A Systematic Review on an Intelligent Reflection Assessment in Video-Based Learning

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Abstract; Video-based learning is much effective and helpful in understanding the context and also supports adaptive learning. Adaptive learning provides the ability to personalize content to the learners, based on individual needs and understandings. Reflection in video-based learning is the most important concept to be considered for analysing the understanding ability, progress in learning and active engagement of learners during the video-based learning process. In order to evaluate the reflections, some automated tools can be used which accepts the feedback as input keywords and process it. In this study, various adaptive learning techniques and algorithms of different Learning Management Systems are analysed. Several assessment methods that helps to evaluate the learners' capability are also studied.It is associated with the reflections provided by the learners that support to determine their cognitive ability. Furthermore, describes few more intelligent systems that recommend supplementary resources to improve the detail study of the specific topics. These kind of systems can be integrated to provide a better learning environment that enhances learners'knowledge level and develops interest in learning.

Keywords: Adaptive Learning, Natural Language Processing (NLP), AI based education, Video analytics, Auto grading

1. Introduction

Education is evolving due to digital technology advancements and the diverse needs of students. Innovations are sought to enhance the process of learning like creativity, critical analysis, evaluation, problem solving, and decision making. Artificial intelligence and Natural Language Processing have emerged as promising technologies with the potential to revolutionize the educational landscape [1]. The learner-facing AI applications master a subject matter and improve its learning effectiveness for learners [2]. Understanding how educational technologies enhance student engagement is becoming increasingly necessary in higher education, and given the communicative nature of courses [3]. Digital technology plays major role in higher education that improves all aspects of the student experience. Educational technology and student engagement is a well-established and rapidly evolving field with significant implications for higher education.

1.1 Background on video-based learning and student reflections

Video-based learning has emerged as a prominent and increasingly favoured method of instruction across various educational contexts, largely attributed to its inherent intuitiveness and engaging nature [4]. Content-based recommendation and learner Comment-based recommendation systems analyse item descriptions to identify items that are of particular interest to the user [5]. The rise of AI-enabled tools such as virtual teaching assistants offer personalized support, instant feedback, and adaptive learning experiences, improving engagement and outcomes for students. These tools extend beyond text-based materials to include image generation, data augmentation, analysis, and even support in coding and mathematics. Video-based learning has found particularly fertile ground in innovative pedagogical approaches such as flipped classrooms and Massive Open Online Courses (MOOCs), where it plays a crucial role in engaging learners in self-organized and networked learning experiences [6]. Learners find difficult with most of the digital content that is not suitable for their learning pace, understanding and knowledge. Most of the LMS fail to use it effectively for real-time adaptation of learner needs. The existing intelligent systems recommend personalized learning paths without considering the proficiency, style, and capability of the learners. These type of learning systems cannot provide personalized and immediate feedback. The architecture diagram of intelligent learning system which can benefit knowledge acquisition and retention that analyzes learners' understanding ability, frequently incorporate assessment questions, learner feedback and reflections is shown in Fig 1.

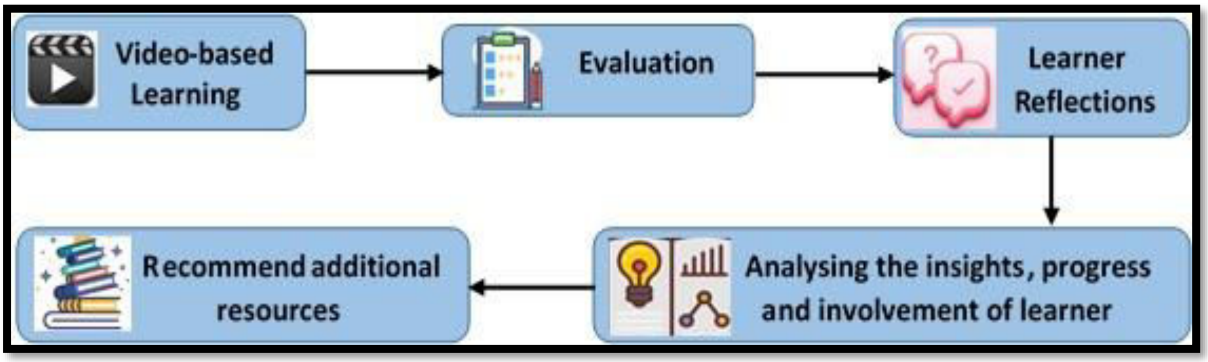

Fig 1: Architecture Diagram of Intelligent Reflection Assessment and Recommendation in Video-Based Learning

An individuals' learning preferences are possibly related to their learning outcomes. Artificial intelligence (AI) and natural language processing (NLP) have emerged as promising technologies with the potential to revolutionize the educational landscape [7]. The learners understanding and learning capability are under wraps of the feedback. Video-based learning offers flexibility and accessibility to learners but, effectively assessing reflection in these environments and providing personalized recommendations remains a challenge. Intelligent systems leveraging techniques like deep learning can play a crucial role in addressing these challenges. Large language models (LLMs) with knowledge graph are necessary in such condition that helps in creating adaptive educational content that is appropriate for student's interests, level and ability [8]. In some cases it is difficult for learners to understand the quick context or content which are recommended by the adaptive systems. The learner motivation, interest, attentiveness are not taken into account. These systems emphasize the learning contexts, ability of learners to generalize knowledge in very less consideration.

1.2 Reflection in video-based learning

Reflection is a pivotal element within video-based adaptive learning methodologies, serving to heighten learner engagement and foster profound comprehension. Through the engagement with video materials, students are encouraged to pause periodically to contemplate their understanding and educational advancement, thereby pinpointing areas of proficiency [9]. This heightened self-awareness empowers learners to adapt their learning strategies, solicit elucidation on intricate concepts, and fortify their grasp of fundamental notions. Furthermore, self-reflection cultivates metacognitive proficiencies, empowering students to evolve into more self-reliant and self-regulated agents in their educational expedition. By integrating reflective protocols, video-based adaptive learning frameworks can tailor content dissemination and progression, ensuring each learner receives a bespoke educational encounter aligned with their distinct requisites and advancement. The incorporation of self-reflection mechanisms within intricate learning architectures presents notable benefits in addressing specific challenges across diverse scientific domains, culminating in enhanced precision, mitigated overfitting dilemmas, and superior performances relative to extant methodologies [6]. Metacognitive calibration, denoting the faculty to precisely self-assess one's performance, underpins error identification and self-surveillance, with individuals exhibiting elevated metacognitive calibration exhibiting greater recruitment of brain regions associated with adept reasoning compared to those with lower calibration levels.

Self-supervised learning frameworks featured within neural networks can effectively amalgamate diverse types of information, effectively exploring deep data features and improving the adaptability of prevailing models to the multiplicity and complexity of data, while simultaneously advancing comprehensive performance levels [10]. This engenders more resilient models capable of managing diverse and intricate datasets with heightened efficacy. When there are large number of students, manual evaluation of numerous freeform submissions is impractical or unfeasible. Traditional methods rely on manual evaluation, which can be lengthy and prone to human bias. With essay-type assessments like reflections, subjectivity is a major concern [11]. Factors like the evaluator's mental state sometimes can influence their judgment, leading to inconsistencies and potential biases in grading. The workload burden on educators is another critical challenge. Grading essays is a time-consuming process. These challenges have prompted researchers to explore automated solutions. This tool aims to scale up individualized feedback efficiently, addressing the challenges posed by large student numbers, thus alleviating the time investment of educators. However, the transition to automated assessment brings its own set of considerations around maintaining the nuanced understanding that reflective writing requires.

1.3 Motivation for automating reflection analysis and feedback

The primary driver is that reviewing narratives of reflections is time-consuming, especially in large class settings. Even short reflection surveys require instructors to review them one by one, making this approach impractical for many educational contexts [12]. The amount of time required for students and the effort required for instructors to review responses are more challenging. There are various reflection tools and methods to analyze also students' learning outcomes can be obtained through feedback. These digital minute papers serve as formative feedback for instructors to address students' problems in class and continuously improve course design [13]. The importance of self-reflection in engineering education has been emphasized as it improves students' learning experience and helps instructors remove learning gaps. Conventional methods sometimes will not give proper feedback for learners to analyze attention in learning. It helps students to identify their misunderstandings and develops metacognitive skills thus improving the performance.

1.4 Objectives and scope of the paper

The artificial intelligence technology is being used to automatically encode cognition, emotion and reflection in students' assessment text using deep learning models. With these models implementing semantic-based text quality evaluation and performing multi-dimensional hierarchical evaluation [14]. To design and implement an autograding system that facilitates the automatic evaluation of student responses. The objectives are to provide immediate, intelligent feedback on student reflection quality, also real-time guidance during the learning process. It is also indispensable for building an intelligent assessment models. To analyze the qualitative responses of students using NLP techniques. To provide tailored learning recommendations by leveraging the capabilities of Large Language Models (LLMs).

2. Related Work

The categories of various adaptive learning techniques of different Learning Management Systems are analysed and are listed in Table 1. CourseMapper is a collaborative annotation and analytics platform based on mind mapping, designed to enhance learner collaboration and engagement with educational video content [15]. It enables personalization of the learning, learning process monitoring, identifying the learning progress, self-reflection, and motivation. Through supporting collaborative annotation of video material, learners can exchange perspectives and insights, can append notes, remarks, and highlights to video resources that helps to improve comprehension and information retention. The latent factor model (LFM) is used to predict learning video features and students' learning interests [16]. Acclaim is a video platform integrated into virtual learning environments, enabling students to record and share performances for assessment and feedback [17]. In videos, time-based comments are added that makes possible for tutors and students to discuss and exchange ideas based on each performance. Instead of traditional assessment, AI technology intelligent assessment can be done that offers new opportunities for personalized feedback.

Table 1. Categories of Learning Management Systems based on Adaptive Learning

Category	Authors & Year	Title	Method/ Approach	Educational Application
Automated Essay Assessment	Pasaribu et al., 2024	Auto-evaluation for Essay Assessment (1D CNN)	Deep Learning (1D CNN)	Automated grading of essays
	Calixto et al., 2021	Formative assessment in online learning	Teacher survey	Math & Science distance learning
	Kaldaras et al., 2024	Assessment rubric with AI context	Case Study + Framework	Information literacy rubrics
	Ke& Ng, 2019	Automated Essay Scoring: Survey	Literature Survey	Overview of AES methods
Feedback Systems	Gombert et al., 2024	Automated assessment to feedback	Case Study + NLP	Essay feedback in AI education
	Banihashem et al., 2024	Peer vs. AI feedback in essay writing	Comparative Study	Essay writing in higher education
	Weidlich et al., 2024	Emotional/motivational effects of feedback	Experimental Study	Formative feedback impact
	Yu et al., 2025	Hybrid intelligence for peer feedback	Hybrid Intelligence (AI+Peer)	Teacher reflection in online learning
	Ba et al., 2025	ChatGPT-assisted feedback in discussions	LLM Integration	Inquiry-based online discussion

Category	Authors & Year	Title	Method/ Approach	Educational Application
	Gombert et al., 2024	Highly informative essay feedback	NLP-driven feedback	AI-supported writing improvement
Reflection in Learning	Li et al., 2025	LLM strategies for reflection assessment	Single vs Multi-agent LLMs	Automated student reflection
	Dehbozorgi &MacNeil, 2019	Semi-automated analysis of reflections	Automated + Human coding	Continuous reflection in courses
	Hung et al., 2014	Video-prompt approach for reflection	Context-aware prompts	In-field reflection levels
	Körkkö, 2021	Reflection framework in teacher education	Theoretical framework	Teacher reflection framework
Personalized Learning	Jegede, 2024	AI in English learning (feedback & personalization)	AI-driven learning tools	Language learning personalization
	Ihichr et al., 2024	Systematic review on adaptive assessment	Literature Review	Adaptive learning theories & algorithms
	Yaseen et al., 2025	Adaptive learning, feedback, and engagement	Empirical Study	Student engagement & digital literacy
	Hankeln et al., 2025	Digital formative assessment research gaps	Conceptual/Framework	Conceptual learning in digital assessment
	Sajja et al., 2024	AI-enabled intelligent assistant	AI system design	Higher education
	González-Castro et al., 2021	Conversational agent in MOOCs	Adaptive Module + Conversational AI	MOOC learners
	Viswanathan, 2012	Teaching via MOOCs	Conceptual/Early study	MOOC-based education
	Wang et al., 2025	LearnMate (LLM-powered)	LLM-powered tool	Online education

Category	Authors & Year	Title	Method/ Approach	Educational Application
Ethical/ Conceptual Aspects	Portaz et al., 2024	Ethical principles in feedback systems	Human factors modeling	Psychomotor learning systems
	Kolluru et al., 2018	AI for adaptive learning	Conceptual	Customized experiences
	Strielkowski et al., 2025	AI-driven adaptive learning	Empirical + Conceptual	Educational transformation
	Córdova-Esparza, 2025	AI educational agents	Conceptual/ Ethical discussion	Opportunities & ethics
Engagement Model	Bedenlier et al., 2020	Tech & engagement in arts/humanities	Systematic Review	Higher education
	Chiu, 2022	SDT for online engagement	Theoretical application of SDT	COVID-19 online learning
	Bond et al., 2020	Mapping research in edtech engagement	Evidence mapping	Higher education
	Stürmer et al., 2024	Simulation-based teacher learning	Empirical Study	Teacher training
	Radović et al., 2024	Self-regulated learning supports	Experimental study	Student learning processes
Intelligent Systems	Hazar et al., 2022	Learner comments recommender	Recommender System	E-learning personalization
	Jhajj et al., 2024	Knowledge Graphs via LLMs	LLM + Knowledge Graph	Intelligent tutoring
	Jing et al., 2023	Adaptive learning research landscape	Bibliometric Study	Publications 2000–2022
	Li et al., 2024	FALCON feedback optimization system	Reinforcement Learning + Memory Networks	Feedback-driven coding optimization
	Ramandanis	Chatbots in	Systematic	Student support

Category	Authors & Year	Title	Method/ Approach	Educational Application
	&Xinogalos, 2023	education	Literature Review	
Video-based Learning / Analytics	Vidanaralage et al., 2022	Gamified video-based learning	Multidisciplinary AI framework	Engagement in gamified learning
	Chatti et al., 2016	Video annotation & analytics	Platform design	Course-based learning
	Hazar et al., 2022	Video-based recommender system	Video processing recommender	E-learning platforms
	Nickl et al., 2022	Video-based simulations	Empirical Study	Teacher education
	Navarrete et al., 2025	Video-based learning review	Systematic Review	Tools, effectiveness
	Tan et al., 2023	Peer-assisted statistics video learning	Empirical study	University statistics
	Manly, 2024	Content modalities in adaptive learning	Panel Data Analysis	Higher education
	Mangaroska & Giannakos, 2018	Analytics-driven learning design	Systematic Review	Design enhancement
Adaptive Learning with LLMs, Emerging AI	Li et al., 2024	Generative AI in adaptive learning	LLM model proposal	Generalized adaptive education
	Kabir& Lin, 2023	LLM-powered practicing system	Prototype system	Adaptive practice
	Chu et al., 2025	LLM agents for education	Survey & Applications	Broad education
	Anggrawan &Satria, 2023	AR for independent learning	Experimental	AR vs traditional learning
	Gong et al., 2025	LLMs for code optimization	Survey	Technical learning systems
	Razafinirina et al., 2024	LLM personalization survey	Survey + Trends	Personalized learning

Category	Authors & Year	Title	Method/ Approach	Educational Application
	Rincón-Flores et al., 2019	Predictive AI adaptive learning	Predictive algorithms	Multicultural learning
	Chen et al., 2024	Encoder+Transformer text gen	Transformer model	Text generation for learning

AI-driven assessment tools can analyze student responses, identify patterns, and provide tailored feedback that addresses individual learning needs. This personalized approach to assessment promotes student engagement and motivation, fostering a more effective and efficient learning experience. LLM-based system, called LearnMate, which generates personalized learning plans and provides real-time support to users by monitoring learning progress, tracking study materials, and offering contextual responses to learner queries [18]. The ability to review one's own performance allows for a deeper understanding of strengths and weaknesses, leading to targeted improvements. Technology provides student satisfaction in accessing new skills development, active involvement in learning, and getting academic achievements. The online learning can provide an efficient platform for students to ask questions, share their own ideas, and receive feedback [19].

Virtual tools can help the students to complete the assignments from anywhere. Through the consumption of educational videos, students can acquire declarative knowledge concerning a specific topic. By engaging in reflective practices on the content viewed, students are able to enhance their understanding and cultivate procedural knowledge. Conventional assessment techniques, like grading assessments and essays, are labor-intensive and costly, hindering educators in delivering prompt and tailored feedback to all learners. Automatic evaluation of assignment submissions and analyzing feedback can be done through AI/ML-driven assessment tools [20]. This mechanism of automated feedback helps students to recognize their strengths and weaknesses, progress, performance enhancement and more. Active engagement in learning, to think critically, to ask questions, and to compare new learning with prior knowledge are involved in reflection analysis.

3. Conceptual Framework

Video-based learning environments provide active learning, their interactions with video content, making reflection assessment for understanding how this meaning-making process occurs [21]. The combination of learning video content and response of student reflection are the synergistic approach to learning, which enhances both declarative and procedural knowledge. Natural Language Processing (NLP), a pivotal technology that enables the inspection of textual reflections, identifying core concepts and areas necessitating improvement [22]. NLP algorithms are used to extrapolate meanings of student reflections, questions, arguments, and evidence presented. By scrutinizing this way, valuable insights of the subject matter and instructional approach to the requirements can be done by the educators.

3.1 Video Content Design and Characteristics

Educational videos encompass a variety of formats like lectures, demonstrations, and simulations. Lectures offer a structured presentation of fundamental concepts and principles, while demonstrations exhibit the application of these concepts. The various methods for identifying the video content and its characteristics are given in fig 2. Simulations enable experimentation with diverse scenarios and observation of resultant outcomes [23]. Video illustrations enhance understanding by demonstrating practical application of concepts. For instance, a video portraying the utilization of a specific algorithm in a self-driving vehicle aids comprehension of its practical implications. Flipgrid, an online communication platform facilitating brief video interactions, proved beneficial for encouraging analytical engagement among student-coaches in an undergraduate program [24].

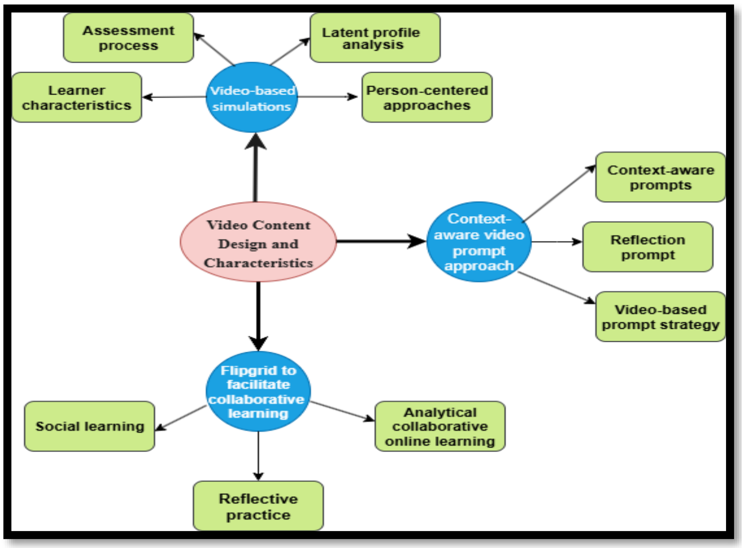

Fig. 2: Various methods used for identifying the video content and its characteristics

Reflection prompts are categorized as open-ended or focused, tailoring students' contemplation of video content. Open-ended prompts stimulate broad thinking and self-exploration, while focused prompts direct attention to specific elements like key concepts, problem-solving techniques, or practical applications. The selection of prompt type hinges on learning objectives and desired student involvement [25]. The prompts may help students to analyze the concepts of video that intersect with prior educational knowledge to answer the relevant questions.

3.2 NLP techniques for reflection analysis

Natural Language Processing techniques are instrumental in scrutinizing student reflections, elucidating meanings, and pinpointing pivotal themes and concepts [26]. Such scrutiny provides insights into the subject matter of students and cognitive process.

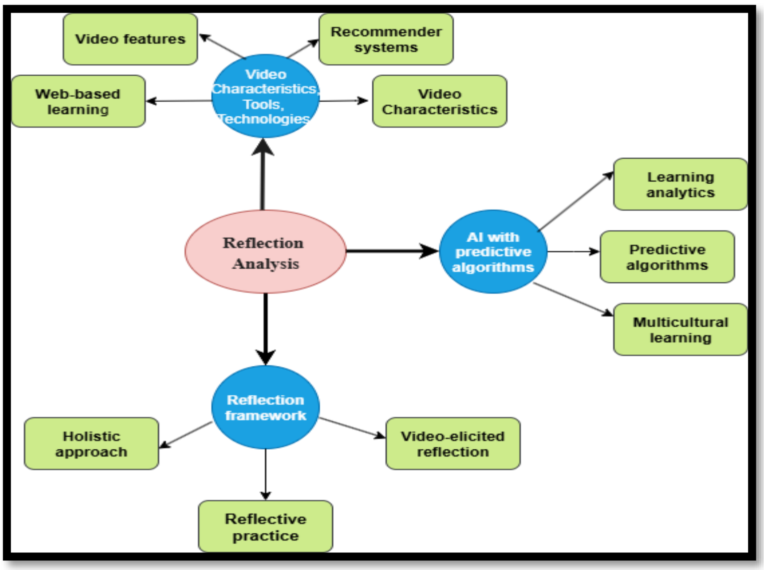

Fig. 3: Different NLP techniques for reflection analysis

Sentiment analysis serves perspective of students regarding video content and the contiguous learning process. It is a specific technique to gauge the exact meaning of text. The fig 3 shows different NLP techniques for reflection analysis. Within the realm of student reflections, sentiment analysis is applied towards video content followed by learning process. Machine Learning algorithms are used to identify patterns in student reflections correlates the different levels of comprehension [27]. ML designing algorithms capable of learning from data. These algorithms recognize patterns in student reflections associated with diverse levels of comprehension. lassification models are used to categorize student reflections based on the depth of analysis and to exhibit critical thinking. These models classify obtained data into various classes and categories. In the context of student reflections, classification models segment reflections predicated on the depth of analysis and critical thinking demonstrated [28]. Regression models estimate student performance on the content of their reflections. These models also predict a outcome variable on a predefined set of predictor variables. Within the arena of student reflections, regression models prognosticate student performance based on the content of their reflections [27]. For example, a regression model could analyze a student's exam score predicated on the vocabulary, related content and sentiment in their reflections.

3.3 Rubric-based vs data-driven scoring methods

Rubric-based assessment is a structured evaluation method that utilizes predetermined criteria to assess performance across diverse domains [29]. These criteria are structured within a rubric that provides a systematic framework for evaluation of quality work.The rubric describes various accomplishment level for each criterion, to allocate scores based on the performance which aligns with the established benchmarks. This kind of transparent scoring mechanism in rubric-based assessment enhances students' expectations and facilitates to give constructive feedback [30]. This strategy is employed to ensure uniform, equal and objective evaluations in educational environments. Rubrics are frequently used in educational assessments to provide a structured approach to scoring, enhancing objectivity and consistency [31]. A set of guidelines for evaluating student work, reducing subjectivity and also to ensure all students are assessed using the same standards. The use of multiple evaluation items in rubrics helps to increase the objectivity of the evaluation that focus on specific aspects of student performance. The fig 4 shows the scoring methods used in assessment process. By clearly defining the expectations for each level of achievement, rubrics enable raters to make more informed and consistent judgments, leading to more reliable and valid assessment outcomes.

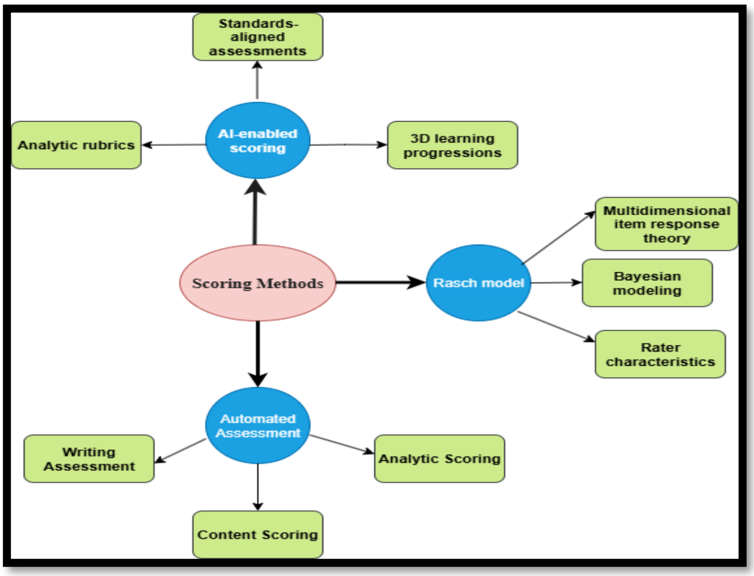

Fig. 4: Scoring methods in assessment process

Data-driven scoring represents a modern approach to assessment that leverages statistical models generated from measurement data to evaluate performance [32]. Unlike rubric-based scoring, which relies on predefined criteria and human judgment, data-driven scoring uses empirical data to identify patterns and relationships that can be used to predict or classify performance. This approach is particularly useful in situations where it is difficult to define explicit criteria or where large volumes of data need to be processed efficiently. Data-driven scoring is becoming increasingly popular in education, engineering, sales, marketing, and healthcare, as the availability of data and the sophistication of analytical techniques continue to grow. Machine learning algorithms are frequently used in data-driven scoring to identify patterns and relationships of data to enable an automated and efficient assessment. These algorithms are trained on large datasets to learn the underlying characteristics of high-quality work. Once trained, the ML models can be used to score new performances automatically, without the need for human raters [33]. This saves time and also reduces the potential for subjective bias. Common ML algorithms used in data-driven scoring uses regression, classification, and neural network models. The specific nature of the assessment task and the characteristics of the available data are considered for selection of algorithms. By analyzing learners behavior and test scores, educators get a proper understanding of individual student needs and tailor instructions accordingly. Automated essay scoring (AES) systems analyze various features of the essay, such as vocabulary, grammar, organization, and content, to assign a score that reflects the overall quality of the writing [34]. These systems can be used in a variety of educational settings, from large-scale tests to small classroom assignments. AES systems helps to save teachers time and provide students with immediate feedback on their writing through automatic scoring.

3.4 Feedback generation models

Feedback generation models provides personalized, useful, context-aware, and effective feedback to learners that enhances the overall learning experience and outcomes. Recent advancements of hybrid intelligence in AI and paradigms have enabled innovative approaches to feedback generation that combine retrieval-based techniques and generative models.

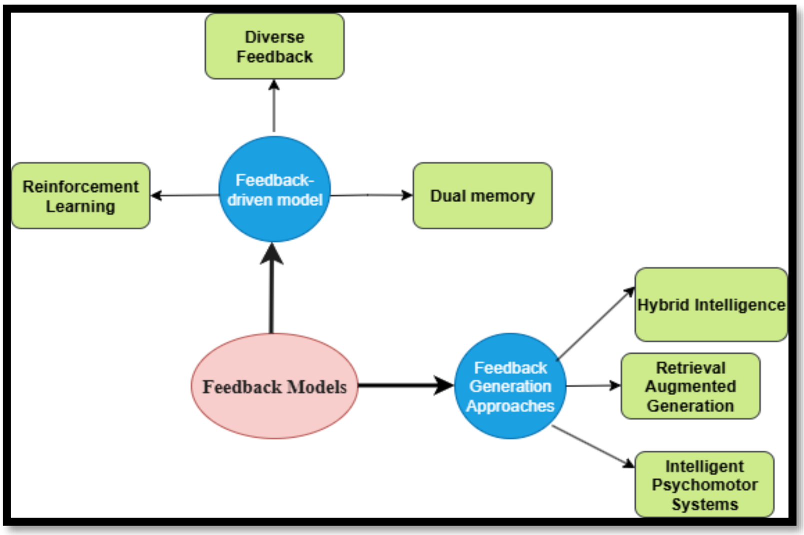

Fig. 5: Feedback generation models and methods

One promising approach integrates retrieval-augmented generation tools, which combine retrieval-based methods with generative models, to deliver tailored feedback that is both comprehensive and engaging [32]. This method is particularly relevant in adaptive psychomotor learning systems, where feedback is insightful, technically accurate, and effective. The feedback generation models and related methods are illustrated in fig 5. In the context of programming tasks, feedback-driven adaptive models use hierarchical memory structures that is combined with reinforcement learning based on human feedback to better align automated generation outputs with user intent [35]. Such models balance long-term knowledge and immediate feedback to optimize performance, highlighting the adaptability through feedback mechanisms. It helps to create adaptable learning environments aligned with standards for intelligent technology systems. AI-powered personalized learning assistants utilize natural language understanding, document analysis, and performance forecasting to provide real-time, adaptive feedback [36]. These systems use machine learning algorithms to track individual learning patterns and adjust feedback, enhance learner autonomy, confidence, and knowledge retention to unique learning styles and needs.

3.4.1Personalization and adaptively in feedback

These are core components of adaptive learning systems that fundamentally enhance educational experiences by tailoring instructional content and feedback to individual learners' needs, preferences, and progress. Adaptive learning employs algorithms of AI and machine learning to dynamically modify learning paths based on continuous assessment of a student's performance, thereby providing personalized real-time feedback that supports effective learning [37]. For example, AI-driven adaptive learning systems continuously analyze learner data to provide feedback that engage students by aligning with student requirements and progress. The real-time feedback loop ensures that students receive just-in-time support, which helps in overcoming difficulties promptly and makes the learning experience more inclusive and effective [38].

Personalized feedback delivery in adaptive learning increases student engagement, active participation and tailoring interactions to individual progress. The adaptivity in feedback motivates students and also helps to identify their strengths and weaknesses in a timely manner, allowing for more efficient learning adjustments [39]. Comparative analyses of adaptive learning platforms reflect diverse approaches to feedback personalization, where the platforms tailor content and assessments based on continuous learner analytics. Furthermore, integrating personalized feedback with adaptive learning technologies harmonizes with students' digital literacy levels, which can moderate the effectiveness of these tools on engagement and educational outcomes [40]. Additionally, machine learning techniques in learning management systems enable automatic analysis of student interaction data and adjusting feedback accordingly.

The Human-Centered learning system allows education providers to personalize adaptive feedback mechanisms, enhancing learning effectiveness where large student populations require scalable and individualized attention [41]. Personalization and adaptivity in feedback of adaptive learning environments create an individualized educational experience that actively engages learners, response and supports the unique learning journeys through continuous and tailored feedback. These kind of feedback mechanisms are vital for improving educational outcomes, enhancing motivation, and successfully integrating technology with pedagogical practices.

4. Methodology

The methodology includes video-based learning modules that are first curated to present fundamental concepts and skills in a clear, segmented format, ensuring accessibility and engagement for diverse learners. Automatic speech recognition and manual transcript reviews are applied to extract key knowledge components from the instructional videos, forming the foundation for assessment item generation. Assessment questions are created using a hybrid approach that combines transformer-based semantic analysis and pedagogical mapping to align each quiz item closely with specific video content, thereby maximizing relevance and targeted learning outcomes. Following the delivery of video content and associated quizzes, learner responses are evaluated for correctness, response time, attempt patterns and open-ended reflection prompts that encourage students to articulate their understanding and identify knowledge gaps.

The system analyzes these reflections to detect misconceptions and learning challenges, then generates targeted, actionable feedback that suggests appropriate re-engagement with pertinent video segments, additional resources, or scaffolded exercises. This feedback loop not only supports real-time learner adaptation but also informs iterative refinement of both video content and assessment design, creating a dynamic, learner-centered adaptive learning environment. Reflection assessment in video-based learning represents an evolving field that requires careful consideration of theoretical foundations, technological capabilities, and pedagogical best practices. The effective reflection assessment must account for the multimodal nature of video-based learning, incorporate appropriate technological tools, and consider individual learner characteristics and contexts.

The continued development of AI and machine learning technologies offers significant potential for enhancing reflection assessment in video-based learning, particularly in areas such as automated feedback generation and pattern recognition in reflective writing [42]. Feedback can include explanations of key concepts, examples, and suggestions for further learning. The feedback generated by the AI engine can include a variety of elements, such as explanations of key concepts, examples of how to apply those concepts, and suggestions for further learning. This comprehensive feedback can help students to deepen their understanding of the material and to develop their problem-solving skills. Effective feedback goes beyond identifying mistakes to also delineate correct procedures. An artificial intelligence system can furnish actionable feedback by recommending precise tactics and materials to aid students in augmenting their comprehension and skills [43]. For feedback to be efficacious, it must offer students clear, actionable steps for enhancement rather than solely pointing out errors.

4.1Collecting video lectures

Educational videos can encompass various formats such as lectures, demonstrations, and simulations. Lectures offer a comprehensive overview of a subject, while demonstrations illustrate specific tasks. Simulations enable students to explore diverse scenarios and observe the outcomes of their actions [44]. Each format presents distinct advantages and limitations, and the optimal choice hinges on the precise educational goals. Live coding demonstrations serve to unveil advanced problem-solving approaches. These demonstrations showcase coding experts in action, frequently accompanied by verbalized reasoning that elucidates their cognitive processes. Observing these presentations allows students to comprehend how professionals tackle coding challenges and derive insights from their errors. Such video content proves especially beneficial for individuals acquiring coding skills [45]. The live coding structure affords a genuine depiction of the coding procedure, encompassing the obstacles and setbacks commonly encountered. Video examples can illustrate real-world applications of theoretical concepts. It can help students to understand the relevance of what they learn and motivate them to engage more actively with the material.

4.2Student responses

In video-based adaptive learning environments, student reactions are influenced by factors such as instructional design, variety of modalities, and the adaptiveness of the learning system to student engagement and performance cues [46]. Studies suggest that video-based learning can improve student engagement, motivation, and outcomes compared to traditional methods. For instance, research on video-based learning in trading markets demonstrated its effectiveness in enhancing engagement and learning outcomes. Well-structured video content was found to effectively maintain student interest. In adaptive learning environments integrating video, the technology can monitor real-time student responses and adjust instructional content accordingly. In adaptive systems that collect detailed biometric and interaction data, including facial expressions and quiz responses, to evaluate comprehension levels and adapt learning pathways [47]. This continuous monitoring enables personalized feedback and modifications in content difficulty based on signals of student understanding, potentially enhancing personalized learning experiences. The use of bite-sized and Peer-assisted video learning formats in university education received positive feedback, with students showing favorable attitudes and achieving good performance without compromising learning outcomes and learner satisfaction [48]. The inclusion of multiple content modalities alongside video, such as text, audio, and interactive elements, in an adaptive system can further enhance learning outcomes.

Panel data analysis has confirmed the positive impact on knowledge acquisition when students interact with diverse content formats in online courses, indicating that adaptability to presentation preferences can enhance engagement and comprehension among a wide range of learners [49]. Qualitative examination of student feedback reveals varying attitudes towards video-based learning, with preferences for factors like video length, interactivity, and presenter style differing among students. However, challenges such as cognitive overload and technical difficulties persist and require strategic design and support for optimal effectiveness. These personalized approaches can promote deeper understanding and motivation, but careful design considerations and robust support are essential to address challenges and maximize advantages.

4.3Model training/selection

BERT-based models are used in classifying self-reflection notes compared to traditional classifiers like Support Vector Machines and Random Forests. Unlike earlier models, the BERT, GPT models with self-attention mechanisms that can capture long-range dependency within text sequences efficiently [50]. This work underscores the effectiveness of BERT, particularly when combined with advanced training methods, in accurately assessing nuanced reflections crucial for adaptive learning systems seeking to personalize educational feedback and support [51]. Large language models such as GPT variants are utilized in adaptive learning scenarios for tasks like context-aware question generation and conversational tutoring. These models are used to generate personalized multiple choice questions to individual learner progress and context by enhancing through adaptive difficulty adjustments. The versatility of T5 suggests its potential utility in adaptive learning contexts where diverse textual interaction modes like summarization and question answering are essential [52]. BERT-based models categorize self-reflection notes that can inform personalized interventions. Whereas, GPT-powered conversational agents simulate the structured reflection prompts for tutors, ultimately enhancing learner engagement and metacognitive skill development [53]. The integration of these models into adaptive learning platforms involves real-time reflection classification and feedback generation to cultivate problem-solving strategies, self-directed learning skills, and self-regulation in learning progress.

4.4Evaluation metrics:

The text data student reflections are preprocessed to eliminate irrelevant information before utilizing it for training machine learning models [54]. Through text data preprocessing, the AI system can enhance the accuracy of its analysis. Feature extraction characteristics from text data, such as word frequencies, sentiment analysis, can be employed to train ML models capable of evaluating students' comprehension and providing tailored feedback [55]. Word frequencies can offer insights to the intricacy of the reflections, whereas sentiment scores give students' understanding towards the subject matter. Video content can be analyzed to extract features such as video duration, number of concepts covered, and visual complexity [56]. In addition to analyzing student reflections, the algorithms analyze the video content itself to extract features such as video duration, number of concepts covered, and visual complexity.

5. Applications and Use Cases

5.1 Classroom and MOOC environments

The utilization of online communication tools, such as Flipgrid, can enhance video-based reflection and interaction among students. These systems serve as a video discussion platform enabling students to create and distribute brief video responses to prompts, fostering dynamic and engaging expression of their thoughts and ideas [57]. This approach can significantly promote reflection and interaction along with facilitating peer feedback. The various articles that describes about different types of learning management systems are categorized and illustrated in fig 6.

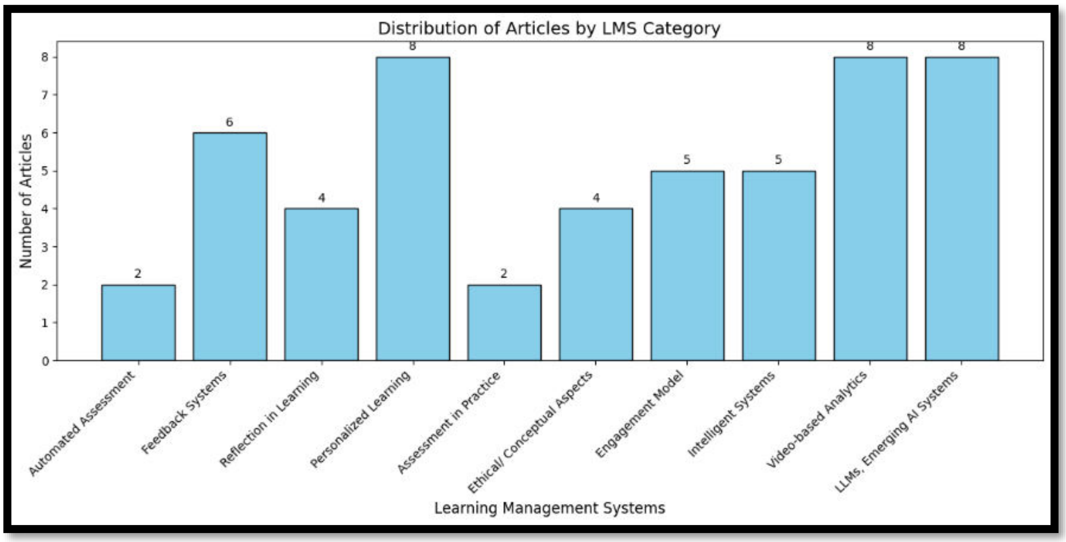

Fig. 6: Articles based on different types of learning management systems

Learning management systems (LMS) commonly offer discussion forums and journaling features tailored for written reflection tasks. LMS platforms such as MOOC courses are equipped with resources like discussion forums for idea exchange and journaling capabilities for private reflection on learning experiences [10]. Specialized reflection platforms provide structured frameworks and prompts to support reflective practices. Complementing general tools with dedicated platforms are specifically crafted to facilitate reflection activities by offering tailored frameworks and prompts. Equipped with various features, these platforms aim to assist students in engaging more effectively and meaningfully in the reflective process [58].

5.2 Formative assessment tools

Formative assessment tools utilized in adaptive learning encompass digital or technology-enhanced methods strategically formulated to offer continuous insights into students' comprehension, competencies, and educational requirements. This facilitates the adjustment of teaching techniques or task allocation to effectively cater to individual students. The primary aim of these tools and their accompanying reports is to customize pedagogical strategies, educational objectives, and assignments to enhance learning outcomes [59]. Further research endeavors are imperative to ensure the pertinence, validity, and provision of in-depth insights into conceptual comprehension by these tools. The formative assessment reports generated through these tools can guide educators' adaptive task allocation practices by accentuating students' subsequent learning aims, errors, or strengths. Nonetheless, these reports in isolation yield modest impacts and should be amalgamated with professional development initiatives to enhance the support for adaptive curriculum planning [60]. Educators adjust formative assessment approaches by formulating varied assessments and leveraging purposeful online tools despite obstacles like student motivation, digital literacy, and technological accessibility.

6. Challenges and Limitations

One of the primary challenges in reflection assessment for video-based learning is ensuring consistency and reliability across different assessors and contexts. The progress of technology is utilized by demonstrating the practicality and advantages of integrating AI into learning systems. Technology-related challenges can impact the effectiveness of reflection assessment in contexts where learners have limited access to reliable technology or lack digital literacy skills. The adaptive feedback system can also be improved using some advanced NLP methods. This model can be enhanced with multimodal analysis with voice or tone for better accessibility of learners.

7. Conclusion and Future Directions

This study highlights the significance of adaptive learning techniques and methods across different Learning Management Systems in enhancing personalized education. By incorporating diverse assessment methods, it effectively evaluates learners' capabilities while leveraging reflections to gain insights into their cognitive development. Moreover, the integration of intelligent recommendation systems enriches the learning process by offering supplementary resources that support deeper understanding of specific topics. Collectively, these approaches foster a more engaging and effective learning environment that not only improves knowledge acquisition but also cultivates sustained interest in learning. Future enhancements can focus on integrating advanced AI-driven personalization and real-time feedback to further refine adaptive learning systems. Additionally, incorporating multimodal data and intelligent recommendation engines can create a more immersive and effective learning environment.

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