

Review

AI-Based Online Education Systems Integrating Real-Time Affective Computing: A Design-Oriented Conceptual Framework

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Abstract

The implementation of an artificial intelligence (AI)-based system for monitoring, forecasting, and learner performance support has been intensified by the rapid expansion of online education systems. Existing online educational platforms completely rely on learning analytics and machine learning to customize content delivery. On the other hand, these platforms fundamentally focus on behavioral and cognitive indicators, whereas the integration of affective computing into learning analytics and adaptive decision-making processes is lacking. During the learning process, emotions like engagement, boredom, and confusion play a vital role. Nonetheless, the integration of adaptive online learning systems is still fragmented and underdeveloped. The latest progress in affective computing and multimodal sensing technologies allow for the inference of the affective state of learners in real-time, which creates a range of potential opportunities to create emotionally sensitive learning spaces. Despite technological innovations, the existing studies do not have a conceptual framework that is unified, design-oriented, and clearly incorporates affective computing with AI-based learning analytics to inform real-time pedagogical adaptation. To address this gap, this study introduces a design-oriented conceptual framework for AI-based online education systems that incorporate real-time affective computing. This conceptual framework combines the theoretical foundation of learning analytics, affective computing, and adaptive learning systems. The suggested framework offers a clear and scalable basis of online learning environments that are affective-aware by offering a clear framework of development, assessment, and consequent empirical validation.

Keywords: affective computing; online learning; learning analytics; artificial intelligence; adaptive learning



Academic Editor: Yolanda Abel

Received: 15 May 2026

Revised: 22 June 2026

Accepted: 23 June 2026

Published: 26 June 2026

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1. Introduction

The concept of online education has completely redefined the design, delivery, and assessment of learning in the contexts of higher education and professional training. Artificial intelligence in terms of its innovations has been at the center of this change, as it is poised to facilitate the automated analysis of interactions between learners, modeling of academic performance, and ad hoc decision-making in digital learning settings. Learning analytics has become one of the leading paradigms of deriving insights out of massive learner data

such as interaction logs, test results, and engagement measures produced during online learning operations (Fan et al. 2024).

The earlier literature shows that learning analytics may be used to identify learners at risk of disengagement early on and implement timely instructional responses to the learners, especially in large-scaled and self-paced online courses (Giannakos et al. 2024). Regardless of these contributions, current learning analytics systems are still largely based on visible behavioral and cognitive measures and provide minimal information about the internal state of affect and motivation of learners. Such a focus limits the ability of AI-based learning systems to explain and adapt.

Although the existing framework of AI-based online education remains fundamentally result-oriented, emphasis on performance metrics like completion rates, grades, and task efficiency at the same time offers limited support to understand the learning process itself. It restricts the ability of an intelligent system to respond to learners' real-time needs, especially when negative affective states emerge during learning activities. According to earlier studies, affective states like frustration, boredom, and confusion can drastically reduce learner engagement and determination in online learning environments (Azevedo and Gašević 2019). As far as design perspective is concerned, the lack of affect-aware systems represents a vital constraint in existing online education system frameworks, as it restrains adaptive decision making to observable behavior instead of learners' underlying affective and motivational conditions (Gašević et al. 2015). To address how to record, interpret, and operationalize learners' data, these limitations and constraints need to be reconsidered.

Educational psychology has always shown that emotions are essential in learning, affecting attention, motivation, self-control, and educational performance. Confusion, frustration, engagement, and other emotions are dynamically interacting with cognitive processes, with long-term effects on the learning path, especially in technology-mediated environments. Online methods of education reduce the affective feedback that instructors receive when working with learners, which is even more limiting in the case of online education (Wang et al. 2024).

Affective computing has become an interdisciplinary domain concerned with enabling computational systems to recognize, interpret, and react to human emotions using multimodal data sources, such as facial expressions, speech traits, and interaction behaviors (Xia et al. 2024). Developments in machine learning and deep learning have led to a significant enhancement of the strength and precision of emotion recognition representations, which allow for a near real-time inference of affective states in naturalistic contexts. Intelligent tutoring systems, game-based learning systems, and online video-based learning have adopted affective computing techniques in educational research. Nevertheless, numerous affect-sensitive education systems are limited to experimental systems and are not commonly connected to larger learning analytics systems or adaptive pedagogical decision-making (Ng et al. 2024).

The adaptive learning systems research emphasizes the significance of dynamically adapting the instructional materials, feedback, and learning paths depending on the learner's conditions and situational dynamics. Historically, adaptive mechanisms are based on performance indicators and knowledge-tracing ones, but recent developments indicate that the consideration of affective data can be an effective way to improve personalization and learner interest. Despite these findings, there is still no cohesive and design-oriented conceptual model which can unequivocally link the findings of affective computing to AI-based learning analytics and adaptive intervention techniques (Gašević et al. 2023). This has meant that solutions do not exist that are viable and easily scalable to institutional contexts (Järvelä et al. 2023). Past studies also highlight that the development of affect-aware learning systems are usually context-specific or fragmented solutions; as

a result, these systems restrict scalability and transferability across learning platforms (Ouyang and Jiao 2021). The development of sustainable and generalizable system architectures for large-scale online education is hindered and confined by this fragmentation across learning analytics, affective computing, and adaptive system design (Kizilcec et al. 2017).

To address these issues, this study proposes a design-oriented conceptual framework of AI-based online education systems that can combine real-time affective computing and learning analytics in supporting adaptive online learning. This research is positioned as qualitative, non-empirical, and design-oriented. Its contribution lies in conceptual synthesis and architectural articulation rather than statistical validation. This positioning aligns with contemporary design-oriented research published in leading educational technology and information systems journals, where conceptual frameworks are advanced as foundations for subsequent empirical investigation (Shingjergji et al. 2025). The conceptual framework is illustrated with benchmark datasets of the learning analytic and affective computing fields to show that it is possible without direct data collection. This study contributes to the literature and offers a unified conceptual foundation and architectural design synthesis by providing a reusable reference framework for affective-based online education systems and by outlining guidelines for future empirical validation and implementation.

2. Theoretical Background and Related Work

2.1. Learning Analytics in Online Education

Learning analytics has become one of the leading paradigms, defined as the systematic measurement, collection, analysis, and reporting of data about learners and their contexts for the purpose of understanding and optimizing learning (Gašević et al. 2015). It derives insights out of massive learner data such as interaction logs, test results, and engagement measures like confusion, boredom, and frustration produced during online learning operations (Molenaar 2022). Recent advancements in artificial intelligence have further improved learning analytics by supporting projective modeling and automated decision-making in online learning platforms (Ifenthaler and Yau 2020). Despite these advancements, the existing learning analytics platforms keep prioritizing behavioral aspects like click-stream, tasks on time, and assessment scores; however, the affective aspect of learning is continuously being neglected (Khalil et al. 2023). It is also observed that some studies have highlighted that learning analytics implementations concentrate on learners' actions based on observation instead of psychological states like boredom and confusion, which limit their explanatory authority.

The significance of learner analytics is evident; there is a need for engagement patterns and emotionally informed analytics in online learning platforms (Henrie et al. 2015). In particular, in self-paced online learning, the ignorance of affective indicators may result in ambiguous interpretations of learning behavior (Shingjergji et al. 2025).

The proposed framework highlights the potential of integrating behavioral, affective, and cognitive indicators using learning analytics (Azevedo and Gašević 2019). Despite a strong analytical foundation, the framework addresses only methodological and analytical challenges and has limitations in terms of an operational real-time adaptive mechanism.

2.2. Affective Computing and Emotion Modeling

Recent studies on affective computing have taken advantage by progressing in deep learning to significantly improve the accuracy and robustness of emotion recognition models (Li and Deng 2022). Studies reveal that convolution neural networks (CNNs) can detect affective states, facial expressions, and audiovisual cues in real time (Geetha et al. 2024). The structural emotional models are specifically appropriate for adaptive learning systems because they can capture continuous affective changes (Kollias et al. 2019). Pekrun's

Control-Value Theory of Achievement Emotions offers an important basis for this study because it explains affective states such as enjoyment, boredom, frustration, and anxiety as results of learners' perceptions of control and task value. The theory supports this study that affective signals should be treated as meaningful inputs for adaptive instructional design rather than as peripheral by-products of learning (Pekrun 2024).

Affective computing plays a vital role in detecting learner affective states during online educational video-based learning and intelligent tutoring interactions. To identify and capture the moments of disengagement or emotional distress, real-time affect detection may provide a valuable response for adaptive instructional approaches (Bosch et al. 2016). This gap highlights the requirement of a system-level framework which integrates affective computing in terms of broader educational analytics infrastructures.

2.3. AI-Driven Adaptive Learning Systems

The aim of adaptive learning systems is to customize instructional content and feedback that is based on the characteristics of learners and their performance. Advanced AI-based adaptive systems leverage machine learning techniques to dynamically adjust learning pathways and instructional strategies in response to learner data. Experimental studies suggest that to enhance customization and self-paced learning, affective information must be integrated into adaptive learning systems (Azevedo and Gašević 2019). Adjusting task difficulties, feedback timings, and instructional staging have revealed that the affect-aware adaptation system is to improve learners' satisfaction and persistence. There are quite a few systems which have integrated affect detection indicators as a supporting feature rather than a core element of the adaptive decision process. The latest advancements in research contribute to an affective feedback adaptive learning system which is designed to enhance learner engagement and self-directed learning. While it can also influence the learning outcomes, the adaptation mechanism was constrained to predefined adaptive strategies and limiting to dynamic pedagogical decision making (Liu et al. 2022). This may lead to limiting the scalability and applicability of affect-aware adaptive learning solutions (D'Mello and Graesser 2012).

2.4. Gaps and Research Opportunities

Although learning analytics provides robust techniques to analyze learning behavior, it still lacks the mechanism of recording internal affective states in real-time (Khalil et al. 2023). According to some recent reviews, it is indicated that studies on learning analytics, affective computing, and adaptive learning have widely advanced in parallel instead of in an integrated manner (Zawacki-Richter et al. 2019). AI-based adaptive learning systems have explained technical feasibility, yet they rely on simplified learner models that exclude emotional dynamics (D'Mello et al. 2014).

According to recent methodological arguments, design-oriented conceptual frameworks can provide actionable guidance to integrate affective computing into scalable online education systems.

2.5. Contribution of Research

This study contributes to the literature by proposing a design-oriented conceptual framework that integrates learning analytics, affective computing, and adaptive learning systems within a unified architecture. Recent studies have highlighted the increasing importance of affective-aware educational technologies, emphasizing that learners' affective states significantly influence engagement, motivation, self-regulated learning, and academic performance in online learning environments (Anwar et al. 2023; Fernández-Herrero 2024).

The proposed conceptual framework enhances creativity through technology in adaptive learning environments, which has insightful responses to learners' behavioral and affective states (Azevedo and Gašević 2019).

By leveraging AI-based affect detection and intervention based on analytics, this study also contributes to sustainability in online education, supports learners' feedback, and personalizes guidance, which leads to improving retention and learning outcomes (Gašević et al. 2019; Kizilcec et al. 2013).

3. Research Design and Conceptual Framework Development

3.1. Research Design and Paradigm

This study is qualitative and non-empirical, adopting a design-oriented research approach to develop a unified conceptual framework for AI-based online education systems integrating real-time affective computing. The objective is to construct a theoretically grounded reference architecture that integrates affective computing, learning analytics, and adaptive learning systems into a coherent design intending to guide future implementation, validation, and educational deployment efforts. Conceptual research plays a vital role in fostering scientific knowledge by integrating fragmented streams of literature and providing theoretical structures that support subsequent empirical investigations (Jaakkola 2020).

The framework was developed through the integration of literature from learning analytics, affective computing, adaptive learning systems, educational psychology, and artificial intelligence in education. Attention was given to studies examining learner engagement, emotion recognition, adaptive instructional support, and intelligent educational technologies (Gašević et al. 2023; Wang et al. 2024). Conceptual frameworks are frequently used to organize existing knowledge and identify relationships among constructs and establish foundations for future design and implementation efforts (Ouyang and Jiao 2021).

This study does not seek to test hypotheses about, measure, or empirically evaluate learner outcomes. Instead, it focuses on constructing a theoretically grounded and internally coherent conceptual framework that addresses a clearly articulated design problem: the absence of unified architectures that integrate affective computing with AI-driven learning analytics for adaptive online education.

3.2. Framework Development Process

Figure 1 shows the process of framework development adopted in this study. The process initiates with the literature review on learning analytics, affecting computing and adaptive learning systems. The identification of the research gap is based on the literature review pointing out that existing AI-based online learning platforms are affective-blind and primarily concentrate on behavioral and cognitive signs without addressing the affective condition of learners (Zawacki-Richter et al. 2019). This is a weakness that restricts the adaptive learning environment in terms of responsiveness and pedagogical performance.

Design goals are obtained at the framework objective designing stage based on interdisciplinary theory in learning analytics, affective computing, and adaptive learning systems. They consist of detecting affect in real time, combining affective and behavioral learner data and making pedagogically significant adjustments without using primary human subject data acquisition (Shingjergji et al. 2025).

The development of the conceptual framework and reference architecture introduced in this study is guided by the proven theories of self-regulated learning, affect-cognition interaction, and AI-driven adaptation (Molenaar 2022). The conceptual framework is defined at a high level of abstraction that can be generalized across platforms and institutional settings.

The illustration phase shows how the proposed framework is possible regarding benchmark datasets in the field of learning analytics and affective computing. An illus-

trative demonstration is used to reach plausibility and internal consistency as opposed to system performance (Zawacki-Richter et al. 2019).

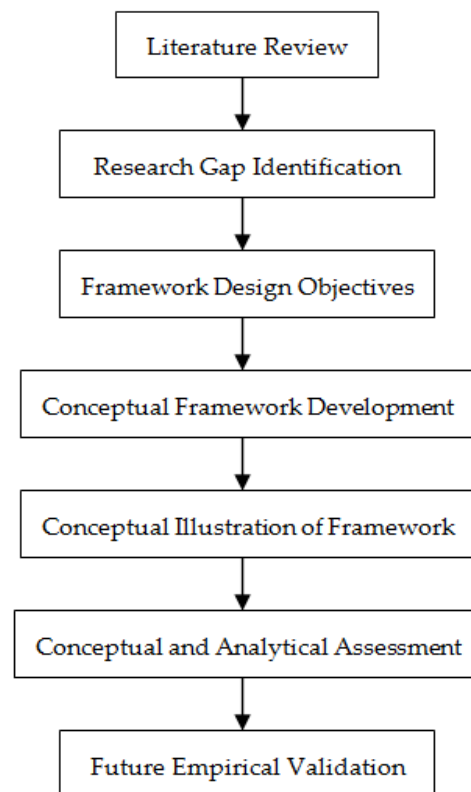


Figure 1. Framework development process.

Lastly, the proposed framework is examined through conceptual and analytical assessment to determine its logical coherence, theoretical grounding, applicability, and potential relevance to affect-aware online education systems. This assessment does not seek to establish instructional effectiveness or empirical performance. Instead, it focuses on evaluating the consistency of the framework's components, the alignment of its underlying theoretical foundations, and its capacity to guide future research and implementation efforts (Jaakkola 2020; Ouyang and Jiao 2021).

3.3. Conceptual Framework Description

The primary outcome of this study is a design-oriented conceptual framework accompanied by a reference system architecture of the affect-aware online education systems. This conceptual framework serves as abstract notations that specify the system components, data flows, and adaptive decision-making processes intended to guide future implementation and empirical investigation (Gašević et al. 2019).

The suggested conceptual framework combines three major functional domains: (i) affective computing; (ii) learning analytics; and (iii) orchestration of adaptive learning. These domains are conceptualized as modules but are interdependent processes that collectively support the real-time interpretation of the behavioral, cognitive, and affective status of learners. This framework provides a coherent design structure that involves affective information as a central component in the adaptive decision-making process and not as an accompaniment.

3.4. Conceptual Illustration of Framework Operation

This study employs a conceptual illustration to explain the logical operation of the proposed framework. Publicly available benchmark datasets from affective computing and learning analytics are solely used in this study for illustrative purposes. Table 1 presents an illustrative mapping between representative benchmark datasets and the components of the proposed conceptual framework, demonstrating how multimodal affective data may be conceptually integrated within the architecture. These datasets are not used for model training, system evaluation, or empirical validation (Pei et al. 2024).

Table 1. Illustrative mapping of benchmark datasets and conceptual framework components.

Dataset Type	Illustrative Purpose	Framework Layer	Expected Output
FER-2013/AffectNet	Shows affect recognition input	Machine learning/affective computing	Predicted affective states
Learning analytics dataset	Shows learner behavior input	Analytics and adaptation	Integrated learner profile
Conceptual multimodal flow	Shows end-to-end conceptual data flow	Full framework	Adaptive pedagogical response

The illustration is organized as a conceptual walkthrough of the framework's layers and intended data flows. First, benchmark affect-aware datasets, such as FER-2013 and AffectNet, are selected because they are widely used in affective computing research and contain labeled facial expression data suitable for illustrating the machine learning and affective inference layer. These datasets are not used to train a new model or report classification performance. Instead, they serve as representative inputs to show how raw affective signals would be pre-processed, normalized, and transformed into affective state estimates, such as engagement, confusion, boredom, or frustration (Pei et al. 2024; Cîrneanu et al. 2023).

Second, learning analytics datasets are used to represent learner behavioral traces in online education. Such datasets typically include clickstream records, time-on-task measures, assessment responses, and participation indicators, which are appropriate for illustrating the behavioral input stream of the proposed architecture. Recent studies show that affective computing and learning analytics are increasingly discussed together because affective indicators can enrich learner modeling and improve adaptive support design. In this study, the learning analytics data are conceptually mapped to the analytics and adaptive layer and combined with affective estimates to demonstrate how the framework would support context-sensitive pedagogical decisions (Lek and Teo 2023; Shingjergji et al. 2025).

Third, the illustrative demonstration shows the intended data flow across the framework, beginning with data acquisition, continuing through pre-processing and feature engineering, and ending with affective inference and adaptive response generation. The expected outputs at the conceptual level are predicted affective states, an integrated learner profile, and adaptive responses such as content sequencing, feedback timing, difficulty adjustment, and instructor alerts. These outputs are presented as design expectations rather than empirical findings. The purpose is to clarify how the proposed architecture can conceptually translate multimodal inputs into pedagogically meaningful adaptive responses (Pei et al. 2024).

The study does not claim software implementation, experimental results, or empirical validation using benchmark datasets. Instead, it offers a transparent proof-of-concept mapping that clarifies how the framework would function if implemented in future work.

Conceptual Illustration of Data Flow

To further clarify the process, an illustrative walkthrough is provided to show how benchmark datasets are conceptually mapped to the proposed framework. The purpose of this illustration is not to evaluate predictive performance but to illustrate the operational logic of the framework and verify the coherence of data flow across its architectural layers.

As an example, a facial expression sample from the FER-2013 dataset enters the data acquisition layer as raw affective input. The image is subsequently transferred to the preprocessing and feature engineering layer, where normalization, feature extraction, and representation learning procedures are conceptually performed. The resulting feature vectors are then processed by the machine learning and affective computing layer to infer learner affective states such as engagement, confusion, boredom, or frustration. The use of benchmark facial expression datasets for affective state recognition is well established in affective computing research (Pei et al. 2024).

Simultaneously, learner behavioral records obtained from a learning analytics dataset, including clickstream interactions, time-on-task measures, and assessment performance indicators, are processed through the same acquisition and preprocessing stages. These behavioral indicators are integrated with the inferred affective states within the learning analytics and adaptation layer to construct a richer learner profile. The integration of behavioral and affective indicators has been increasingly advocated for to support more comprehensive learner modeling and adaptive educational systems (Cîrneanu et al. 2023; Lek and Teo 2023).

Based on the integrated learner model, the framework generates adaptive pedagogical responses. For example, if the learner exhibits prolonged confusion combined with declining engagement indicators, the system may recommend additional instructional guidance, simplified learning resources, adaptive feedback, or instructor intervention. Finally, these adaptive recommendations are delivered through the presentation and feedback layer in the form of learner-facing support, instructor alerts, or dashboard visualizations (Anwar et al. 2023; Fernández-Herrero 2024).

This illustration does not constitute empirical validation or software implementation. Rather, it serves as a illustrative use case that demonstrates the logical consistency and operational feasibility of the proposed architecture using representative benchmark datasets commonly adopted in affective computing and learning analytics research (Pei et al. 2024; Lek and Teo 2023). The illustration indicates how the proposed framework could facilitate the integration of affective computing and learning analytics within adaptive online learning environments and highlights opportunities for future empirical investigation. Table 2 provides an illustrative example of the conceptual flow of affective data across the five layers of the proposed framework.

Table 2. Illustrative data flow across the proposed framework layers.

Framework Layer	Example Input	Processing	Output
Data Acquisition	FER-2013 image	Capture facial data	Raw affective data
Preprocessing	FER-2013 image	Normalization and feature extraction	Feature vector
ML and Affective Computing	Feature vector	Affective classification	Predicted affective states
Learning Analytics	Clickstream data	Behavioral analysis	Engagement profile
Adaptation	Combined profile	Decision logic	Adaptive feedback
Feedback	Adaptive strategy	Presentation	Learner feedback

3.5. Conceptual and Analytical Assessment

The assessment of this study is analytical and conceptual. Instead of determining the learning efficacy experimentally, the assessment is concerned with the architecture, coherence, and conceptual capability of the suggested framework. The criteria of assessment of the proposed framework is based on (i) the internal consistency of the elements of the framework; (ii) its correspondence to logical coherence; (iii) theoretical grounds; (iv) design completeness; and (v) its alignment with the current educational technologies (Liu et al. 2022).

For instance, the popular measures used in the field of affective computing (e.g., classification accuracy, precision, recall) and learning analytics (e.g., predictive performance indicators) are cited as possible measures of evaluation in future empirical research. Nevertheless, no performance optimization or statistical comparison is done within the extent of this study (Liu et al. 2022).

The analytical evaluation is complemented by the illustration presented in Section 3.4, which provides a proof-of-concept walkthrough of the framework using illustrative benchmark datasets. This illustrative demonstration supports the assessment of logical coherence, design completeness, and operational feasibility prior to prototype implementation and empirical validation.

3.6. Implementation and Ethical Considerations

This study is conceptual in nature and does not involve primary data collection. Nonetheless, ethical considerations remain important due to the sensitive nature of affective information and the increasing use of artificial intelligence in educational settings (Molenaar 2022; Giannakos et al. 2024).

Future implementations of affect-aware educational systems should carefully address issues related to privacy, transparency, informed consent, algorithmic bias, data security, and responsible AI use. Particular attention should be given to ensuring that affective data are collected and processed ethically while preserving learner autonomy, trust, and human oversight in educational decision-making (Gašević et al. 2023; Feldman-Maggor et al. 2025).

The proposed framework therefore incorporates ethical governance as a foundational design consideration rather than a secondary implementation concern. Future empirical studies should further investigate ethical safeguards, explainability mechanisms, and governance frameworks for affect-aware educational technologies (Shingjergji et al. 2025; Khalil et al. 2023).

4. Proposed Framework and System Architecture

4.1. Overview of the Framework

The conceptualized framework is an online education system based on AI that incorporates the application of real-time affective computing to dynamically detect, interpret, and react to the affective and behavioral state of learners in the context of online learning processes (Li and Deng 2022). The framework is presented as a reference architecture rather than an implemented or operational system, as shown in Figure 2.

Online learning is theorized as closed-loop adaptive learning in which the interactions between the learners are described as multimodal and processed using computational models to deduce affective and cognitive states. Such inferences are used in adaptive pedagogical strategies and hence further interaction with learners, which will eventually affect the next interaction with the learner, leading to a feedback loop (Matcha et al. 2020).

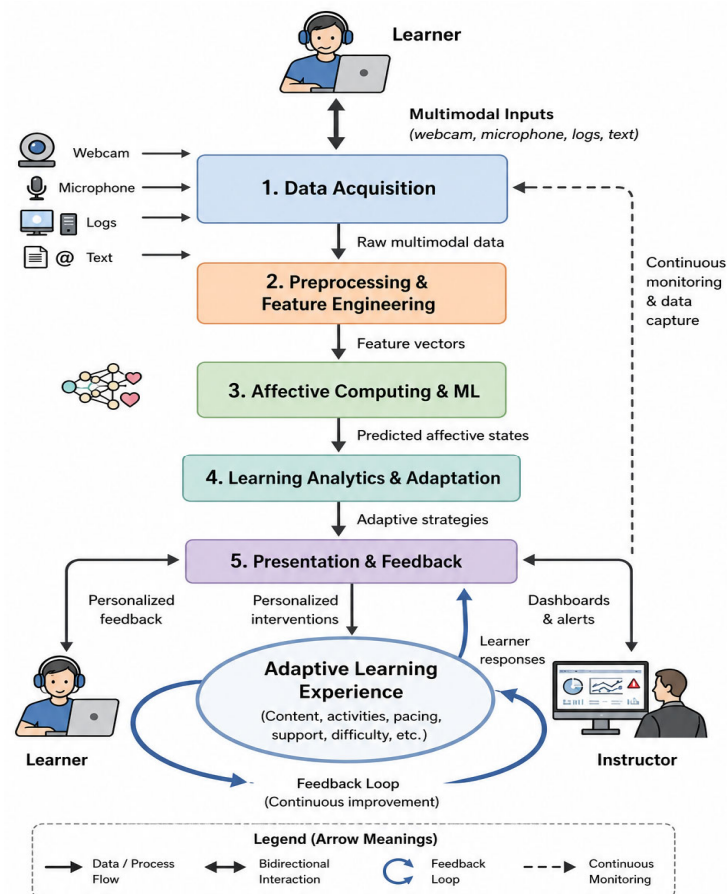


Figure 2. Overview of the system architecture and data flow of the framework.

4.2. Framework Conceptual Layers

The framework is structured to have five layers, as described in Table 3, that are connected to each other, and each layer has a different functional responsibility.

Table 3. Proposed framework layers and functions.

Framework Layer	Function	Data Input	Output
Data Acquisition	Collect multimodal learner interactions	Webcam, microphone, logs, text	Structured raw data
Preprocessing and Feature Engineering	Clean, normalize, and extract features	Raw multimodal streams	Feature vectors
Affective Computing and ML	Infer affective states	Feature vectors	Predicted affective states
Learning Analytics and Adaptation	Analyze data, generate interventions	Predicted states + performance metrics	Adaptive strategies
Presentation and Feedback	Deliver adaptive responses	Adaptive strategies	Dashboards, content adjustment

4.2.1. Data Acquisition Layer

This layer captures multimodal learner interaction data generated during online learning activities. The following activities are used for data sources:

- Behavioral interaction logs (click-streams, time on task).
- Textual input (forum discussions, written assignments).
- Optional audiovisual streams (via webcam and microphone).

The layer is developed with the goal of integrating with the current learning management systems and facilitating ongoing data capture (Shingjergji et al. 2025).

4.2.2. Preprocessing and Feature Engineering Layer

Raw multimodal data consists of heterogeneous and often contain substantial noise. This layer transforms raw multimodal data into structured representations that can be processed by machine learning models through the following processes:

- Data cleaning and normalization;
- Temporal alignment;
- Feature extraction.

Such processes are guided by established practices in learning analytics and affective computing research. These preprocessing steps follow best practices in affective computing and learning analytics to generate structured feature representations suitable for machine learning models (Li and Deng 2022; Kollias et al. 2019).

4.2.3. Machine Learning Layer and Affective Computing

This analytical core uses machine learning models that predict the affective states of the learners, which include engagement, confusion, boredom, and frustration. The framework facilitates multimodal and unified affect recognition, which allows for flexible application based on the availability of data and privacy concerns (D'Mello and Graesser 2012; Kollias et al. 2019). The outputs are affective state predictions accompanied by confidence indicators.

4.2.4. Learning Analytics and Adaptation Layer

This layer combines affective outputs, as well as behavioral and performance indicators based on learning analytics. Adaptive pedagogical strategies are produced according to this integrated learner model, such as:

- Content sequence;
- Timing of feedback;
- Adjusting difficulty;
- Alerts and warnings.

The adaptive logic incorporates affective information instead of taking it as a support signal (Ouyang and Jiao 2021).

4.2.5. The Presentation and Feedback Layer

Adaptive responses are provided to stakeholders in the form of:

- Learner-facing feedback;
- Instructor dashboards;
- Institutional-level aggregated analytics.

This level bridges the adaptive feedback loop and aims for reflective practice and system refinement (Järvelä et al. 2023).

4.3. Characteristics and Evaluation of the Framework

The framework is a modular and design-oriented conceptual architecture which makes its components independent of each other to evolve independently. The main attributes are real-time data pipelines, integration through an API platform, scalable machine learning

services, and privacy-sensitive data processing systems (D'Mello and Graesser 2012). The framework is also capable of real-time adaptation and retrospective analysis, which makes it useful in different educational contexts. Future empirical studies may adopt a multi-layered strategy to assess technical performance and pedagogical effectiveness, as well as to examine the precision of an affect detection model in real-time and the reliability of multimodal integration. Such evaluations should focus on assessing the utility, feasibility, and relevance of the framework instead of just enhancing predictive performance.

4.4. Contribution of the Framework

This conceptual framework contributes to the literature as below:

- It integrates affective computing and learning analytics in a unified architecture;
- It enables real-time affect-aware adaptation in online learning systems;
- It provides a reusable reference model for future empirical and system-oriented research.

The proposed framework further contributes by integrating already established fragmented research domains and positioning affective states as a central component of adaptive learning design rather than an auxiliary feature. The design establishes an apparent link between affective data flow and analytics-based decision systems. Conversely, it also defines the theoretical relationship between engagement, instructional adaptation, and learner affect. Furthermore, this framework facilitates future researchers and developers to implement and operationalize its features by continuous improvement practically in the real world. This framework provides a foundation for building more responsive and pedagogically aligned AI-based learning systems.

5. Discussion and Implications

5.1. Theoretical Contributions

The paper provides an addition to the growing body of literature because it aims to suggest a design-oriented conceptual framework which systematically combines affective and AI-based learning analytics to support adaptive online learning. In contrast to previous methods, where affective information is considered peripheral, the proposed framework makes affective states one of the central elements of the adaptive decision-making layer rather than as a supplementary analytical variable and ensures that pedagogical interventions are informed by learners' real-time affective and cognitive states (Gašević et al. 2023; Ouyang and Jiao 2021; Pekrun 2024).

Methodologically, the research paper demonstrates how conceptual synthesis may be applied to develop conceptual architectures in educational technology without involving primary data collection. The framework also promotes theoretical integration within the research on learning analytics, affective computing, and adaptive learning, which has long been fragmented in the field and is capable of guiding future empirical research, system implementation, and educational innovation (Jaakkola 2020).

5.2. Practical Implications

From a practical perspective, the framework may serve as a reference architecture for educational institutions and platform developers seeking to implement affect-aware AI systems in online learning environments. To instructors, affect-aware dashboards and alerts could be useful in making better informed pedagogical decisions. To system designers, modular architecture enables affective technologies to be ethically integrated in a scalable manner. So, to support responsible innovation in alignment with the quality of education, this framework emphasizes the significance of integrity, privacy of data, and precision in implementing affect-aware systems.

5.3. Limitations

This framework has not been implemented or empirically evaluated in real learning environments; therefore, the study is limited to conceptual design and theoretical analysis. There is no empirical validation on real learners, and the data fusion on multimodal systems is represented at an abstract level. The integration of affective computing with learning analytics in system design is not assured by default; issues like sensor dependability, ethical consideration, and institutional willingness may also influence implementation outputs. Therefore, the effectiveness of learning and improvement in engagement or behavioral change should not be considered within the confines of this study.

5.4. Future Research Directions

The proposed framework needs to be empirically proven by pilot implementation and evaluation in real-world online learning environments. Further research on multimodal fusion should be studied, and ethical issues (bias, transparency, and learner agency) should be investigated in the future. Future studies should also progress beyond conceptual illustrations, concentrate on longitudinal rationale, and examine the effects of affect-aware adaptation on learning patterns over time. Moreover, the development of an authentic AI-based platform integrating affect-aware systems capabilities is significant, permitting educational instructors and learners to understand how affective data guides adaptive decision making. Further research should also include a dashboard for teachers to explore, which could transform affective analytics into actionable pedagogical insights. This would lead to an impactful comparison between affect-aware and solely cognitive adaptive systems and help determine the potential advantages and value addition of integrating affective intelligence into AI-based education systems.

5.5. Conclusions of Discussion

By integrating affective computing, learning analytics, and adaptive pedagogy within a unified reference architecture, the proposed framework provides a systematic foundation for the next generation of affect-aware AI-based online education systems. The study furnishes a reference architecture which detects the affective and behavioral state, along with adaptive intervention mechanisms within a unified system design, so the findings of this study should be interpreted as conceptual instead of empirical. The contribution is design-oriented and hence flexible, scalable, and ethically aligned, which places the framework as a foundation of future empirical and technological advancement. Future research should focus on operationalizing the framework in authentic educational environments, examining its effectiveness, usability, scalability, and ethical implications. Such investigations will be necessary to determine the practical value of affect-aware AI systems in supporting personalized and responsive online learning.

Author Contributions: Conceptualization, S.U.J.; literature review, S.U.J.; methodology, S.U.J.; framework, S.U.J.; discussion and implications, S.U.J. and S.H.; writing—original draft, S.U.J.; review and editing, S.U.J., A.-C.K. and C.-Y.T.; supervision, A.-C.K. and C.-Y.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Telekom Malaysia Research & Development Sdn. Bhd. (TM R&D), grant number (RDTC/261175). The APC was funded by Telekom Malaysia Research & Development Sdn. Bhd.

Institutional Review Board Statement: Not applicable. The current research did not involve primary data collection. It is a conceptual paper, discussing the key concept of AI-based online education systems mainly through literature reviews.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. This study did not involve primary data collection; it uses publicly available benchmark datasets such as FER-2013 and AffectNet solely for illustrative purposes to explain the logical operation and data flow of the proposed conceptual framework.

Acknowledgments: The authors would like to acknowledge the financial support provided by the TM R&D grant (RDTC/261175). AI tools assisted only to support language editing and clarity during manuscript preparation and with grammar refinement. All ideas, tables, figures, and conclusions were generated by the authors, who take full responsibility for the content of the manuscript.

Conflicts of Interest: The authors have no competing interests.

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