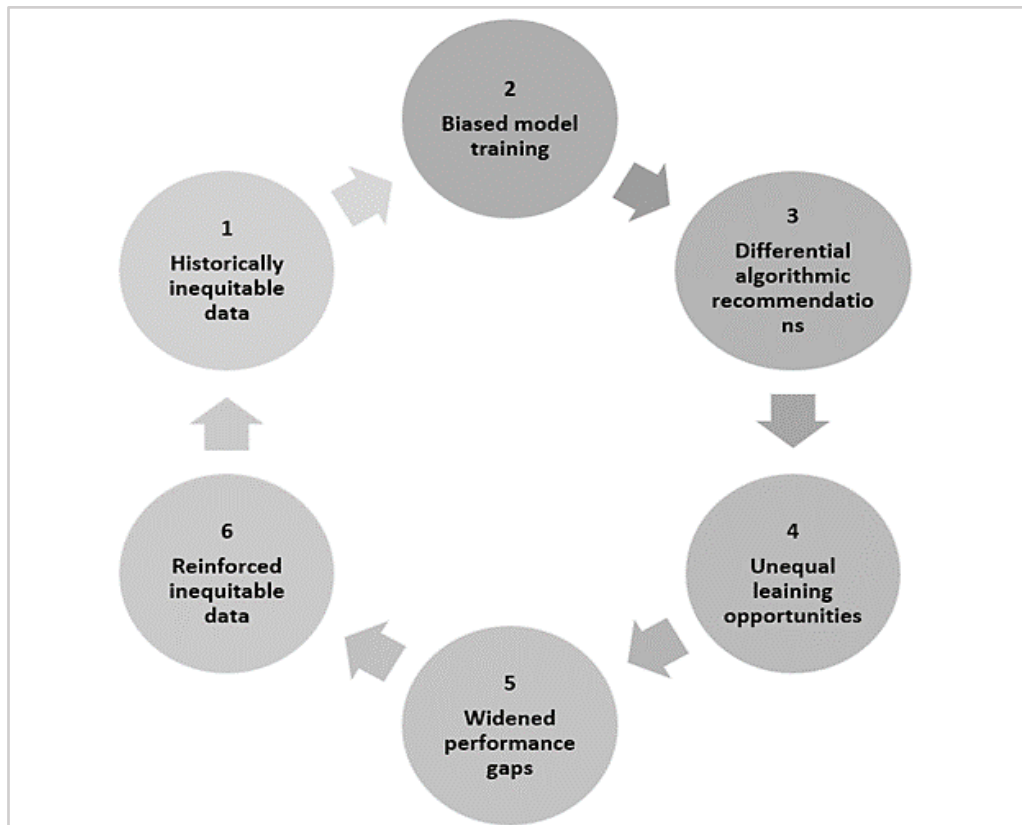


Figure 5. Cycle of amplification of algorithm bias in ML-based adaptive learning systems, generated based on Asamoah and Amarteifio (2025) and Elbasi et al. (2025)

Privacy of data, surveillance and GDPR/FERPA compliance

The magnitude of data collection needed in the case of adaptive learning systems based on ML, such as clickstream data, assessments, engagement measures, and in certain instances, biometric and affective data, are subject to serious privacy concerns (Bettahi et al., 2025; Elbasi et al., 2025; Idris-Tajudeen et al., 2025). As noted by Bettahi et al. (2025) continuous time modelling amplifies surveillance risks by inference of fine-grained behaviour. The issue of GDPR and FERPA compliance will continue to be challenging, with most systems operating within the legal grey area concerning data ownership, maintenance, and secondary use. Federated learning and differential privacy are suggested as possible solutions but are not used as widely (Elbasi et al., 2025).

Transparency, explainability, teacher trust

One of the key shortcomings of ML-ALS is that models are opaque at the educator level, especially when using deep learning systems, which decreases educator trust and agency (Elbasi et al., 2025; Luo et al., 2025; Meylani, 2024). Although XAI tools like SHAP and LIME can enhance interpretability, they are not very common in real systems. Human-in-the-loop solutions are more pragmatic as they integrate the role of educators in the process of decision-making (López-Meneses et al., 2025).

Informed consent, student rights, and autonomy

The poor level of informed consent is the most frequently reported, in most cases students do not know how their data is gathered and re-used (Asamoah & Amarteifio, 2025; Enaifoghe, 2026). The institutions are supposed to guarantee rights to data access, correction, and deletion, which are, however, hardly implemented. Moreover, the ML systems facilitate sensitive inferences of personal properties, which pose a threat of deeper privacy (Bettahi et al., 2025).

Institutional accountability and gaps in governance

The absence of institutional AI regulations frameworks in the field of higher education is a critical problem (Enaifoghe, 2026; Meylani, 2024; Mustafa et al., 2024). Individual safeguards cannot withstand without ethics committees, auditing systems and participation of students. Long-term forecasts show that unless there is instantaneous governance development, AI integration can worsen inequity and institutional risk.

Results

A five layer framework of responsible knowledge translation

Based on the synthesis of the technical, outcomes and ethical evidence above and directly on the governance, pedagogy and design perspectives, as discussed in 19 studies totaling included studies, we present a five-layer conceptual framework of responsible ML-based adaptive learning system knowledge translation in higher education. It is a hierarchical, iterative and reflexive framework: every layer is informed and responsible to the layers both above and below it. The framework is schematically displayed in Figure 6.

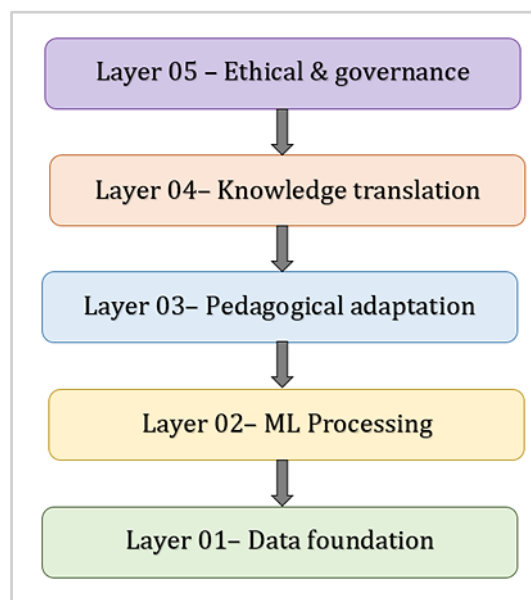


Figure 6. Five Layer Framework of Responsible Knowledge Translation of ML Based ALS in Higher Education, which was synthesized based on Enaifoghe (2026), Elbasi et al. (2025), Mustafa et al. (2024), López-Meneses et al. (2025), and du Plooy et al. (2024)

Layer 1: Data Foundation Data in ML pipelines must be ethically gathered, consented to, and representative, and data minimization as well as governance policy should be stringent, defining how long data is retained, accessed, and secondary use is restricted (Bettahi et al., 2025; Enaifoghe, 2026).

Layer 2: Fair and Interpretable ML Processing builds fairness constraints, like demographic parity and equalised odds, into model training and prioritizes explain ability via embedded XAI tools and accuracy-interpretability tradeoff (Elbasi et al., 2025; Essa et al., 2023; Levin, 2024).

Layer 3: Pedagogical Adaptation This layer matches the output of the ML layer with the evidenced based learning theories like mastery learning, spaced repetition, and scaffolding to ensure educational and not strictly engagement-based optimization. Human-in-the-loop ML also extends educator knowledge into the adaptive processes (du Plooy et al., 2024; Hariyanto et al., 2025; López-Meneses et al., 2025; Peng & Li, 2025).

Layer 4: Knowledge Translation is concerned with converting algorithms outputs into practical insights to educators, students, and institutions, including dashboards, learning analytics, and curriculum level decision support systems (Deng, 2024; Luo et al., 2025; Meylani, 2024).

Layer 5: Ethics and Governance determines the general accountability with AI ethics committees, algorithmic audits, regulatory compliance (GDPR/FERPA), third-party bias assessment, and involvement of students in governance processes (Asamoah & Amarteifio, 2025; Enaifoghe, 2026; Meylani, 2024; Mustafa et al., 2024).

Discussion

Principal findings

The findings from the 19 included studies are broadly consistent with previous systematic reviews, particularly regarding the positive potential of ML-based personalization and adaptive learning. Previous reviews such as du Plooy et al. (2024), Merino-Campos (2025), and Peng and Li (2025) similarly report positive educational outcomes associated with AI-supported personalization and adaptive learning. However, differences in reported outcomes are evident because studies use different learner populations, institutional contexts, ML techniques, and outcome measures. The present review extends previous work by synthesizing ML techniques, educational outcomes, ethical challenges, and knowledge translation within a single review framework. The five-layer knowledge translation framework is proposed in this systematic review as a conceptual framework for responsible implementation, it must therefore be understood as a conceptual synthesis rather than an empirical outcome evaluated within the included literature.

The practical and theoretical implications

The suggested five-layer framework builds on the current AI governance models in education by incorporating the technical, pedagogical, and governance aspects of AI governance through a coherent framework based on evidence of all the studies included. Theoretically, it corrects the current techno-centric nature of AI-ALS research, in which algorithmic-performance measures are central and pedagogy and ethical governance are marginal issues. In practice, the framework provides a roadmap of staged implementation of institutions, starting with the data governance infrastructure (Layer 1), then fairness-conscious ML development (Layer 2), pedagogically aligned adaptation (Layer 3), knowledge translation mechanisms (Layer 4), and overall governance and accountability structures (Layer 5). This sense of urgency is supported by the fact that Mustafa et al. (2024) note the strong global growth of AI-ALS in a short time and that an insufficient approach to governance creation can serve to solidify the already existing prejudices and privacy threats. Moreover, Asamoah and Amarteifio (2025) asserted that the implementation should be context-dependent because some higher education systems have institutional, cultural, and resource disparity necessitating flexible deployment policies to guarantee equity.

Limitations of this review

This review has several limitations. First, the review corpus comprised of 19 review-type studies and therefore represents a review of reviews rather than a synthesis conducted directly from primary empirical studies. This creates a potential risk of double counting where the same underlying primary studies may be represented across multiple included reviews. Second, findings reported in the included reviews could not be independently verified against the original primary studies. Third, reporting bias may be cascaded from primary studies into individual reviews and subsequently into this review. In addition, differences in outcome measures prevented formal meta-analysis, requiring narrative synthesis. The rapid evolution of ML and AI technologies may also limit the continuing relevance of some reported techniques.

Conclusions

In conclusion, ML-based adaptive learning systems have significantly transformed personalized learning in higher education by enabling real-time learner modelling, tailored content delivery, predictive analytics, and intelligent feedback at scale. The evidence clearly supports their effectiveness in enhancing student outcomes, including performance, engagement, and knowledge retention across varied educational contexts. At the same time, the review underscores that current implementations raise serious ethical concerns, including risks of reinforcing inequality through biased algorithms, compromising student privacy through extensive data collection, limiting transparency in decision-making processes, and lacking adequate governance mechanisms (Asamoah & Amarteifio, 2025; Elbasi et al., 2025; Enaifoghe, 2026; Meylani, 2024). Addressing these challenges requires coordinated efforts that extend beyond technical solutions to include institutional policies, regulatory frameworks, and active stakeholder engagement, particularly involving students as key participants in governance processes.

The five-layer knowledge translation framework proposed in this study provides a practical and comprehensive approach for institutions seeking to balance the benefits of ML-driven personalization with the need for ethical responsibility. Its successful implementation depends on collaboration among developers, educators, researchers, policymakers, and learners. Future research should focus on longitudinal studies assessing long-term impacts on learner autonomy, cross-institutional comparative analyses, participatory design approaches involving students, validation of fairness interventions in real-world settings, and the development of standardized evaluation frameworks for educational AI. As projected, the responsible integration of ML in higher education will remain a critical challenge in the coming decade, requiring sustained attention and innovation (Mustafa et al., 2024).

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Ethics Approval

In this systematic review, there was no primary data collection of human subjects. There was no institutional ethics approval needed.

Conflict of interest statement

The author declares no conflict of interest.

Data availability statement

No new data were generated or analyzed for this review, as it is based entirely on the published literature cited herein.

Author Contribution

As the sole author, I am responsible for all aspects of this review, including conceptualization, literature search and screening, data extraction and synthesis, and drafting and revising the manuscript.

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