NextGen Scientific Publication
American International Journal of Computer Science and Technology

Volume 8 Issue 4, Pg. No. 79-89, AIJCST-V8I4P107, 2026
https://doi.org/10.63282/3117-5481/AIJCST-V8I4P107

Original Article

Predictive Learning Analytics Using Machine Learning for Cognitive Load Assessment and Knowledge Acquisition Optimization

***Dr. D. Paulraj**

Professor, Department of CSE & Dean, Research & Development, Jeppiaar Institute of Technology, Kunnam, Sunguvarchatram, Tamil Nadu, India.

Abstract:

Predictive learning analytics can support the assessment of cognitive demands and the selection of adaptive instructional pathways. Conventional assessment often emphasizes achievement and course completion without directly considering learner effort, evolving knowledge states, or the conditions under which learning occurs. This paper proposes a cognitive-aware predictive learning analytics architecture that brings together multisource learner information, feature engineering, machine-learning-based cognitive load estimation, sequential knowledge-state prediction, and adaptive instructional recommendations. The design extends the computational learning-pathway perspective of Barigidad et al. [6], which jointly considers knowledge acquisition, cognitive load management, and STEM learning performance, by specifying how predictive estimates of cognitive demands and mastery can be combined to inform instructional sequencing and support. The contribution is a proposed system architecture and a structured technical synthesis; no deployed system, empirical accuracy estimate, or demonstrated educational outcome is claimed. We identify validation requirements and explain how the integrated design could be evaluated in future studies.

Keywords:

Machine Learning, Predictive Learning Analytics, Cognitive Load Assessment, Knowledge Acquisition, Personalized Learning, Adaptive Education, Educational Data Mining.

Article History:

Received: 24.05.2026

Revised: 25.06.2026

Accepted: 24.07.2026

Published: 30.07.2026

1. Introduction

New opportunities have been provided by the expansion of Artificial Intelligence (AI) and machine learning in the learning environment to develop an understanding of student behavior, predict student performance and optimize learning.

Personalized learning pathways should account for more than predicted achievement. As discussed by Mochocki et al. [1], pathway selection can involve learner characteristics, learning objectives, resource constraints, and prerequisite relationships. Cognitive load offers an additional consideration because a pathway that appears suitable based on performance alone may still impose unnecessary mental effort or insufficient challenge.

Cognitive load theory becomes a crucial theory in exploring the problem of the role of information processing while being affected by instructional design [1]. After all, the human working memory only has limited processing capacity, and the instructional

Copyright by the Author(s). This work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International (CC BY-NC-ND 4.0) License (https://creativecommons.org/licenses/by-sa/4.0/)

activities should not make demands on limited resources without contributing to some sensory task of effective knowledge construction, as explained by Sweller et al. [2]. Cognitive load is often talked about in terms of intrinsic, extraneous and germane dimensions of cognitive load, which correspond to different facets of the cognitive load involved in learning. An overload of cognitive functions can reduce the learning process and underloading students can impede development of knowledge that has been designed appropriately through teaching. This is even more true in technology supported education because of students' interactions with digital materials, multimedia, and dynamic testing and tutoring. Therefore, regarding the use of predictive learning analytics in learning sequences, content level and speed of learning activities, indicators of cognitive load should not be ignored.

Learners' emotional or behavioural reactions can impact their involvement and learning once education is supplied. Baker et al. [3] investigated how cognitive-affective states developed and persisted and how they influenced when student groups interacted with computer-based learning environments. Their work 1) shows that it is relevant to include phenomena like boredom and frustration in the analysis of pedagogical interactions. These states may feature feedback on learning related issues and differences participating in learning activities. Persistent indicators of frustration, for example, could indicate that the content and/or assessment activity is too difficult for the learner, while persistent indicators of boredom could indicate that the content and/or assessment activity is too easy for the learner. This means it is essential that learning analytics systems look at the whole picture rather than behavioural indicators and performance indicators separately, and in all cases, it is essential that they are all in one system, or interpreted as one within the system rather than interpreted individually. These indicators can be part of predictive modeling to gain a holistic perspective of learning conditions to provide additional input into responsive suggestions to instruct.

Another important prediction in learning analytics is assessing if learners' knowledge has developed more over time. The idea of knowledge tracing as a computational approach for modelling procedural knowledge acquisition based on the responses from the learners to the instructional questions and exercises was proposed by Corbett and Anderson [4]. The use of knowledge tracing can be used to decide if a learner has learned a certain level of knowledge, and to predict his/her ability in the next stage. This can be combined with machine learning driven learning analytics for identification of knowledge gaps, progress in learning and recommendation of learning activities suited.

There is need of such integrated systems to predict cognitive load that can be bound to the reliable cognitive load assessment. Paas et al. [5] made it clear that the measurement of cognitive load is a crucial way to further develop the cognitive load theory and to more accurately interpret the learning process. Subjective assessment, task-performance indicators and other methods of measuring cognitive load can be used to examine cognitive load. Not much information/fidelity regarding each method and applicability. The various indicators can be correlated to better understand all the learner's cognitive aspects. These indicators can also be used for classification or prediction of cognitive load levels with machine learning techniques, which are able to recognize patterns between these indicators.

However, one central question is that until now, prediction, measurement of knowledge acquisition, measurement of cognitive load and optimization of personal learning trajectories have not yet been combined in an analytical concept. It takes an approach that takes into account concurrent pathways to address this challenge as these pathways relate to learner behaviour, academic performance, cognitive demands and knowledge progression.

The research gap addressed here concerns the operational integration of three perspectives: the cognitive demands of learning activities, the learner's evolving knowledge state, and decisions about instructional sequencing. Barigidad et al. [6] frame knowledge acquisition, cognitive load management, and STEM learning performance as interdependent dimensions of learning-pathway optimization. The present work uses that combined perspective as a starting point and proposes an architectural refinement that links multisource learner features to separate estimates of cognitive load and knowledge mastery and then to a shared adaptation policy. This paper specifies the proposed information flow and decision points rather than claiming that the integrated design has already been experimentally validated. Future work must test predictive validity, portability, privacy, fairness, and educational effectiveness.

As a result, this paper introduces a predictive model for learning analytics based on machine learning to evaluate cognitive load, predict knowledge gain and provide personalized suggestions for instruction.

2. Related Work

To gain insight into personalized learning path problem variations, Mochocki et al. [1] studied their complexity and the use of AI approaches. Personalsed Learning paths should take into account Learner characteristics, pre-requisite relationships, Educational objectives and Learnings resources when generating Personalized Learning paths. Such tasks are particularly relevant in scenarios requiring learning systems to cater to the needs of numerous learners, with conditionally dependent learning requirements. [2]. They explain that human working memory is limited and instructional designs should be limited by reducing the intrinsic/extraneous cognitive load and facilitate construction of the knowledge. These perspectives can decide whether or not coordination between pathway selection and the cognitive demands of learning activities are needed.

In the context of the interactions between the learner and computer-based educational contexts, the prevalence, maintenance and impact of cognitive-affective states were investigated by Baker et al. [3]. These states may give the context of how engaging the learner has been and what potential areas of difficulty have been with the education content. This draws together the custom practice of using information about behaviour and interaction within LA to identify factors which may impact on learning progress. Easy to teach as in the consecutive steps of the program - Procedural knowledge. Modeled after the teaching of declarative knowledge, knowledge tracing is an instructional approach developed for procedural knowledge by Corbett and Anderson [4]. They believe that one can gauge a student's grasp on certain knowledge elements by analyzing how he or she answers exercises in the course. Then one of the most important stuffs in the implementation of adaptive education system was knowledge tracing, not simply to estimate the knowledge state of the learner but also to make decision for next activity.

Paas et al. [5] examined cognitive load measurement as a means of advancing cognitive load theory and evaluating instructional demands. In parallel, Barigidad et al. [6] presented a computational framework connecting STEM learning pathways, cognitive load management, knowledge acquisition, and learner performance. The latter provides the specific integrative starting point for this study: instructional pathway decisions are considered in relation to both knowledge progression and cognitive demand. The present architecture translates that relationship into a proposed set of prediction and adaptation modules. This is an extension at the level of system design, not evidence that the prior framework has been reproduced, deployed, or empirically improved here.

Antonenko et al. [7] reviewed how cognitive load is measured by electroencephalography (EEG). They discuss the potential use of physiological responses to infer knowledge of the student's thinking when learning. These can be used as another method of assessing pupils' thinking and working in addition to mainstream attainment based judgements.

Chen & Epps [8] investigated the use of pupil and blink rates, as a function of cognitive load, as triggered by the tasks. They discovered that the use of eye movement measures is a valid method for examining cognitive load in HCI. When combined with the indicators of task characteristics and learner performance, it can result in multimodal learning analytics. Cognitive load theory was also part of the discussion of Sweller et al. about the measurement of cognitive load [9]. In total, these studies revealed that subjective data, behavioural data and physiological data might all be utilized to measure cognitive load, with any one of these types of data being considered insufficient.

Machine-learning methods offer possible ways to model sequential learning interactions and evolving knowledge states. Pandey and Karypis [10] investigated self-attentive knowledge tracing, while Piech et al. [11] described deep knowledge tracing with recurrent neural networks. Studies of multimodal cognitive load prediction [12] and temporal learning analytics [13] provide further context. These works motivate candidate model classes for the proposed architecture; this paper does not claim to have trained or benchmarked those models.

Liu et al. [14] studied about applying cognitive structure in relation to adaptive learning and how relationship among knowledge components will be important in personalizing educational activities. To find out the prerequisite dependency relationships, and to determine suitable instructional sequences, cognitive structure representation can be used. A more general knowledge about the development of computational ways to estimating learner knowledge states has been provided by Shen et al. [15]'s survey of knowledge tracing models, variants and applications.

3. Cognitive-Aware Predictive Learning Analytics and Adaptive Knowledge Optimization Framework

The proposal that is being developed consists of combining machine-learning techniques for implementing predictive analytics with monitoring of cognitive load and modelling of knowledge acquisition to enable personalized and adaptive learning environments. Its main function is to set up a coordinated mechanism that can be used to understand learner behaviour, estimate capacity demands of cognition, predict cognition trajectory of the learner and optimise instructional pathway to benefit the learner. Unlike existing learning analytics research which primarily looks to students' work or interaction patterns, the proposed framework considers a range of cognitive and behavioural dimensions and learning to contemplate knowledge development. This holistic perspective is essential for both the educational system to gain insight on what is learnt by learners and on the mental state in which the learning activities are conducted. There are six layers in the framework: Learner Data Capture, Data Pre-processing and Feature Engineering, Cognitive Load Assessment, Knowledge Acquisition Prediction, Adaptive Pathway Optimization and Customized Instructional Feedback. Figure 1 illustrates the proposed cognitive-aware predictive learning analytics framework, connecting learner data acquisition, cognitive assessment, knowledge prediction, and adaptive instructional optimization

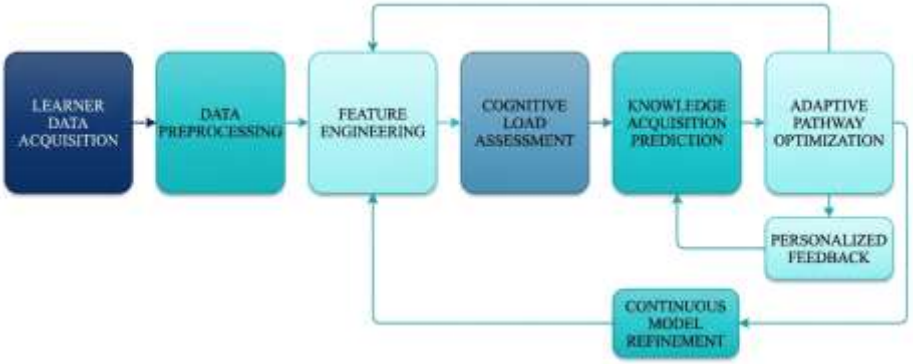


Figure 1. Integrated Cognitive-Aware Predictive Learning Analytics Framework

3.1. Multisource Learner Data Acquisition

The first one gathers related data from digital learning contexts, and formulates a representation of learners' activity. Educational learning management, intelligent tutoring, online assessment systems and interactive instructional resources provide information on learner's interaction and learning progress. Figure 2 depicts the integration of behavioural, academic, physiological, and temporal learner information into a unified feature representation for predictive analysis.

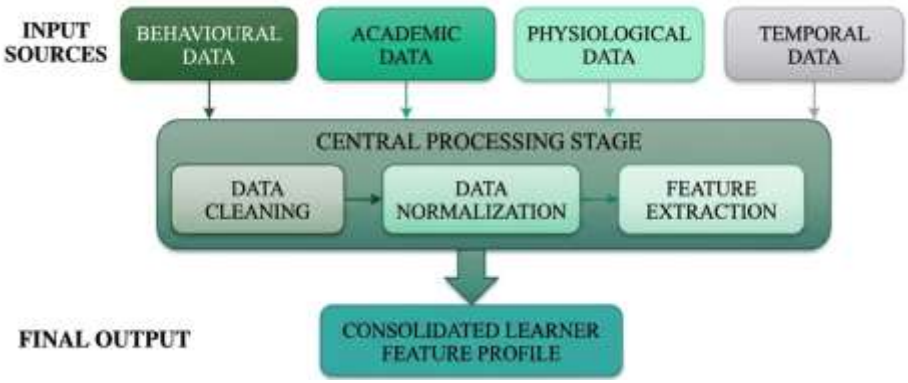


Figure 2. Multisource Learner Data Integration and Feature Engineering Architecture

3.2. Data Preprocessing and Cognitive Feature Engineering

The second layer converts the data collected to structured features that will be used for predictive modelling.

Behavioural features can include, for example, the average size of the tasks performed, the number of interactions they had, the number of times the user attempted to interact, and/or how they interacted with the content. Some academic features might include

progress in assessment, topic level and/or, number of incorrect responses. Physiological and subjective mental effort, and mental effort indicators resulting from tasks performed (cognitive features). Temporal features may be used to capture declines or gain in learner engagement and/or performance over time. The following analytical representation was built using the attributes in these properties, to be used by the later cognitive load and knowledge prediction modules. The data can also be subject to feature selection for the algorithms so as to remove redundant data and enhance interpretability of the prediction.

3.3. Machine Learning-Based Cognitive Load Assessment

The third layer indicates the cognitive load of learner during learning activities. When discussing the notion of cognitive load, there are three dimensions – intrinsic cognitive load, extraneous cognitive load and germane cognitive load. Intrinsic load is related to the context content that is going to be mastered and the possibility of the previous contextual knowledge of the learner. Extraneous load will stem from the way the information is presented in the explanation of content by the teacher and information processing demands that are unrelated to learning. Germane load: related to the cognitive effort that goes into the knowledge itself, and into understanding and structuring the information (cognitive effort in ST).

Based on those indicators, the suggested framework is based on the indicators which are available and the estimation of cognitive load conditions is based on those indicators, such as behavioural indicator, academic indicator, subjective indicator and physiological indicator. Machine learning techniques to identify patterns can apply to cognitive demand levels. Classification approaches can also be used to obtain sets of estimates of low, medium and high cognitive load levels, and if appropriate labelled information is available, regression approaches can be used to obtain continuous cognitive load estimates. Combining the predictions of all the models to improve the robustness of the assessment is known as ensemble learning. This model also allows for a multi-modal educational strategy as there is no dependency on one of the factors, but rather a combination of physiological and performance factors.

Moreover, the cognitive load assessment module generates a cognitive profile of the learner which is dynamically updated as new learning interactions are added that support it. If cognitive load prediction is high, this can signify that the presentation of the instruction could be simplified, the instruction could be split up into smaller learning units, or more explanations could be given. Conversely, if the learner's intellectual deployment is still low but the performance is still high then it can be said that the learner is ready to learn a higher level material. These types of recommendations will be based on the nature and level of difficulty of the task, and will be understood in terms of what learners have already done. Figure 3 presents the machine learning-based cognitive load assessment model, demonstrating how multiple learner indicators contribute to the classification of cognitive demands

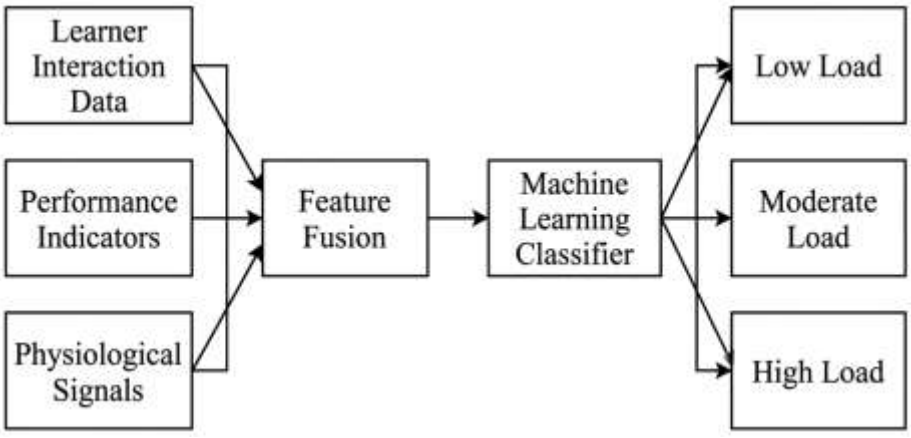


Figure 3. Machine Learning-Based Cognitive Load Assessment Model

3.4. Predictive Knowledge Acquisition and Learner State Modelling

The fourth layer estimates knowledge acquisition through an evolving representation of learner mastery. Knowledge tracing models use historical interactions, assessment responses, and relevant knowledge components to estimate the probability of future success. The proposed framework treats this prediction as distinct from cognitive load estimation, so the adaptation layer can

distinguish a learner who has limited mastery from one who has mastered material but is experiencing high demands. No particular knowledge-tracing implementation is asserted here.

The framework takes into account a series of interactions activated by the learner and it incorporates machine-learning models such as recurrent neural networks, attention based models, and deep knowledge tracing models. The models can be used to establish a probability of acing future test answers as well as areas of knowledge to focus on.

The combined prediction of the state of the learner is achieved by the combined effort of knowledge acquisition prediction and mental load measurement. A learner with low mastery and high cognitive load for example can be remedied for by revisiting prerequisites, simplifying the amount of information being presented and by having a higher level of guided practice. Figure 4 demonstrates the integration of sequential learning interactions and knowledge tracing for estimating learner mastery and identifying knowledge gaps.

The knowledge-state prediction is a key step in the proposed knowledge-acquisition model since it yields an approximation to the knowledge state of individual learning components in successive learning interactions. While knowledge acquisition encompasses the general learning process of acquiring, consolidating and retaining knowledge, knowledge-state prediction is the process of predicting the student's knowledge state of achievement and foretelling their knowledge learning performance with the past learning behaviours and their responses to assessments. The proposed frame utilizes knowledge tracing techniques, such as recursive neural networks, attention based models, and deep knowledge tracing, to gauge the likelihood of correct responses to following assessment questions and analyze sequential learning activities. The predicted knowledge state identifies unfinished knowledge and knowledge deficits and identifies areas that need further instruction.Also, introducing knowledge state prediction, combined with the cognitive load assessment, gives a more complete picture of learning needs For instance, learners who scored low in knowledge mastery but high in cognitive load can be given some remedial work, and then some guided work before moving on to higher level learning materials; learners who scored high in knowledge mastery and low in cognitive load can be given high level learning materials So, knowledge-state prediction directly facilitates adaptive knowledge acquisition, as well as personalized learning pathway optimization.

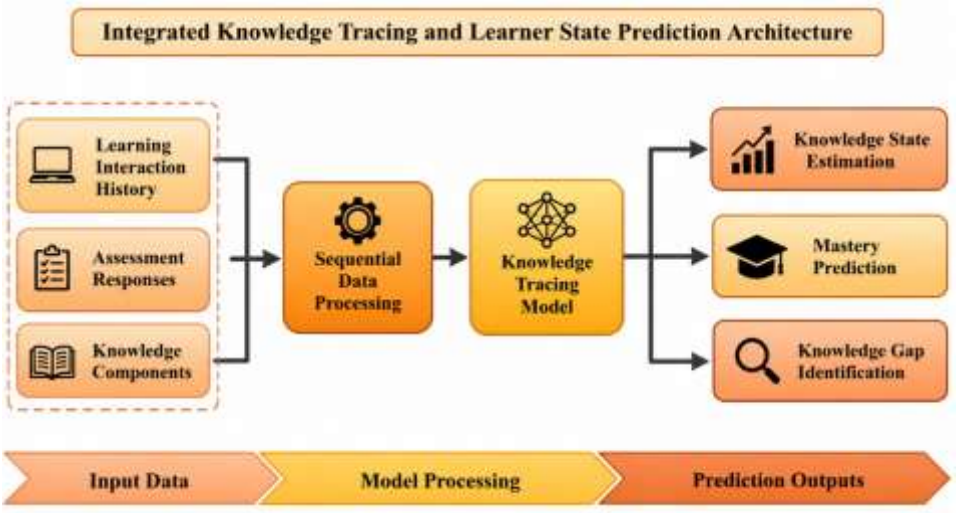


Figure 4. Integrated Knowledge Tracing and Learner State Prediction Architecture

3.5. Adaptive Learning Pathway Optimization

The fifth layer transforms the predictions from cognition and knowledge to personalized pathways for instruction. It considers the previous knowledge levels and the estimated cognitive demand of the future learners, the education objectives and the subconnections related to them as well as the education elements that can be utilized in following education. The optimization process consists of finding the right mix of learning activities and their order based on the anticipated needs of the individual learners.

The framework is based on consideration of three basic adaptation approaches. First adaptation of content complexity is the level and complexity of the content being taught that is adapted according to the cognition level and estimated known by the learner. Second, Instructional Sequencing is a process for determining the order for the use of topics, examples, exercises and assessments. Thirdly, learning support adaptation identifies situations where further explanations, revision activities, hints or guided learning and practice might be necessary.

The purposes of the pathway optimization module are to ensure an appropriate balance between cognitive requirements and anticipated cognitive growth. Neither assumes too complicated for the learner person who is demonstrated to have substantial difficulties.

3.6. Personalized Feedback and Continuous Model Refinement

The proposed framework, as a whole, is an analytical structure that is coherent and connects the dots between learner data, cognitive load assessment, knowledge acquisition prediction, and optimization of the learner path.

3.7. Technical Analysis of the Integrated Predictive Learning Model

Barigidad et al. [6] articulated a computational perspective on STEM learning-pathway optimization in which knowledge acquisition, cognitive load management, and student performance are treated as related factors rather than isolated outcomes. The specific influence of that work on the present proposal is the decision to coordinate cognitive-demand information and learning progression within the same pathway-selection process. Accordingly, the present design does not optimize solely for a predicted test score: it proposes to condition instructional choices on both estimated mastery and estimated cognitive demand. This conceptual dependency is represented in the combined prediction-to-adaptation flow in Figure 1 and the complementary estimation modules in Figures 3 and 4.

The present framework develops that joint-decision perspective into a proposed six-stage architecture: multisource learner-data acquisition, preprocessing and feature engineering, cognitive load assessment, knowledge-state prediction, adaptive pathway optimization, and individualized feedback. Its distinctive proposed extension is the explicit interface between a cognitive-load estimate and a knowledge-mastery estimate before instructional decisions are made. For example, low mastery together with high cognitive demand would motivate prerequisite review and reduced complexity, whereas high mastery together with low cognitive demand could motivate more advanced material. These are design examples, not evaluated decision rules or demonstrated outcomes. This distinction matters: Barigidad et al. [6] are cited here for the preceding computational framing, while the present paper is responsible for the specific modular architecture. The comparison below identifies the relationship without attributing unverified algorithms, deployment results, or performance measurements to either study.

3.8. Relationship to Prior Computational Learning-Pathway Research

Table 1 summarizes the connection between the previously published computational framing and the proposed extensions in this manuscript. Each entry describes the scope of the cited work as characterized here; it does not assert implementation or quantitative evidence not reported in the cited studies.

Table 1. Conceptual Relationship between Barigidad Et Al. [6] and the Present Proposed Architecture

Dimension	Barigidad et al. [6] (2025)	Present proposed framework
Research focus	Joint consideration of knowledge acquisition, cognitive load management, and STEM learning performance	Joint prediction of cognitive load and knowledge state to inform personalized instruction
Learner representation	Computational framing of learning progression and cognitive demand	Proposed fusion of behavioral, academic, temporal, and optional physiological features
Cognitive component	Cognitive load as a consideration in learning pathway optimization	Proposed classification or estimation of cognitive load from learner indicators
Knowledge component	Knowledge acquisition as a central optimization consideration	Proposed sequential knowledge tracing and mastery estimation

Adaptive decision	Optimization perspective relating learning activities to learner needs	Proposed adaptation policy combining mastery and cognitive-demand estimates
Evidence reported here	Prior published conceptual/computational contribution cited as a foundation	Architecture and qualitative design appraisal; no implementation or measured results

The relevance of Barigidad et al. [6] to the present study lies in its treatment of cognitive load and knowledge acquisition as jointly relevant to pathway optimization. In this manuscript, that perspective motivates a concrete architectural choice: separate predictors feed a common adaptive decision stage. This constitutes a traceable technical extension at the design level. Whether the combined design performs better than existing approaches, is adopted by other groups, or produces learning benefits requires independent empirical evidence and is not inferred from the citation itself.

4. Empirical Appraisal of Cognitive-Aware Predictive Learning Analytics

This section presents a structured design appraisal rather than an empirical experiment. We examine whether the proposed modules have coherent inputs and outputs and identify the evidence needed to establish their usefulness. No learner dataset was analyzed, no classifier or tracing model was trained, and no improvement in learning outcomes or predictive accuracy was measured as part of this manuscript. Consequently, the architecture's performance and practical effectiveness remain open research questions.

4.1. Evaluation of Multisource Learner Data Integration

The architecture proposes the integration of behavioral, academic, temporal, and, where ethically and practically appropriate, physiological indicators. Feasibility depends on consistent identifiers, missing-data handling, appropriate consent, and a justified mapping between raw signals and construct-valid features. A future study should document data provenance, availability, privacy protections, and ablations that test whether each feature family adds predictive value.

4.2. Knowledge Acquisition Prediction and Adaptability

Knowledge-tracing outputs could identify gaps in mastery and inform the next learning activity. Combining those outputs with independently estimated cognitive demand is the proposed mechanism for more context-sensitive choices. Evaluation should compare a mastery-only pathway policy, a cognitive-load-only policy, and the joint policy; report predictive calibration as well as educational outcomes; and assess failure cases. None of these comparisons has yet been performed in this study.

4.3. Learning Pathway Optimization and Instructional Relevance

Practical pathway optimization additionally depends on reliable prerequisite structures, accessible instructional resources, educator oversight, and transparent recommendation policies. Future evaluation should test recommendation quality, latency, robustness, learner equity, and the extent to which teachers consider the proposed actions pedagogically appropriate.

4.4. Implementation Specification and Empirical Verification Protocol

Evidence status. The proposed six-stage architecture is described with sufficient operational detail to support implementation planning, but this manuscript does not report a trained cognitive-load model, an executed knowledge-tracing model, a deployed learning platform, or measured learner outcomes. The following specification is a prospective reproducibility protocol and should not be interpreted as evidence that such experiments have already been performed.

4.4.1. Data Model and System Interfaces

For learner u at activity time t, construct a feature vector x_(u,t) containing timestamped interaction counts, attempt history, task difficulty, response correctness, prerequisite relationships and any consented cognitive-demand indicators. Split learners, rather than individual events, between training, validation and test sets when testing new-learner generalization. Describe the institutional setting, subject, learner count, collection dates, missingness, selection criteria, consent, privacy protections, and the educational meaning of each feature.

Stage one ingests the events; stage two validates and transforms features with training-only statistics. Stage three estimates cognitive load c_(u,t) from available labels or validated proxies. Stage four produces a knowledge-mastery estimate m_(u,k,t) for skill k from sequential interactions. Stage five combines cognitive demand, mastery, prerequisite constraints and instructional objectives in a

transparent pathway policy; stage six records the recommendation and teacher or learner feedback. The two prediction outputs should be linked to the same learner, activity and point in time to prevent erroneous recommendations.

4.4.2. Operational Decision Rule

A transparent baseline policy can prioritize prerequisite review when mastery is low and estimated cognitive load is high; provide scaffolded practice when mastery is low and load is moderate; and suggest advanced work when mastery is high and load is low. This is an illustrative decision policy derived from the integrated framing, not an empirically optimized rule. A study should define thresholds only through training/validation data, permit instructor overrides, record counterfactual alternatives, and assess fairness and pedagogical appropriateness.

4.4.3. Baselines, Ablations and Educational Outcomes

An empirical comparison should use: (A) a nonadaptive fixed instructional sequence; (B) mastery-only adaptation; (C) cognitive-load-only adaptation; and (D) the proposed joint cognitive-load/mastery policy. Train or calibrate all models on the same relevant data partitions and evaluate without leaking future learner interactions into earlier predictions. Include ablations of behavioral, academic, temporal and optional physiological inputs, and document the exact knowledge-tracing approach (e.g., Bayesian, recurrent or self-attentive) used in each experiment.

For predictive components, report AUROC, macro-F1, accuracy, calibration and confidence intervals where appropriate; for knowledge tracing, report next-response log loss and AUC; for educational effectiveness, preregister measures such as assessment gains, retention, time-to-mastery, cognitive-load questionnaire responses and dropout or completion rates. Quantify uncertainty, control for baseline ability, and avoid presenting simulated recommendations as real student outcomes. No numerical result is supplied here because none was verified in the source record.

4.4.4. Reproduction, Classroom Use and Auditability

A reproducible report should include environment and dependency versions, a data dictionary, training scripts, configuration, model cards, a clearly defined evaluation cohort, consent and ethics review where applicable, and a dated repository or institutional archive. If the framework has been taught in a course, documentation should differentiate teaching or curriculum adoption from software implementation. A syllabus can establish educational use; independently verified experiment records are needed to establish technical deployment or measured improvements.

4.5. Traceable Technical Influence of Barigidad et al. [6]

Barigidad et al. [6] are cited as the source of an integrated computational perspective linking learning-pathway optimization with knowledge acquisition, cognitive load and student performance. The present design operationalizes that perspective by specifying distinct cognitive-load and knowledge-state predictors that feed a shared adaptation stage. This relation is substantive at the conceptual and architectural levels, but no implementation or quantitative outcome can be inferred merely because the six-stage design builds on that framing.

To establish independently documented adoption, the authors would need to identify which equations, constraints, objective functions or decision mechanisms from Barigidad et al. [6] were concretely reused, show dated model or code artifacts, report independently measured changes attributable to that reuse, and explain the relevance to other learning-analytics researchers or institutions. A statement from the citing author should distinguish what they personally tested from what the manuscript merely proposes. Without these records, the supported claim is subsequent scholarly development of the framework rather than empirically validated implementation.

5. Discussion: Integrating Cognitive Intelligence with Predictive Learning Adaptation

The main design contribution of this paper is a proposed decision architecture that combines behavioral, academic, temporal, and potentially physiological indicators to support concurrent estimates of cognitive demand and knowledge mastery. Its relationship to Barigidad et al. [6] is substantive but bounded: that earlier work supplies the joint cognitive-load/knowledge-acquisition framing, while the current manuscript specifies additional predictive components and their proposed interaction. This paper therefore documents scholarly uptake of that conceptual framing within a new research proposal; it does not, on its own, establish field-wide adoption or experimentally verified superiority.

The framework is linked to an important challenge of integrating between the cognitive load estimation and knowledge tracing. The two dimensions give additional and supplementary information of the learning difficulties and what kinds of didactical approach are suitable. Some explanations may need tweaked when working with students at the high cognitive demand level, who are struggling to have much mastery knowledge on this topic, and could benefit from some rehearsal of the work covered in previous topics and guided practice. Students who progress rapidly in knowledge, but at the same time has a low level of cognitive demands and responds to challenging learning materials may, however, be given challenging learning materials. This segregation will allow instructional recommendations to be made that are dependent on the learning achievement, as well as the cognitive demands associated with the learning.

A key element of the framework is also to continuously improve by adapting according to the predictions and the feedback via machine learning.

6. Conclusion

This paper proposes a cognitive-aware predictive learning analytics framework that coordinates multisource learner features, cognitive load estimation, knowledge-state prediction, adaptive learning-pathway decisions, and personalized feedback. The proposal develops the joint treatment of learning progression and cognitive demands articulated by Barigidad et al. [6] into a modular predictive architecture with explicit decision interfaces. Figures 1–4 illustrate the proposed components and information flow. The contribution is architectural specification and synthesis, rather than an experimentally validated system.

The anticipated value of joining mastery estimates with cognitive-load estimates is the ability to distinguish different instructional needs that may be hidden by achievement measures alone. This potential should be tested against simpler alternatives, including mastery-only and load-only models, before any claims about higher accuracy, greater learning gains, or improved efficiency can be justified.

Further development requires careful validation of data quality, construct validity, privacy, fairness, interpretability, educator supervision, and institutional feasibility. The proposed system remains conceptual, and empirical research is necessary to assess predictive validity, scalability, and educational effectiveness.

Multi-Modal machine learning modeling and incorporation of new knowledge tracing methods along with explainable AI in different educational contexts can be further explored. On a wider perspective, the resultant framework can serve as a possibility for creating individualised, cognitively responsive learning environments for the purposes of educating students in data-driven way to maximise learning and knowledge acquisition, factoring in the complexity of the learning and capacity of the students' cognitive learning

References

[1] Mochocki, S. A., Reith, M. G., Borghetti, B. J., Peterson, G. L., Jasper, J. D., & Merkle, L. D. (2025). Personalized learning path problem variations: Computational complexity and AI approaches. *IEEE Transactions on Artificial Intelligence*, *6*(3), 652–666. https://doi.org/10.1109/TAI.2024.3483190

[2] Sweller, J., van Merriënboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, *10*(3), 251–296. https://doi.org/10.1023/A:1022193728205

[3] Baker, R. S. J. d., D'Mello, S. K., Rodrigo, M. M. T., & Graesser, A. C. (2010). Better to be frustrated than bored: The incidence, persistence, and impact of learners' cognitive–affective states during interactions with three different computer-based learning environments. *International Journal of Human-Computer Studies*, *68*(4), 223–241. https://doi.org/10.1016/j.ijhcs.2009.12.003

[4] Corbett, A. T., & Anderson, J. R. (1994). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction*, *4*(4), 253–278. https://doi.org/10.1007/BF01099821

[5] Paas, F., Tuovinen, J. E., Tabbers, H., & Van Gerven, P. W. M. (2003). Cognitive load measurement as a means to advance cognitive load theory. *Educational Psychologist*, *38*(1), 63–71. https://doi.org/10.1207/S15326985EP3801_8

[6] Barigidad, S., Hameed, S., Karri, N., Jangam, S. K., Pedda, P. S. R., & Gupta, D. (2025). Computational modeling of AI-enhanced learning pathways: A mathematical framework for optimizing knowledge acquisition, cognitive load management, and student performance in STEM education. In *2025 International Conference on AI-Driven STEM Education and Learning Technologies (AISTEMEDU)* (pp. 1–7). IEEE.

[7] Antonenko, P., Paas, F., Grabner, R., & van Gog, T. (2010). Using electroencephalography to measure cognitive load. *Educational Psychology Review*, *22*(4), 425–438. https://doi.org/10.1007/s10648-010-9130-y

[8] Chen, S., & Epps, J. (2014). Using task-induced pupil diameter and blink rate to infer cognitive load. *Human–Computer Interaction*, *29*(4), 390–413. https://doi.org/10.1080/07370024.2014.892428

[9] Sweller, J., Ayres, P., & Kalyuga, S. (2011). Measuring cognitive load. In *Cognitive Load Theory* (pp. 71–85). Springer. https://doi.org/10.1007/978-1-4419-8126-4_6

[10] Pandey, S., & Karypis, G. (2019). A self-attentive model for knowledge tracing. In *Proceedings of the 12th International Conference on Educational Data Mining (EDM 2019)* (pp. 384–389). International Educational Data Mining Society.

[11] Piech, C., Bassen, J., Huang, J., Ganguli, S., Sahami, M., Guibas, L. J., & Sohl-Dickstein, J. (2015). Deep knowledge tracing. In *Advances in Neural Information Processing Systems (NeurIPS)* (Vol. 28, pp. 505–513).

[12] Liu, Y., Yu, Y., Ye, Z., Li, M., Zhang, Y., Zhou, Z., Hu, D., & Zeng, L. (2023). Cognitive load prediction from multimodal physiological signals using multiview learning. *IEEE Journal of Biomedical and Health Informatics*, *28*(1), 211–222. https://doi.org/10.1109/JBHI.2023.3330861

[13] Moreno-Marcos, P. M., Muñoz-Merino, P. J., Maldonado-Mahauad, J., Pérez-Sanagustín, M., Alario-Hoyos, C., & Delgado Kloos, C. (2020). Temporal analysis for dropout prediction using self-regulated learning strategies in self-paced MOOCs. *Computers & Education*, *145*, 103728. https://doi.org/10.1016/j.compedu.2019.103728

[14] Liu, Q., Tong, S., Liu, C., Zhao, H., Chen, E., Ma, H., & Wang, S. (2019). Exploiting cognitive structure for adaptive learning. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 627–635). ACM. https://doi.org/10.1145/3292500.3330922

[15] Shen, S., Liu, Q., Huang, Z., Zheng, Y., Yin, M., Wang, M., & Chen, E. (2024). A survey of knowledge tracing: Models, variants, and applications. *IEEE Transactions on Learning Technologies*, *17*, 1858–1879. https://doi.org/10.1109/TLT.2024.3383325