# Multimodal Methods for Analyzing Learning and Training Environments: A Systematic Literature Review

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Recent technological advancements have enhanced our ability to collect and analyze rich multimodal data (e.g., speech, video, and eye gaze) to better inform learning and training experiences. While previous reviews have focused on parts of the multimodal pipeline (e.g., conceptual models and data fusion), a comprehensive literature review on the *methods* informing multimodal learning and training environments has not been conducted. This literature review provides an in-depth analysis of research methods in these environments, proposing a taxonomy and framework that encapsulates recent methodological advances in this field and characterizes the multimodal domain in terms of five modality groups: Natural Language, Video, Sensors, Human-Centered, and Environment Logs. We introduce a novel data fusion category — *mid fusion* — and a graph-based technique for refining literature reviews, termed *citation graph pruning*. Our analysis reveals that leveraging multiple modalities offers a more holistic understanding of the behaviors and outcomes of learners and trainees. Even when multimodality does not enhance predictive accuracy, it often uncovers patterns that contextualize and elucidate unimodal data, revealing subtleties that a single modality may miss. However, there remains a need for further research to bridge the divide between multimodal learning and training studies and foundational AI research.

CCS Concepts: • **Applied computing** → **Education**; **Computer-assisted instruction**; **Interactive learning environments**; **Collaborative learning**; **E-learning**; **Computer-managed instruction**;

Additional Key Words and Phrases: multimodal data, data analytics, learning analytics, multimodal learning analytics, mmla, learning environments, training environments

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## 1 INTRODUCTION AND BACKGROUND

### 1.1 A Brief History

Recent advances in the learning sciences, bolstered by technological progress, are driving the personalization of educational and training curricula to meet the unique needs of learners and trainees. This shift is underpinned by data-driven approaches that are integrated into the field of *learning analytics* [61]. Learning analytics focuses on gathering and evaluating data on learners' and trainees' behaviors—specifically, their approaches to learning and training tasks [94, 166]. For example, intelligent tutoring systems like Practical Algebra Tutor [78] focus on diagnosing student errors, open-ended environments like Betty's Brain [84] adaptively scaffold learning, and teacher-feedback tools (e.g., [72, 124]) assist educators in enhancing instruction through insights into student behaviors.

A central research question in learning analytics is, *What types of data are necessary to gain insights into learner behaviors and performance, and enable meaningful support that advances student learning and training in different scenarios?* [108, 151]. Initially, the scope of data collection and analysis was constrained by available technology and computational methods in educational settings. Early learning analytics predominantly analyzed log data from computer-based environments, establishing correlations between students' behaviors and their digital interactions, thus forming the foundation for many contemporary theories and methods in the field [71, 108].

Advances in sensor and data collection technologies are extending learning analytics beyond traditional log-based analyses [108]. In physical learning spaces, log data is insufficient to capture all learner actions, affective states, and collaborative behaviors. Researchers now integrate additional data collection devices, such as video to capture physical interactions, microphones for conversations, biometric sensors for stress levels, and eye trackers for attention [151].

This enriched data collection provides a more comprehensive understanding of students' affective, cognitive, psychomotor, and metacognitive states, advancing multimodal learning analytics (MMLA) [12, 13, 158]. MMLA has matured over a decade of research, disseminated through journal special issues [52, 96, 109], conferences [60], an edited volume [64], and systematic reviews [4, 22, 39, 50, 100, 130, 158]. This review focuses on *applied research methods* in MMLA, building on this substantial foundation.

### 1.2 Related Work

Recent work in MMLA research, surveys, and reviews have explored the MMLA landscape through various lenses: multimodal data fusion [22], conceptual models and taxonomy [50], statistical and qualitative assessments [121, 131], virtual reality [118], technology and data engineering [26], and ethical considerations [4]. Our review focuses on applied methods supporting data collection and analysis in multimodal learning and training environments, explicitly centering on methodologies for collecting, fusing, analyzing, and interpreting multimodal data using learning theories. We extend and modify existing taxonomies to reflect recent advances in MMLA.

Di Mitri et al. [50] introduced the Multimodal Learning Analytics Model (MLeAM), a conceptual framework outlining the relationship between behavior, data, machine learning, and feedback in MMLA. This framework provided a taxonomy and introduced the concept of data observability, distinguishing between quantifiable input evidence and inferred annotations (e.g., emotions, cognition). The *observability line* demarcates these domains, crucial for AI-mediated

transformation from input to hypotheses in MMLA research. Chango et al. [22] surveyed fusion methods in MMLA, categorizing studies by fusion type and application stage within the multimodal pipeline. They proposed three fusion types: *early* (feature-level integration), *late* (decision-level integration), and *hybrid* (a combination of both). This classification clarifies fusion approaches and their relevance to educational data mining.

Integrating insights from both surveys, we propose a classification focused on *feature observability*, distinguishing between sensory data and human-inferred annotations. This adapted scheme refines our understanding of data fusion in MMLA and creates a refined taxonomy, which we present in Section 2.

### 1.3 Scope of This Review

For this paper, we define a *data collection medium* as a unique type of raw data stream (e.g., video, audio, photoplethysmography (PPG) sensor). A *modality* is a unique attribute derived from data from one or more streams, each conveying different information, even from the same medium [108]. *Modality groups* are distinct sets of modalities conveying similar information, derived via inductive coding (see Figure 1). *Multimodal* is a combination of either multiple modalities **or** multiple data streams. For example, the same video data stream can be used to derive the affect and pose modalities, and the affect modality can be derived from audio and video streams. Both examples are considered multimodal. We use "papers" and "works" interchangeably, including publications outside of conferences and journals (e.g., books and book chapters). Our definitions aim to characterize the scope of our review, not to establish a "universal" definition of multimodality and multimodal analysis.

Our review includes all papers from our literature search not excluded by our criteria (see Appendix B.2.2). This includes multimodal learning and training analysis done "in passing." For example, a paper focused on multimodal composing environments that performs multimodal learning analysis as a byproduct is included. We are interested in the methods used for multimodal analysis, not just those where it is the primary focus. We examine studies that engage in data collection and analysis across various mediums and modalities, encompassing fully physical settings (e.g., physical therapy), mixed-reality contexts (e.g., manikin-based nursing simulations), and online educational platforms (e.g., computer-based physics instruction). Notably, our review excludes virtual reality environments due to their current scalability challenges in educational settings [37].

### 1.4 Contributions

This paper presents a systematic literature review on methodologies for multimodal learning and training environments and makes several novel contributions:

- A **comprehensive review** of the research methods used in multimodal learning and training environments, the challenges encountered, and relevant results that have been reported in the literature. Simultaneously, we also identify the research gaps in the data collection and analysis methodologies;
- A **congruent framework and taxonomy** that reflects the recent advances in multimodal learning and training methodologies;
- An **additional data fusion classification** that we call *mid fusion* (i.e., it is between *early fusion* and *late fusion*) that allows for differentiating processed features relative to the observability line.
- A graph-based **corpus reduction procedure** using a citation graph, which we refer to as *citation graph pruning*, that allows for programmatically pruning literature review corpora. This is described in detail in Section 3.2.1.

### 1.5 Structure of our Literature Review

The remainder of this literature review is structured as follows. Section 2 presents our theoretical framing and taxonomy for multimodal methods in learning and training environments. Section 3 details the procedures for our literature search, study selection, feature extraction, and analysis. Section 4 presents our findings for each component of our framework (each subsection corresponds to a box in Figure 1), including an analysis of each of the 5 modality groups (Section 4.2). Section 5 presents three research categories ("archetypes") that best characterize the multimodal learning and training field. Section 6 highlights current trends, state-of-the-art, results, challenges, and research gaps, addressing limitations and future research directions. Section 7 concludes with a recap of this work's contributions.

## 2 FRAMEWORK AND TAXONOMY

In this section, we provide a detailed description of the multimodal learning and training analytics process, outlining both the overarching framework and the specific features that constitute our taxonomy.

### 2.1 Framework

We constructed our theoretical framework by integrating established multimodal learning analytics frameworks and through inductive analysis of the papers in our review corpus. The framework decomposes the multimodal learning and training analytics process into four primary components depicted in Figure 1: (1) the learning or training environment, (2) multimodal data, (3) learning analytics methods, and (4) feedback.

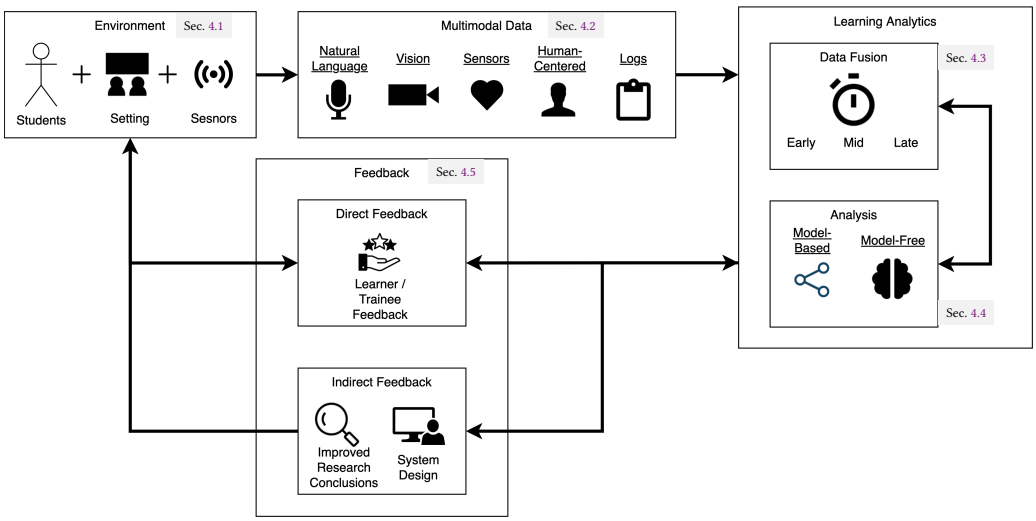



Fig. 1. Multimodal Learning and Training Environments Literature Review Framework

The *environment*, as the context for learner activities, is categorized as either **learning** or **training**, with the former supporting knowledge acquisition and the latter focusing on skill proficiency (Section 2.2.1). Learning environments range from physical classrooms and tutoring centers to online learning centers (e.g., Khan Academy) and individual or group-based computer learning environments. Skill-based training happens through practice and repetition and can include military training, nursing training, physical training, workplace training, etc. We further dissect the environment

into sub-components: *human participants* (Sections 2.2.7 to 2.2.10), *setting* (which includes physical, virtual, or blended spaces; Section 2.2.6), and data collection *sensors* (Section 2.2.2). The framework's second component is *multimodal data* (Section 2.2.3), comprising the environmental sensor data streams and the modalities derived from them, which we classify into five modality groups: (1) *natural language*, (2) *vision*, (3) *sensors*, (4) *human-centered*, and (5) environment *logs* (detailed in Sections 4.2.1, 4.2.2, 4.2.3, 4.2.4, and 4.2.5, respectively). The next block in our Figure 1 framework is *learning analytics*, which involves the methods for analyzing multimodal data (Section 2.2.4), and is divided into *data fusion* (*early*, *mid*, *late*, and hybrid; Section 2.2.5) and *analysis* approaches. Analysis approaches can be *model-based* or *model-free*, further detailed in Section 2.2.11. Finally, *feedback* is the output of MMLA, differentiated into (1) *direct* feedback for students and instructors, and (2) *indirect* feedback for researchers and system designers (Section 4.5).

## 2.2 Taxonomy

In this section, we delve deeper into each component of our framework, exploring features extracted from our corpus.

*2.2.1 Environment Type.* Our paper explores a spectrum of environments on a learning-training continuum (Figure 2), from traditional classrooms to online courses, categorized along two dimensions: the learning-training axis [95, 104, 115, 155] and the physical-virtual space continuum [19, 38, 117].

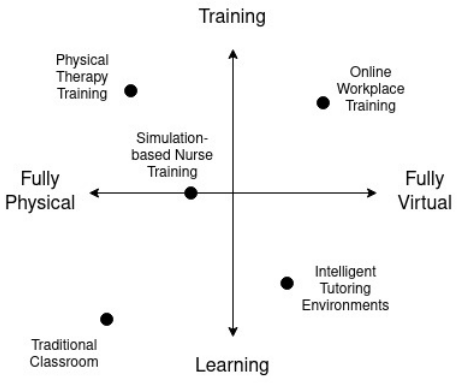



Fig. 2. Learning-Training Continuum

Multimodal methods in learning environments aim to enhance educational outcomes by analyzing student engagement and learning patterns. In contrast, training environments focus on skill acquisition and task proficiency, serving individuals from personal development to professional enhancement in fields like healthcare [51], athletics [95], and the military [69]. These settings range from fully virtual simulations to physical training drills, with augmented and mixed realities bridging the gap. MMLA objectives differ between learning and training, necessitating context-specific strategies. While the distinction between learning and training can be ambiguous, as seen in game-based platforms [92, 159], our review spans this spectrum. We employ a fuzzy qualitative categorization to place each study within this continuum, acknowledging the complexity yet utility of this approach for analyzing MMLA research sub-communities.

*2.2.2 Data Collection Mediums.* Current learning and training environments use several computational measures of performance and behaviors such as evaluating learning gains, establishing and progressing toward desired objectives, and employing effective plans of action to achieve these objectives. Multimodal data can provide the basis for computing these measures, ranging from logs and surveys to analyses of student artifacts. A diverse array of *data collection mediums* plays a pivotal role in gaining a comprehensive understanding of learners' progress, interactions, strategies, and struggles within these environments. The mediums listed in Table 1 (and all definitions in Section 2.2) were identified through our qualitative analysis of the corpus.

In the context of video data, we distinguish between depth cameras and traditional cameras. Though both fall under the video medium, depth cameras are typically employed with the motion modality to emphasize skeletal features.

Furthermore, the scope of the motion medium extends beyond general video data, encompassing technologies such as real-time location systems (e.g., accelerometers, gyroscopes, or magnetometers). These technologies offer diverse approaches to capturing raw motion data, providing granularity in understanding participants' physical movements.

| Medium | Definition |
|---|---|
| Video | Sequences of image frames captured from a camera source [27, 55, 117]. |
| Audio | Audio signals captured by a microphone [114, 115, 143]. |
| Screen Recording | Sequences of image frames displaying a device's screen contents [5, 74, 86]. |
| Eye | Eye movement data and gaze points captured by tracking devices [21, 112, 144]. |
| Logs | Participant's actions within the system and its state data [10, 120, 136]. |
| Sensor | Specialized sensors used to gather participants' physiological data [69, 75, 87]. |
| Interview | Structured or unstructured conversations between researchers and participants [11, 95, 105]. |
| Survey | Standardized sets of questions administered to participants [38, 43, 116]. |
| Participant-Produced Artifacts | Materials produced by study participants using various mediums, including physical objects created for a task or written responses to formative assessment questions [8, 20, 106]. |
| Researcher-Produced Artifacts | Materials produced by the researchers that contribute to analysis and findings, such as observational notes [69, 93, 139]. |
| Motion | Raw motion data collected via various different devices/technologies [51, 95, 155]. |
| Text | Raw textual input [159]. |

Table 1. Data collection mediums.

Researcher-produced artifacts can range from detailed field observation notes capturing contextual nuances to data labeling. This often requires manual coding that enhances data interpretability and contributes to more nuanced analyses and findings. Similarly, participant-produced artifacts constitute a valuable dimension in capturing participants' engagement and comprehension. These artifacts include materials such as physical objects crafted by participants or pre/post-test results. We constrain participant-produced artifacts to include artifacts collected during learning and training experiences, which excludes *post hoc* artifact collection.

*2.2.3 Modalities.* We previously defined *modalities* as unique attributes characterized by one or more data streams, where each modality conveys different information. Table 2 shows several modalities that are used for analyzing and understanding participants' interactions with and within learning and training environments. In this context, it is important to note that multimodality can arise from a combination of multiple modalities and multiple data streams. For example, the same video data stream could be used to derive both the *affect* and *pose* modalities. Similarly, *affect* can be derived from separate audio and video data streams.

*2.2.4 Analysis Methods.* We use the term *analysis method* to refer to specific techniques for deriving insights from multimodal data in learning and training contexts, which vary depending on research goals and data characteristics, and are presented in Table 3. The methods range from supervised and unsupervised techniques (like classification and clustering) to qualitative analyses. More recently, deep learning algorithms have been developed for analyzing multiple data streams [63, 64], and reinforcement learning techniques are being developed for educational recommendations [87]. Evaluating these methods is essential for understanding current trends in data analysis and informing future

| Modality | Description | Modality Group |
|---|---|---|
| Affect | Participant's emotional or affective state [48, 120, 143]. | NLP, Vision, Sensor |
| Pose | Participant's physical position, location, or body posture [5, 137, 140]. | Vision, Sensor |
| Gesture | Participant's gestures and body language [6, 115, 158]. | Vision |
| Activity | Participant's observable actions or activities [62, 86, 119]. | Vision, Sensor |
| Prosodic Speech | Elements of speech beyond word meaning, e.g. volume, pauses, and intonation [104, 136, 138]. | NLP |
| Transcribed Speech | Textual speech transcribed from audio [11, 38, 85]. | NLP |
| Qualitative Observations | Researcher observations about the participant and study task [75, 92, 157]. | Human-centered |
| Logs | Participant's environment actions and system state data [10, 65, 98]. | Logs |
| Gaze | Participant's eye gaze, e.g., movement, direction and focus [54, 55, 162]. | Vision, Sensor |
| Interview | Notes from interviews between researchers and participants [9, 53, 74]. | Human-centered |
| Survey | Participant's responses to surveys/questionnaires [112, 114, 116]. | Human-centered |
| Pulse | The participant's pulse, indicating their heart rate [81, 82, 148]. | Sensor |
| EDA | Participant's electrodermal activity [80, 91, 132]. | Sensor |
| Temperature | Participant's body temperature [83, 112, 132]. | Sensor |
| Blood Pressure | Participant's blood pressure [82, 112, 148]. | Sensor |
| EEG | Participant's electroencephalography activity [65, 112, 132]. | Sensor |
| Fatigue | The level of fatigue experienced during the activity [81, 82]. | Vision, Sensor |
| EMG | Participant's electromyography activity [49, 51]. | Sensor |
| Participant Produced Artifacts | Artifacts produced by the participant during the study, e.g., pre/post-tests [21, 99, 106]. | Human-centered |
| Researcher Produced Artifacts | Artifacts produced by the researcher about the study and participants, e.g., field notes [27, 57, 105]. | Human-centered |
| Spectrogram | Representation of audio frequencies in the form of a spectrogram [90]. | NLP |
| Text | Participant's raw text data generated in the study environment [159]. | NLP |
| Pixel | RGB pixel values from cameras or sensors [119]. | Vision |

Table 2. Modalities, their definitions, and the modality groups they fall into (detailed in Section 4.2).

research. This review concentrates on the examination and interpretation of the data through these methods and not on the analytical techniques themselves, unless such meta-analysis yields further valuable insights.

*2.2.5 Data Fusion.* In multimodal learning and training, data fusion is essential for leveraging multiple data sources to enhance the understanding of learning processes. Data fusion integrates information from diverse sources, creating a unified representation that enables enhanced analysis and understanding relative to unimodal studies. Such integration facilitates deeper insights into learners' cognitive states, emotions, and behaviors, informing personalized educational interventions and the use of adaptive pedagogical strategies.

| Method | Definition |
|---|---|
| Classification | Assigning pre-defined labels to input data based on feature analysis through supervised learning (often via deep learning approaches) [5, 120, 138]. |
| Regression | Predicting continuous numerical values through supervised learning to understand input-output relationships [48, 117, 136]. |
| Clustering | Grouping data based on patterns or similarities using unsupervised learning [6, 19, 27]. |
| Qualitative | Manually examining and interpreting data to uncover patterns or themes [74, 75, 92]. |
| Statistical | Using statistical methods (e.g., correlation) to analyze data and draw conclusions [85, 89, 106]. |
| Network analysis | Studying relationships and interactions using graph-based approaches [23, 38, 104]. |
| Pattern Extraction | Identifying meaningful patterns or structures within data, including techniques like Markov analysis and sequence mining [102, 112, 144]. |

Table 3. Analysis methods.

The conventional classification of data fusion methods in MMLA, as reviewed by Chango et al. [22], includes early, late, and hybrid fusion. *Early fusion* merges raw data from different sources at the initial processing stage and is useful for capturing inter-modal interactions but faces challenges with data heterogeneity and model complexity. *Late fusion* involves first analyzing each modality separately with outcomes integrated later, allowing for detailed, modality-specific insights but potentially missing inter-modal dynamics. *Hybrid fusion* combines these approaches, integrating data at various processing stages to harness both inter-modal relationships and in-depth, unimodal analysis, though it increases complexity and necessitates strategic feature selection.

We contend that the traditional three-state categorization inadequately captures the nuances of multimodal analysis. Our qualitative review reveals difficulties in classifying data fusion practices due to ambiguities in defining *raw* versus *processed* features. For example, some researchers might classify the joint position data measured by a Microsoft Kinect camera as a raw feature, and thus permissible in early fusion, since it is available from the camera without any additional processing. However, others might classify this as a processed feature, and thus part of hybrid or late fusion, since the Kinect camera is computing this data from the raw depth data, regardless of whether this computation is obfuscated to the end user. Thus we've introduced a new category, *mid fusion*, which involves moderately processed data integration, as conceptualized by Di Mitri et al. [50] using the observability line. To elaborate, Di Mitri et al. state, "*The distinction between observable/unobservable is conceptual and can vary in practice.*" [50]. Here, *early fusion* combines unprocessed, observable features; *mid fusion* combines observable features that have undergone some processing; and *late fusion* combines processed features that cross into the hypothesis space, becoming inferences rather than direct observations.

For example, a Kinect sensor's raw pixel or depth data are suitable for early fusion, while joint position data, processed but observable, fit mid fusion. In contrast, inferred constructs like motivation, derived from joint data, align with late fusion. The *mid fusion* category, while interpretatively flexible, clarifies ambiguities and aids in identifying MMLA sub-communities by their fusion methods. For a detailed definition of observable modalities, see section 2.2.3. Following Chango et al.'s methodology [22], we also introduce an *other* category for studies not conforming to the four primary groups or lacking specified fusion points. These categories are summarized in Table 4 and illustrated in Figure 3.

*2.2.6 Environment Setting.* Analyzing the contextual settings in which these studies occur, we categorize these environments based on the nature of the setting. In a **Virtual** setting, activities occur entirely within a virtual space [5, 138, 143].

| Category | Description |
|---|---|
| Early Fusion | Draws inferences and computes analytics from multiple sources of raw data at the earliest stage of processing before any modality-specific analysis [80, 142, 158]. |
| Mid Fusion | Represents a compromise that mixes early and late fusion for analysis. Combines processed, observable features generated from individual sources with analysis using other sources of data within the input space [43, 54, 55]. |
| Late Fusion | Analysis is performed on individual modalities, and the inferences generated are combined to generate outcomes at a later stage, i.e., in the hypothesis space [107, 117, 120]. |
| Hybrid Fusion | Combines the strengths of both early and late fusion methods. Data from various sources are combined at multiple stages of processing [5, 6, 119]. |
| Other | Studies that do not fit into the early, mid, late, or hybrid categories, or where the fusion point was not specified or fusion was not performed [74, 75, 92]. |

Table 4. Data fusion approaches.

A **Physical** setting is where activities take place in a real-world environment [115, 136, 158]. **Blended** settings combine elements of both virtual and physical environments [6, 48, 120]. **Unspecified** settings refer to environments that are not clearly described in the paper [43, 87]. We aim to unveil the contextual relevance of multimodal learning and training by discerning how these approaches manifest in computer-based spaces, traditional classrooms, and blended scenarios combining virtual and physical elements. Additionally, acknowledging instances where sufficient information is not provided directs our attention to research gaps and unexplored areas within the literature.

*2.2.7 Domain of Study.* We recognized the importance of identifying the subject matter domain that study participants engage in, thus defining five domain categories. **STEM+C** includes participants engaged in Science, Technology, Engineering, Mathematics, and Computing disciplines, encompassing healthcare and medicine [6, 136, 138]. **Humanities** focuses on activities related to literature, debate, and oral presentation [115, 120, 143]. **Psychomotor Skills** emphasizes activities that develop motor skills and coordination [51, 65, 98]. The **Other** category covers subjects outside the previously mentioned categories [99, 139]. **Unspecified** papers include those that do not provide sufficient information about the subject matter [8, 18, 87]. This categorization helps us better contextualize the use of multimodal analytics, exploring how they apply across diverse domains. These categories are intentionally broad, as we discovered that additional granularity hindered our ability to analyze and interpret current trends in the multimodal design of subject-related environments. Importantly, papers reporting results from multiple studies have labels corresponding to the domain of each separate study [139, 155].

*2.2.8 Participant Interaction Structure.* We categorized papers by how they enabled interactions with participants — i.e., **Individual** [18, 21, 82] or **Multi-Person**, which often emphasized collaborative or group dynamics [119, 123, 157]. It is noteworthy that some papers analyzed both individual and groups of learners, reflecting the diversity in studies even within individual publications [8, 19].

*2.2.9 Didactic Nature.* This refers to the approach used for delivering the learning and training, resulting in yet another lens through which we can understand, analyze, and differentiate learning and training environments. We define four categories. **Formal** instruction occurs in traditional classrooms, online courses, or other structured environments with clear objectives [19, 38, 75]. **Informal** learning takes place in unstructured environments without set goals, such

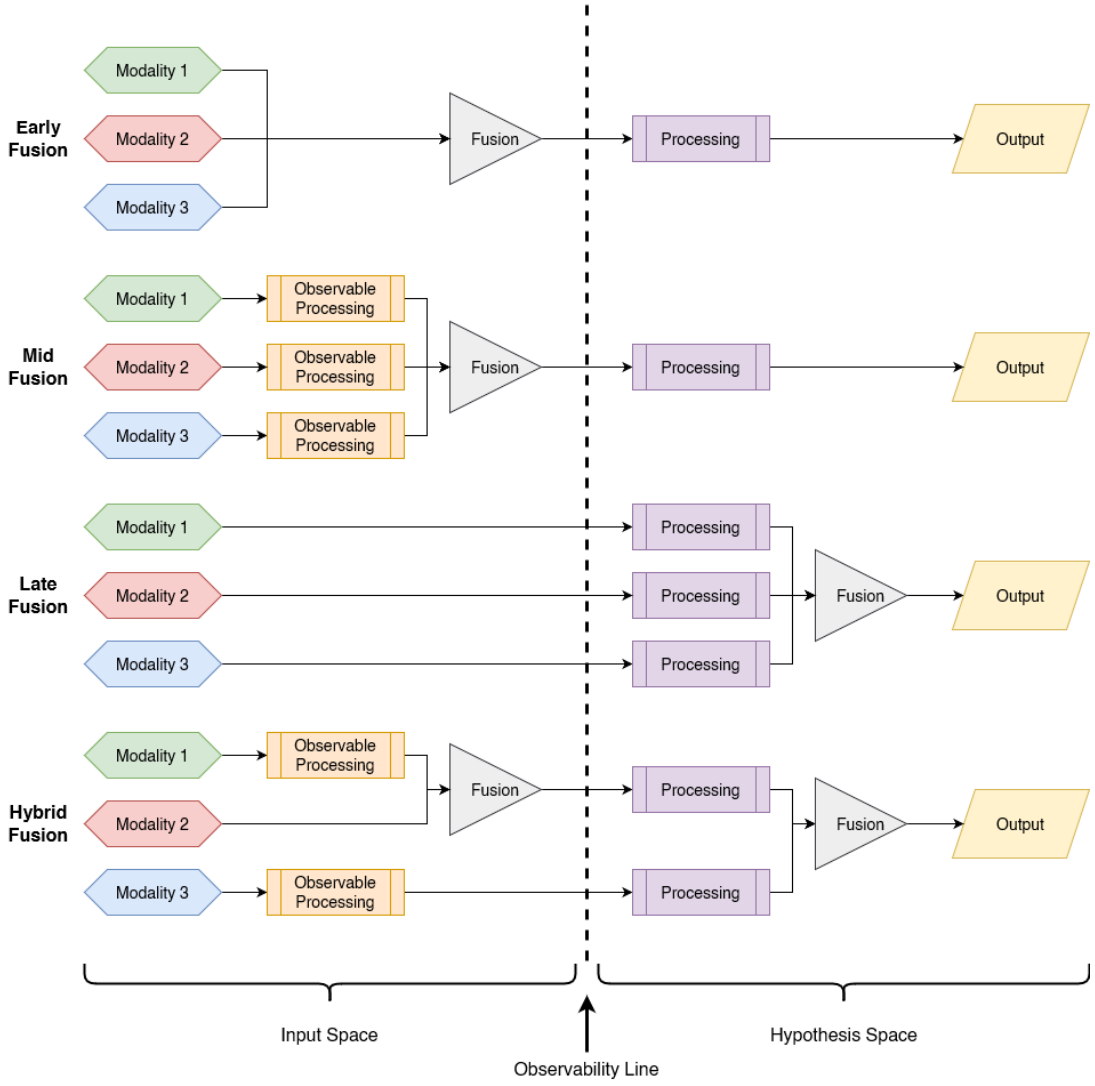



Fig. 3. Multimodal data fusion scheme according to when fusion is performed relative to the observability line.

as using Minecraft to support diverse learners [27, 54, 112, 159]. **Training** focuses on skill development, practical training, and professional development in specific fields [57, 95, 99]. The **Unspecified** category includes papers that lack sufficient information about the didactic nature of their studies [48].

*2.2.10 Level of Instruction or Training.* We sought to delineate the level of participants' instruction or training, defining four categories to provide valuable insights into the educational contexts targeted by the analyses in our corpus. **K-12** participants are those in kindergarten through $12^{th}$ grade [55, 110, 155]. **University** participants include undergraduate and graduate students [38, 65, 98]. **Professional Development** participants are involved in professional development training [49, 51, 119]. The **Unspecified** category refers to papers that lack information about the participants' level

of instruction or training [19, 43, 92]. It is important to note that studies featuring multiple groups of participants, or those reporting results across various studies, may have been assigned multiple labels.

*2.2.11 Analysis Approach.* Our systematic categorization of analysis methodologies identified two principal approaches: **Model-based** and **Model-free**. Model-based analysis employs a formal model to reveal the data's intrinsic structure and the interrelationships between variables. This approach involves hypothesizing about data structure and variable connections, often using mathematical functions to delineate the relationships in machine learning, or computational models to simulate system dynamics in cyber-physical systems. Conversely, model-free analysis eschews these assumptions, relying instead on empirical statistics (like correlations) to discern patterns and relationships directly from the data. It is important to note that these categorizations are not exclusive; a study may be classified as both model-based and model-free if it incorporates both types of approaches.

## 3 METHODS

This section outlines the methodology we employed to compile our literature corpus and ensure comprehensive coverage of pertinent research. We utilized a combination of quantitative (graph-based) and qualitative (quality control) techniques to refine our corpus to a representative yet manageable size. We introduce a novel graph-based method for literature corpus reduction, termed *citation graph pruning* (CGP) that is detailed in Section 3.2.1. CGP employs a directed citation graph that considers each paper's citation network to identify and exclude outlier papers with minimal connections to the corpus, thus deemed beyond the review's scope. This graph-based pruning method is a unique contribution to literature review methodologies and has not been previously reported. Additionally, our quality control process, elaborated in Section 3.2.2, is derived from Kitchenham's systematic review procedures [77]. For an exhaustive description of our search strategy, corpus distillation, and feature extraction methods, refer to Appendix B.

### 3.1 Literature Search

Our literature search employed 42 search strings, collaboratively developed by the authors to encapsulate the relevant work for this review. We generated 14 search phrases, each queried thrice with variations of *multimodal* (multimodal, multi-modal, multi modal), detailed in Appendix B. Searches were conducted programmatically using Google Scholar via SerpAPI [129], chosen for its accurate retrieval of organic search results. For each search string, we selected the top five pages (100 publications) as ranked by Google Scholar, resulting in 4,200 papers. After removing 2,079 duplicates through hashing, and excluding 1 non-English paper, we obtained 2,120 unique papers.

### 3.2 Study Selection

After the initial search, we distilled the corpus quantitatively via citation graph pruning, which we discuss in Section 3.2.1. Subsequent distillation, performed qualitatively, is discussed in Section 3.2.2.

*3.2.1 Citation Graph Pruning (Quantitative Corpus Reduction).* For visualization and analysis, we used NetworkX to construct a *citation graph* from the initial 2,120 papers. This graph, a directed acyclic graph (DAG), features nodes representing papers identified by their Google Scholar UUID and directed edges denoting citations, i.e., paper A cites paper B. The degree of a node (paper) $p$ is defined as the sum of incoming and outgoing edges, representing papers citing and cited by $p$, respectively. SerpAPI was utilized to retrieve the citation lists.

We first eliminated all 0-degree nodes, assuming their irrelevance to the field or lack of influence on subsequent research. Further analysis of the DAG's structure revealed one major component with 1,531 papers and 44 smaller,

disconnected components (sizes 2-5), detailed in Appendix B.2.1. The disconnected components were then removed. Subsequent pruning involved iteratively removing 1-degree nodes until no new 1-degree nodes emerged, a process we term *citation graph pruning*, outlined in Algorithm 1. This pruning reduced the corpus to 1,063 papers.

**Algorithm 1** Citation Graph Pruning Algorithm

**Require:** Acyclic directed graph $G = (V, E)$

**procedure** DEGREE TRIMMING($G, n$)
  $S, D \leftarrow \{\}, \{\}$
  **for all** $v \in V$ **do**
    **if** $\deg(v) <= n$ **then** $S = S \cup \{v\}$
  **for all** $v \in S$ **do**
    **for all** $e \in E$ **do**
      **if** $v \in e \wedge e \notin D$ **then** $D = D \cup \{e\}$
  **return** $(V \setminus S, E \setminus D)$
**procedure** SUBCONNECTED GRAPH TRIMMING($G$)
  $[S_1, S_2, S_3, ..., S_n]$ = ConnectedComponent($G$), where each $S_i = (V_i, E_i)$
  $j = \arg\max\{|V_1|, |V_2|, |V_3|, ..., |V_n|\}$
  **return** $(V_j, E_j)$
**procedure** ITERATIVE TRIMMING($G$)
  **while** True **do**
    $G'$ = DegreeTrimming($G, 1$), where $G' = (V', E')$
    **if** $|V| == |V'|$ **then**
      **break**
  **return** $(V', E')$
$G'$ = DegreeTrimming($G, 0$) ▷ Remove 0-deg vertices
$G'$ = SubconnectedGraphTrimming($G'$) ▷ Keep largest connected subgraph
$G'$ = IterativeTrimming($G'$) ▷ Iteratively remove 1-deg vertices until equilibrium
**return** $G'$

*3.2.2 Quality Control (Qualitative Corpus Reduction).* Upon manually reviewing the 1,063 titles post-pruning, we found many papers irrelevant to our review's focus, such as those on training multimodal neural networks and applying multimodal methods in medical imaging. Using regex keyword searches (specified in Appendix B.2.2), we identified 217 titles for potential exclusion. After careful consideration, we removed 204 papers, retaining 13 for further evaluation, thus narrowing our corpus to 859 works. Consistent with Kitchenham's guidelines [77], we refined our corpus by sequentially reviewing titles, abstracts, and full texts, applying majority voting for exclusions, as detailed in Appendix B.2.2. This process reduced our corpus to 388 from title evaluation, 127 from abstracts, and 75 from full-text assessments. Subsequent feature extraction led to the exclusion of two additional papers deemed outside our review's scope, culminating in a final corpus of 73 papers.

### 3.3 Feature Extraction

Once the corpus was finalized, we extracted several features from each of the 73 papers. This included identifying information (e.g., title, authors, publication year), and information related to the paper's methods (e.g., data collection medium, modalities, and analysis methods). Specifically, we extracted the following features from each paper (as outlined in Section 2.2): UUID, title, authors, publication year, environment type, data collection mediums, modalities, analysis

methods, fusion types, publication, environment settings, domains of study, participant interaction structures, didactic natures, levels of instruction, and analysis approaches. We detail our feature extraction scheme and each feature's set of values in Appendix B.3.

### 3.4 Analysis Procedure

Leveraging our Figure 1 framework, we conducted a qualitative thematic analysis on the extracted features from our corpus. This yielded descriptive statistics and identified dominant trends for each framework component. We classified multimodal data into five comprehensive modality groups: (1) *natural language*, (2) *vision*, (3) *sensors*, (4) *human-centered*, and (5) *logs*. For each group and the entire corpus, we explored the state-of-the-art, challenges, research gaps, and outcomes of multimodal learning and training analyses. Furthermore, we distilled multimodal learning and training research into three distinct research types, termed *archetypes*. Our thematic findings for each framework component are detailed in Section 4, the archetypes in Section 5, and a comprehensive discussion of the corpus and field in Section 6.

## 4 FRAMEWORK INSIGHTS

We present our findings for the individual components in the Figure 1 framework (i.e., environment, multimodal data, data fusion, analysis, and feedback) in the subsections that follow. For reference, terminology definitions are enumerated in Section 2.2.

### 4.1 Environments

We investigate learning and training environments for the three components specified in our framework, i.e., setting, learners/trainees, and data. Setting refers to the environment where the learning and training occur, learners and trainers refer to the environment participants, and sensors refers to the data collection mediums used in the environment.

*4.1.1 Setting.* In Section 2.2.6, we categorized environments into four types: virtual, physical, blended, and unspecified. Our corpus revealed that virtual environments were predominant. We attribute this trend to the increasing reliance on online platforms for educational engagement, a phenomenon that the COVID-19 pandemic likely accelerated (evidenced by a spike in our corpus's use of virtual environments in 2020). We initially hypothesized that recent technological advances may have engendered a rise in virtual multimodal learning and training; however, a temporal analysis of our corpus' use of environment settings did not support this. 51/73 papers (70%) incorporated at least some virtual component (i.e., used either virtual or blended environments), which suggests most multimodal learning and training research relies, at least in part, on virtual environments to collect and analyze data [6, 138, 143]. In addition, we consider the distribution of learning versus training environments, as described in Section 2.2.1. There were more than three times as many learning environments papers (57/73; 78%) [38, 54, 74] relative to training environments papers (16/73; 22%) [51, 53, 95]. This imbalance underscores the focus of educational literature on knowledge acquisition. In contrast, the lower frequency of training settings reflects a narrower scope centered on skill enhancement and professional development. Notably, environments emphasizing physical activity were largely absent from our corpus. This includes environments focusing on activities like rehabilitative therapy and athletic training, as well as *embodied learning* [141] environments that require students to physically engage in the learning activity.

*4.1.2 Learners/Trainees.* This review examines key elements of the learner's domain, including the domain of study, participant interaction structure, didactic nature, and level of instruction or training. These elements collectively contribute to a comprehensive understanding of the learner's experience and the educational context. Our corpus

predominantly focuses on STEM+C domains of study (55/73; 75%) [20, 57], with humanities (11/73; 15%) [107, 115] and psychomotor skills (5/73; 7%) [65, 98] being less represented. Four papers did not specify the domain of study, and two addressed domains outside of STEM+C, humanities, and psychomotor skills. This distribution suggests a significant emphasis on STEM+C education, reflecting global trends toward these disciplines' importance in technology-driven societies and their relevance to the job market and societal advancement.

Individual-focused learning and training environments are the most prevalent participant interaction structure (45/73; 62%) [9, 139], compared to multi-person environments that are present in 31 (42%) papers [53, 110]. This indicates most studies focus on individual learning and training experiences that allow for personalized and self-paced progress. However, the notable presence of multi-person settings underscores the importance of collaborative and social learning environments in educational research. The didactic nature of environments is predominantly formal and pedagogical (45/73; 62%) [86, 91, 144], followed by training (15/73; 21%) [53, 93, 106] and informal learning (12/73; 16%) [27, 65, 159]. This suggests that formal instruction is the predominant mode, with a smaller yet notable focus on training and informal learning, often including more interactive, practical, or workplace-based scenarios. University-level instruction is the most common (36/73; 49%) [21, 105], followed closely by K-12 environments (30/73; 41%) [82, 101]. Professional-level learning is less frequent (5/73; 7%) [51, 105]. The prominence of university-level participants reflects the research emphasis and academic focus of higher education, while the strong representation of K-12 participants indicates ongoing interest in foundational education practices. The underrepresentation of professional settings suggests a research gap in lifelong learning and continuing education.

The data on learner characteristics in our corpus highlights a landscape where STEM education is prioritized, individual learning experiences are valued, formal instruction is the standard, and university and K-12 education levels are emphasized. However, the presence of other educational levels and informal learning contexts indicates that there exists a diverse range of learning experiences and instructional approaches. This diversity presents both challenges and opportunities for educators and researchers, emphasizing the need to tailor educational strategies to various learning environments and address the unique requirements of different learner demographics.

*4.1.3 Data Collection Mediums.* Figure 4 presents the distribution of the various data collection mediums used by the papers in our literature corpus. As depicted, the current state-of-the-art in data collection mediums reflects a diverse array of technologies and methodologies, with video leading (61/73; 84%) [117, 157], followed by audio (37/73; 51%) [23, 154]. These two mediums indicate a preference for rich multimedia data that can capture the complexities of learning and training, as well as interactions within the environments. Logs (33/73; 45%) [65, 110] and participant-produced artifacts (30/73; 41%) [8, 80] are also popular, suggesting a strong inclination toward capturing learner behaviors and outputs directly from both the environments and the participants themselves.

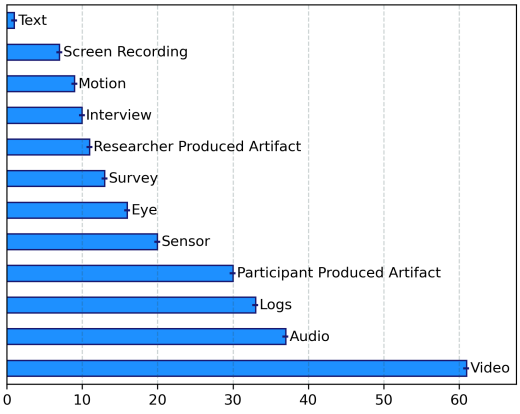


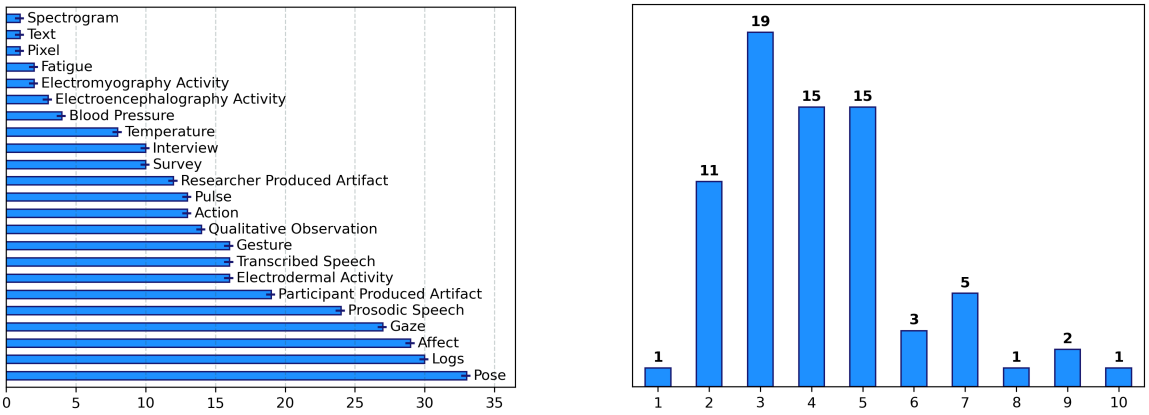

Fig. 4. Data collection mediums distribution. The x-axis refers to the number of corpus papers.

Despite these advances, the field faces challenges in integrating data from disparate sources and ensuring data quality and privacy. For instance, sensor data (20/73; 27%) [87, 148]

presents challenges in standardization and interpretation. Although less prevalent, eye-tracking and motion capture data raise concerns about intrusiveness and the need for sophisticated analysis techniques. There is also a notable gap in text-based data collection (only one paper [159] in the corpus), as learning and training environment research currently relies primarily on transcribed speech.

### 4.2 Multimodal Data

Figure 5 breaks down the different modalities used in our corpus.




(a) Frequency counts for the number of papers in our corpus containing each modality.

(b) The number of modalities used per paper, i.e., how many papers (y-axis) used $n$ modalities (x-axis).

Fig. 5. A breakdown of the individual modalities used in our corpus both in terms of frequency count (left) and the number of modalities used per paper (right).

"Pose" is the most prevalent modality, appearing in some form in roughly 45% of papers (33/73) [51, 93, 107]. Logs, affect, gaze, and prosodic speech modalities are also common. At least one of the top five modalities appears in all but eight papers in our corpus (65/73; 89%). The remaining modalities appear less frequently, with raw text, raw pixel value, and audio spectrogram only appearing in one paper each. A large majority of papers (60/73; 82%) use 2-5 modalities in their multimodal analyses. One paper used only a single modality[1], and one paper used 10 modalities. We hypothesize that researchers typically choose between 2-5 as a compromise between overhead and informativeness, but more research is required to evaluate this quantitatively.

Diving deeper into the multimodal data, we identified five modality groups that best characterize the types of data driving multimodal learning and training methods: natural language, vision, sensors, human-centered, and logs. The following subsections present our findings with respect to each modality group. For each modality group, we identify the individual modalities it comprises and discuss our findings with respect to its prevalence in the corpus, current state-of-the-art, challenges faced, research gaps, and results achieved.

*4.2.1 Natural Language.* 35 out of the 73 (48%) corpus papers collected and analyzed some form of natural language data. The natural language modality group comprises prosodic speech (24/73; 33%), transcribed speech (16/73; 22%), raw

[1]By our definition of "multimodal" in Section 1.3, we consider a paper to be multimodal if multiple modalities are used during analysis *or* multiple data collection mediums are used. One paper [27] collected both video and audio data, from which the authors derived a single modality: researcher-produced artifacts. For this reason, there is one paper in our corpus that uses only one modality in its analysis pipeline, still adhering to our multimodal definition.

text (1/73), audio spectogram (1/73), and affect (when derived from text or audio; 2/73). All but three natural language papers included prosodic or transcribed speech, but only eight papers incorporated both. Because prosodic speech is devoid of semantic meaning, and transcribed speech lacks important prosodic information, combining the two provides a more holistic language representation. However, research combining the two modalities was not well-represented in our corpus and represents a notable research gap.

Traditional machine learning methods were the most prevalent quantitative approaches in the natural language modality group. In particular, support vector machines [90, 115, 137] and logistic regression models [43, 85, 114] were often used with natural language features. Other approaches like random forest [101], linear regression [136], and naive Bayes [137] were also used, typically to predict outcomes such as learning or training gains. There was a noticeable lack of deep learning approaches for natural language processing (NLP) in our corpus. While some papers incorporated recurrent neural networks (e.g., LSTM models [70]), these were a relative rarity. Very few used transformer [150] models like BERT [47], which was surprising given their prevalence in contemporary NLP. This indicates that the multimodal methods for learning and training environments using natural language lag behind the current state-of-the-art in NLP [149]. However, this is likely in large part due to the small sample sizes and noisy data innate to learning and training environments that are insufficient to train many deep learning models, which we discuss in Section 6.

Education- and training-specific datasets are often small, imbalanced, and contain domain-specific terminology that language models may not have encountered frequently during training [29, 30, 85, 86, 114]. These issues complicate the effective training of deep learning models [9, 28, 32, 114, 139]. Additional challenges include the complexity and time cost of cleaning, processing, and labeling data. Software packages like NLTK [88], openSMILE [56], and TAACO [40, 41] facilitate the programmatic extraction of audio- and text-based features, yet this can result in large, opaque feature sets [119]. Conversely, manual preprocessing and feature engineering can be time-intensive, potentially limiting the data researchers are willing to collect and analyze [79, 85]. This helps explain why qualitative analysis of smaller sample sizes is common in natural language studies.

Qualitative analyses using natural language primarily involve presenting descriptive statistics, case studies, and researchers' observations, and conducting various forms of qualitative coding [53, 92, 107]. Many natural language studies focus on collaborative learning and training [89, 110, 136], favoring multi-person environments to leverage the richness of collaborative discourse. However, analyzing transcribed speech poses challenges. Several studies noted that automatic speech recognition (ASR) is a bottleneck in multimodal pipelines using transcribed speech [79, 136, 159]. Learning environments often consist of multiple groups participating simultaneously, creating noisy conditions that hinder ASR accuracy, particularly in K-12 settings [79] and among non-English speakers [159].

Only one paper in the corpus used raw text as input [159], which is surprising given the prevalence of text-based transformer models [17, 47, 122]. Considering the capabilities of large language models (LLMs), text-based features could significantly enhance multimodal learning and training pipelines, as raw text quality does not depend on ASR. One potential avenue for leveraging textual features is through conversational agents, which were notably absent in our corpus. While several works addressed multimodal agents or tutors [43, 86, 143], these agents typically provided summative performance metrics or canned responses. No studies addressed conversational agents that engage dynamically with learners as peers, mentors, or collaborators.

Despite these gaps and challenges, natural language features consistently produced positive outcomes. Researchers successfully correlated and predicted various learning outcomes using these features. This was especially evident in studies focusing on collaborative learning and training, where the collaborative environments provided discourse rich in natural language features. Collaboration was examined both as an independent and dependent variable [136, 137, 158].

In collaborative settings, natural language features frequently were the most informative among all modalities [85]. Additionally, natural language features were usually the most predictive when combined with features derived from other modalities. This reinforces previous work, where multimodal data harnessed more predictive power than any individual modality [131]. Researchers often reported that including natural language features in the multimodal pipeline led to improved predictive performance [110]. Overall, the results reported in our corpus clearly indicate that natural language features have: 1) high correlations with performance outcomes, and 2) provide enhanced predictive capabilities when combined with features derived from other modalities.

*4.2.2 Vision.* Among the five groups of modalities analyzed, vision-based modalities were the most utilized, appearing in 59 out of 73 papers (81%). The vision modality group includes papers that collected data using cameras or eye-tracking devices and analyzed it for pose recognition, affect detection, gesture recognition, activity recognition, fatigue estimation, participant gaze, or raw image pixel data. Pose, affect, and gaze were the most common, present in 33 (56%), 25 (42%), and 27 (46%) of the 59 papers, respectively. Gesture recognition appeared in 16 papers (27%), activity recognition in 11 papers (19%), and fatigue estimation and raw pixel data in 2 and 1 papers, respectively.

This distribution is expected. Pose recognition was the most frequent due to the availability of off-the-shelf deep learning models and the use of Microsoft Kinect cameras, which facilitate pose data collection. Gaze tracking was common with specialized hardware like eye-tracking glasses. Affect recognition was also prevalent, again supported by off-the-shelf models. Notably, raw pixel data was the least used, appearing in only one paper. Researchers typically processed raw images using other models before analysis, highlighting the importance of mid-fusion techniques. This pattern reveals a mismatch between core and applied computer vision research, with the latter relying on pre-trained models due to smaller datasets.

In terms of analysis methods, there was a slight preference for quantitative techniques in the vision subset, with 69% of papers using model-based methods compared to 63% in the full corpus. Despite this, many papers combining qualitative and quantitative analysis also used vision data. Only 24% of the vision papers employed mixed-methods analysis, often combining classification with the qualitative analysis of classes.

*4.2.3 Sensors.* We identified 20 papers (27%) in sensor-based learning and training research, covering various physiological and behavioral data modalities. These papers focused on affective responses (11/73; 15%), body pose analysis (7/73; 10%), electrodermal activity (16/73; 22%), pulse rate (11/73; 15%), activity (5/73; 7%), blood pressure (4/73; 5%), temperature (8/73; 11%), electroencephalography (3/73; 4%), electromyography (2/73; 3%), fatigue (2/73; 3%), and gaze tracking (8/73; 11%).

Of these 20 papers, 12 were learning-based, and 8 were training-based. This suggests sensors are more frequently used in training-based research, which represents only 22% (16/73) of the full corpus but 40% of papers using sensors. Within MMLA, wearable sensors monitor learners' emotional and physiological states, predict behavior and performance, provide real-time feedback, and enable multimodal data integration [53, 69, 148]. Sensor use ranges from classroom environments to specialized training scenarios (e.g., CPR instruction [51]), serving as assessment tools and mechanisms for real-time educational interventions. However, integrating and interpreting sensor data presents challenges, particularly for accurate and practical real-time applications [49, 132].

The state-of-the-art in sensor-driven multimodal learning and training analytics features advanced predictive modeling, real-time feedback systems, and multimodal data fusion. However, there is a need for more granular data analysis to identify subtle patterns and correlations not apparent through traditional methods. Contextual and behavioral analytics link physiological responses to specific learning activities in real-time. Signal processing methods aggregate

sensory information into physical or learning characteristics, such as relative learning gains [148], team dynamics [53], and shared physiological arousal [102]. The field also requires robust, interactive visualizations that convey complex sensory data intuitively, and Explainable AI (XAI) methods to clarify how sensor data contributes to predictive models, enhancing interpretability [125, 127].

There is a noticeable gap in longitudinal studies to assess the sustained impacts of sensor-based technologies. Expanding sensor research to diverse learning contexts and demographics will help us understand its broader applications. Sensor research often occurs in controlled environments, so scaling for widespread use and ensuring generalizability across diverse settings remains challenging. One example is Echeverria et al.'s study [53] using accelerometer data in nurse training simulations, which could benefit from integrating additional sensory inputs (e.g., gyroscope) to conduct multidimensional analyses. Investigating user experience and acceptance of wearable technologies in education, particularly regarding comfort, usability, perceived effectiveness, and privacy, is also needed.

*4.2.4 Human-Centered.* Human-centered modalities (qualitative observation, interview, survey, researcher-produced artifacts, and participant-produced artifacts) offer insights into participants' experiences, perceptions, and behaviors, often identifying nuances that quantitative analyses overlook. Out of 73 papers, 45 (62%) incorporate at least one human-centered modality, indicating a strong focus on human experiences. Participant-produced artifacts are the most common (19/73, 26%), followed by qualitative observation (14/73, 19%), researcher-produced artifacts (14/73, 16%), and both interview notes and survey responses (10/73, 14%). Participant artifacts often include diverse materials, with pre- and post-tests being the most prevalent for calculating learning gains [54, 123, 157]. The considerable use of qualitative observations highlights the importance of insights gained through direct human interpretation of behaviors. Common combinations include qualitative observations and participant artifacts [85, 86, 157, 158], participant artifacts and researcher artifacts [38, 123, 137, 140], and interview notes and qualitative observations [9, 74, 105, 158]. One study applied clustering, NLP, and linear modeling to researcher artifacts detailing student behaviors [27].

A predominant strategy involves transforming human-centered modalities into quantifiable data for statistical analysis. Examples include López et al. using survey data [89], Ochoa and Dominguez using participant-produced artifacts [106], and Bert et al. using both participant-produced artifacts and interview transcriptions [11]. This shows a preference for quantifiable insights from human-centered modalities. Fourteen papers focus on qualitative analysis, emphasizing rich, qualitative insights. Most papers adopt multiple analysis methods, with only 16/45 using one method exclusively, 15/45 integrating two methods, and 13/45 using three. Worsley and Blikstein [158] employ four analysis methods to identify correlations between multimodal data, experimental condition, design quality, and learning, using both human-annotated and automatically annotated data.

Human-centered approaches pose challenges related to subjectivity, scalability, resource intensiveness, and generalizability. The subjectivity of human-centered modalities introduces biases [97, 103]. These approaches are resource-intensive, requiring trained researchers for data collection, coding, and analysis. Manual collection and analysis can be time-consuming and often does not scale well, especially in large-scale educational settings. Despite these challenges, human-centered approaches offer transparent and interpretable insights. These insights highlight gaps in integrating qualitative and quantitative methods. Developing methodologies that combine qualitative nuance with quantitative rigor is essential. The lack of standardized coding practices for human-centered modalities hampers replicability and comparability. Establishing standardized coding frameworks is crucial to enhance the reliability and credibility of machine learning analyses. Additionally, automating human-coding processes is a vital research need.

*4.2.5 Logs.* Thirty papers (40%) incorporated log data (log-analysis papers). Logs, often from computer-based environments, link complementary modalities to learning outcomes and behaviors. Logs are frequently combined with video (25/30, 83%), eye-tracking (12/30, 40%), audio (12/30, 40%), participant-produced artifacts (11/30, 36%), survey responses (6/30, 27%), sensors (8/30, 26%), and motion (3/30, 10%). This highlights the diverse ways environmental logs are contextualized. Human-centered artifacts were less commonly combined with log data. Overall, log-analysis papers focus on computer-based learning environments and individualized instructional or informal activities.

The state-of-the-art in log-analysis features various approaches. Nearly all classification and regression papers used machine learning algorithms, such as support vector machine, random forest, naive Bayes, and logistic regression [62, 91, 162], to predict students' achievement, engagement, or emotional state. Deep learning approaches like CNNs [137] and LSTMs [98, 110] were used in only three papers. Statistical methods were used to correlate learning variables (e.g., perceived student emotion) to outcome variables (e.g., learning gains).

Analyzing logs presents hurdles, including time-cost, data scarcity, generalizability, and engineering expenses. Temporal aspects introduce difficulties, such as aligning time frames, handling different sampling rates, and managing time-series data. These complexities often result in smaller datasets, limiting scope and scalability. Data scarcity exacerbates the challenge of producing generalizable findings, while high software development and engineering costs hinder integrating modern features like real-time collaboration tools.

These challenges create gaps in log-analysis research. There is a deficiency in applying methods and findings from one educational setting to another, likely due to diverse educational contexts. Embracing standardized log formats and consistent practices would help overcome this barrier, leading to more unified research approaches and broader applicability of insights. The low adoption rate of industry standards like xAPI [135], LTI [1], and Learning Management Systems (LMS) in educational technology research reflects a broader issue of aligning with best practices. Addressing these gaps and embracing these standards could enhance interoperability, scalability, and more robust analysis of educational data, paving the way for more impactful and transformative educational research and practices.

### 4.3 Data Fusion

The choice between different types of fusion depends on the characteristics of the data, the nature of the environmental task, and the desired level of integration, and we observed multiple approaches to data fusion in our corpus. Each fusion strategy has strengths and limitations, and researchers often select the most suitable approach based on the specific requirements of their study and research goals. One noteworthy observation in this corpus is that several papers do not explicitly explain or justify their fusion choices.

Figure 6 shows the distribution of fusion types across the 73 papers in the corpus. 54 (74%) perform early, mid, late, or hybrid fusion. The distribution of fusion types reveals that mid fusion is the most prevalent (27/73; 37%), showcasing its popularity for integrating modalities by combining derived, observable features. Hybrid fusion follows closely with 19 papers (26%), utilizing a combination of early, mid and/or late fusion strategies. Early fusion is observed only in 3 papers, while late fusion is employed in 8 papers. 20 papers (27%) adopt other types of fusion strategies, no fusion, or do not explicitly mention data fusion. For reference, Figure 3 illustrates the differences between fusion types.

*4.3.1 Early Fusion.* In early fusion, the joint feature representation incorporates information from all fused modalities, enabling the model to learn relationships and patterns directly from the raw, integrated features. This approach is advantageous when the modalities offer complementary information. In our corpus, early fusion was utilized in less than 5% of the papers and is not always suitable, as it is not always clear what features are the most important until

after processing and analyzing them. Further, early fusion is often computationally prohibitive, as the dimensionality of raw data is typically higher than that of its processed output.

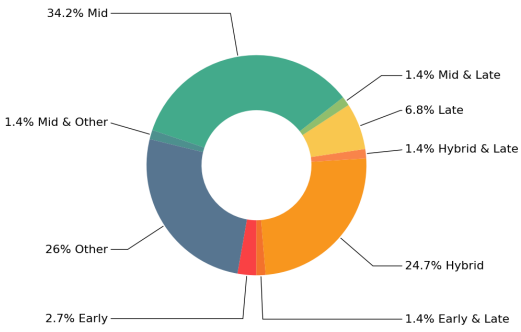



Fig. 6. Distribution of Fusion Types

*4.3.2 Mid Fusion.* Mid fusion combines features derived after prior processing but within the observable input space. It is advantageous when individual modalities require unique processing and combining feature-level decisions is more effective than integrating raw features. 27/73 papers (37%) used mid-fusion, suggesting mid fusion is more suitable for addressing the challenges and objectives of multimodal learning and training relative to early fusion.

*4.3.3 Late Fusion.* In late fusion, modalities are processed independently until the hypothesis (decision) space, where their outputs are aggregated to make overall inferences. This approach is suitable when modalities are semantically more independent, and their contributions are better understood when combined at a later stage. In our corpus, 8 papers (11%) employed late fusion, with 3 of them also employing other types of fusion [20, 21, 142]. Most papers used late fusion for classification purposes (one used regression [117]).

*4.3.4 Hybrid Fusion.* Hybrid fusion integrates information at different stages of the analysis pipeline, and its design varies based on the learning or training task, analysis goals, and data characteristics. Hybrid fusion was employed in 19 out of the 54 (35%) papers that performed fusion, highlighting the significance of this approach. Most papers (14/19; 74%) incorporated at least 4 modalities. Classification was the predominant analysis method (15/19; 79%).

### 4.4 Analysis

We defined analysis approaches as either model-based or model-free (see Section 2.2.11), depending on each paper's data, research questions, and analysis methods. Model-based methods rely on assumptions about data and system operations, while model-free methods demand careful attention to data quality and reliability. While these methodologies differ and are often associated with distinct research communities, they are best used together to complement each other's strengths and weaknesses.

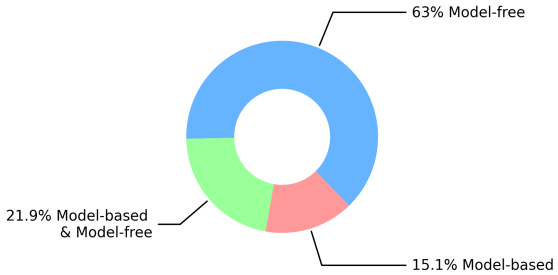



Fig. 7. Analysis approaches percentage distribution.

As shown in Figure 7, 46 corpus papers (63%) used model-based methods, 16 papers (22%) employed model-free methods, and 11 papers (15%) opted for both. This distribution, with 78% (57/73) of papers employing model-based analysis, indicates a strong preference for developing models to inform analysis processes. Conversely, model-free approaches, which make up 37% (27/73) of papers, offer a valuable alternative for investigating learning and training outcomes in a more exploratory manner.

*4.4.1 Model-Based.* Model-based methodologies, such as machine learning models, employ mathematical frameworks to generate results from given inputs. Among papers using only model-based approaches, common analysis methods include classification (34/46; 74%), statistical analysis (17/46; 37%), regression (8/46; 17%), and clustering (7/46; 15%). These methods train models using data samples to predict output variables (e.g., learning outcomes). When qualitative and pattern recognition techniques use model outputs to guide their analysis, they are also considered model-based. A notable aspect of model-based approaches is their focus on individual experiences (31/46; 67%) over collaborative ones (17/46; 37%), likely due to the complexities of mathematically representing intricate social interactions in group settings. Modeling an individual's cognitive, behavioral, and emotional states is challenging; thus, accurately reflecting collaborative dynamics in models is mostly confined to a niche within MMLA and social network analysis.

*4.4.2 Model-Free.* Model-free methods adopt a comprehensive, exploratory strategy, focusing on relationships between variables without assuming a specific link between input and output. Predominantly, these involve qualitative (11/16; 69%), statistical (9/16; 56%), and pattern recognition (3/16; 19%) methods. Qualitative methods are used in scenarios like use case and interaction analysis, where observations and learning theories guide the understanding of learning processes. Statistical and pattern recognition methods provide descriptions and correlation metrics between learning activities (e.g., behaviors and strategies) and outcomes. Serving as a counterbalance to the limitations of model-based methods, model-free approaches are widely used in collaborative settings. They are instrumental in dissecting social signals and provide insights into the dynamics of collaboration, including group health and communication.

### 4.5 Feedback

This review focuses on MMLA analysis methods, with feedback being a significant yet secondary aspect of the MMLA framework. Feedback in multimodal learning analytics is a bidirectional process essential for completing the analysis cycle, categorized as either *direct* or *indirect*. Direct feedback involves learners or system users and aims to enhance user performance or other metrics. Indirect feedback represents feedback not intended for the end user (e.g., feedback that improves system design).

Direct feedback can take two forms. One form is the prototypical feedback in the context of a learning or training environment for improving the user's performance. Although an exhaustive review of direct feedback literature is outside this paper's scope, seminal works by Hattie & Timperley [68] and Adarkwah [3] provide foundational insights. Users also contribute to MMLA in many forms by offering feedback, integral to user-centered design [2]. Conversely, indirect feedback does not involve the end user but informs system improvement or research findings. It arises from observing user-system interactions or studying learner behavior, leading to enhanced system design or theoretical understanding. Improved research conclusions occur when the study of learners and trainees in these environments leads to new understandings of the subjects and their populations. Such feedback is vital for advancing MMLA research.

## 5 ARCHETYPES

Following the analysis in Section 4, we reexamined our corpus to classify prevailing research objectives in applying multimodal methods to learning and training environments. We identified three primary research objectives, termed *archetypes*: *Designing and Developing Methods*, *Analyzing Outcomes*, and *Exploring Behaviors*. These archetypes, detailed in subsequent subsections, often overlap within studies; for example, method development research may also yield insights into participant behaviors and outcomes. While these archetypes broadly define the field, they are not exhaustive, and some studies may not align precisely with these categories.

### 5.1 Designing and Developing Methods

The Designing and Developing Methods archetype encompasses studies that focus on designing, presenting, and evaluating multimodal research methods that can be applied to learning and training environments. These studies prioritize methodological innovation over the derivation of generalizable findings about a population. Although the developed methods often aim to predict outcomes (Section 5.2) and discern behaviors (Section 5.3), the primary focus remains on the method itself, not the implications of its findings on the study participants. These methods are typically quantitative, utilizing supervised learning techniques such as classification [54, 98, 132] and regression [55, 110, 117], and their efficacy is reported through performance metrics like F1-score [5, 10, 162]. Data collection often involves video, audio, and log data [85, 89, 139]; targeting modalities such as affect, pose, prosodic speech, and logs [120, 139, 143]; employing data fusion techniques like mid or hybrid fusion [18, 48, 95] using model-based approaches [55, 98, 117].

Our corpus reveals a broad spectrum of tasks addressed by Designing and Developing Methods research, ranging from personalized feedback in CPR training [98] to engagement detection in educational games [120], and skill classification in sports [95]. The versatility of multimodal methods is evident in the diverse settings, domains, instructional levels, and didactic approaches, without a dominant trend in any specific area.

However, a notable gap in the corpus is the limited focus on evaluating the impact of these methods on end users (stakeholders) and the lack of stakeholder involvement in the method development process. While methods for tasks like feedback generation [49, 51, 107] and engagement detection [5, 18, 120] are presented, their practical effectiveness in enhancing learning outcomes and engagement is seldom empirically validated. Furthermore, the integration of stakeholder feedback into the development of methods is rare, which can lead to a disconnect between the objectives of researchers and the needs of practitioners [14]. This aspect will be further discussed in Section 6. Although some studies in our corpus do consider stakeholder impact [9, 107, 143], such instances are infrequent and not representative of the corpus as a whole.

### 5.2 Analyzing Outcomes

The Analyzing Outcomes archetype focuses on specific outcome metrics, such as learning gains, engagement levels, and accuracy rates. The goal is to uncover findings that apply to broader populations, distinguishing it from the Designing and Developing Methods archetype, which focuses on refining analytical techniques. Outcome analysis typically employs supervised learning methods like classification [19, 83, 98] and regression [55, 117, 143], along with insights from model behaviors, statistical patterns, and unsupervised methods [65, 85, 132].

Outcome analysis has been applied across various learning and training contexts, focusing on constructs like attention and engagement [9, 55, 142], task performance and accuracy [10, 43, 95], learning outcomes [21, 49, 148], and collaborative outcomes [90, 137, 157]. Despite diverse environments, common outcome variables provide generalizable insights. However, this archetype has limitations. Focusing on outcome variables often overlooks the complexities of learning processes, risking interventions tailored to high-performing learners and neglecting individual differences [59]. Additionally, like the Designing and Developing Methods archetype, these studies often exclude stakeholder perspectives, potentially leading to biased conclusions.

### 5.3 Exploring Behaviors

The Exploring Behaviors archetype investigates human behavior and experiences in learning and training contexts by employing an exploratory approach to uncover influencing factors. This research examines a variety of human signals

that vary temporally, socially, and spatially, and are tailored to specific learning objectives. Unlike other archetypes, it often incorporates qualitative observations [27, 74, 81, 82], and employs data exploration techniques like correlation analysis [89, 104] and pattern recognition [6, 38, 102, 123]. Data fusion in this context is typically qualitative [11, 75, 159], involving the manual integration of multimodal data sources. This approach enables triangulation of student and trainee behaviors, providing richer context to researchers, statistical analyses, or data visualizations, thereby facilitating deeper insights into the behaviors under study.

Exploring Behaviors research aims to fill knowledge gaps in learning theory and technological applications by investigating human behavior in educational contexts. Reilly et al. [123] applied a Markov transition model to assess how students' physical behaviors during a collaborative programming task correlate with collaboration quality, task performance, and learning gains. Noel et al. [104] utilized correlation analysis alongside social network metrics and annotated behaviors to investigate collaborative dynamics in a software engineering course. Closser et al. [27] conducted a qualitative study, using a coding scheme to analyze students' actions, speech, and gestures in embodied learning activities to understand their conceptualization of measurement. These studies, often grounded in learning theory, employ multimodal learning analytics to dissect the components of effective collaboration, showcasing the nuanced insights that multimodal methods can provide into collaborative learning processes. This research spans various mediums, modalities, and settings, with a discernible focus on collaboration.

## 6 DISCUSSION

Sections 4 and 5 reveal several trends in multimodal learning and training, including key results, challenges, research gaps, and future research directions. In the following subsections, we discuss each of these and address the limitations of our literature review. Overall, we characterize the current state of the field by presenting several key insights:

- **Environments**: Learning environments outnumber training environments 7:2, mostly focusing on STEM environments with a virtual component (virtual or blended).
- **Participants**: Participants are primarily university or K-12 students, with multi-person environments slightly more common than individual ones (3:2).
- **Data and Modalities**:
  - Video, audio, logs, and participant-produced artifacts are the most common data collection mediums.
  - Pose, logs, affect, gaze, and prosodic speech are the most popular modalities.
  - Most papers use 2-5 modalities, focusing on vision analysis and human-centered modalities (e.g., artifacts, surveys, and interviews).
- **Analysis Methods and Approaches**:
  - Classification (for predicting outcomes), statistical analysis (for feature selection and correlation), and qualitative analysis (case studies, coding, and thematic analysis) are the most common analysis methods.
  - Model-based papers outnumber model-free ones 3:1.
- **Data Fusion**:
  - 75% of papers use early, mid, late, or hybrid fusion.
  - Mid fusion is most prevalent, followed by hybrid fusion.
  - Fused modalities often yield better results than unimodal ones, suggesting researchers should explore data fusion for a holistic understanding of behaviors and outcomes.

- **Publication Mediums**: The British Journal of Educational Technology (BJET) and International Conference on Learning Analytics & Knowledge (LAK) are the most popular venues for publishing multimodal learning and training research.

### 6.1 Reported Results

The results of our corpus's papers illustrate that multimodal methods are often successful at predicting learning and training outcomes, as well as identifying the most important features for predicting those outcomes [86, 137, 138]. Vrzakova et al. point out that even when multimodality does not improve a model's predictive capabilities, patterns in the multimodal data can be informative. Often, multimodal patterns help contextualize and add interpretability to the unimodal primitives by revealing nuances that cannot be identified by one modality alone [154]. These same patterns can also highlight performance differences among students and trainees:

> Our results demonstrate how NLP and ML techniques allow us to use different modalities of the same data, voice and transcript, and different modalities of different data sources, voice data from interviews, answers to a goal orientation questionnaire, and answers to open ended questions about energy, in order to better understand individual differences in students' performances. [79]

Human-centered approaches allow researchers to dive deeper and gain a more holistic understanding of learning and training processes. The richness innate to human-centered data (e.g., contextual qualitative observations, tangible artifacts produced by participants and researchers, participant perspectives gleaned from interviews and surveys, etc.) allows researchers to gain unique insights into participants' experiences and behaviors by identifying subtleties that more opaque (often quantitative) approaches may miss.

Our corpus's results also establish that multimodal methods are generally better-performing and more informative relative to unimodal approaches. This is largely due to different modalities conveying markedly different types of information, which helps create more holistic representations of learners that are much richer than is possible with only a single modality. Ma et al. [90] demonstrate this via several key findings:

> The results showed that Linguistic + Audio + Video (F1 Score = 0.65) yielded the best impasse detection performance...
>
> We found that the semantics and speaker information in the linguistic modality, the pitch variation in the audio modality, and the facial muscle movements in the video modality are the most significant unimodal indicators of impasse.
>
> ...all of our multimodal models outperformed their unimodal models...

These results underscore the considerable advantages of employing multimodal methods to understand learning and training experiences, behaviors, and outcomes. By integrating diverse modalities, researchers can uncover patterns that combine to create rich, holistic depictions of students' learning and training. This comprehensive perspective is crucial for capturing the complexities of learner and trainee experiences and behaviors, and suggests that multimodal approaches are not merely additive, but synergistic, offering opportunities for more informative and in depth analyses that are invaluable for advancing educational practice and research.

### 6.2 Challenges, Limitations, and Research Gaps

In Worsley and Blikstein [158], a primary "takeaway" is that various strategies for employing multimodal learning analytics offer a "meaningful glimpse" into complex datasets that traditional approaches may miss. However, multimodal data complexity presents challenges. Liu et al. [86] note that "data from different sources are often difficult to integrate." Temporal data alignment and sampling rate issues frequently arise, making data collection and labeling time-consuming and requiring "significant human time and effort" [85].

A major challenge is the lack of data. Most studies analyze small groups, making it difficult to use quantitative algorithms, which explains the limited use of deep learning. Kubsch et al. cite data scarcity as a "major challenge for building robust and reliable multimodal models" [79]. Small datasets hinder the development of scalable approaches, which several researchers noted:

> ...the design and sample size of the focus group do not allow us to generalize the results. [105]

> The limited number of pair work EEs does not allow us to make any strong claims in terms of the framework's reliability. [99]

> ...the size of the dataset used is relatively small, and the subject pool is not overly diverse, limiting our ability to explore culture or ethics-related factors in the model reliably. [23]

> ...training a model on a reduced dataset introduces a bias to the model, affecting the validity of the model's predictions when the data inputs come from a different distribution than the training set. [79]

Large, open-source datasets curated for researchers in multimodal learning and training environments are lacking. This represents a major research gap. Despite several papers mentioning data scarcity as a noteworthy challenge, few papers focus on compiling such datasets or developing methods for smaller datasets. Current methods are often one-off and not designed to generalize. Researchers rely on derived, observable features (e.g., affect and pose; particularly in computer vision) as model input rather than raw features (e.g., pixel values). This differs from core computer vision approaches and creates useful space for exploring end-to-end model training using raw inputs in the future.

The field lags behind core AI and ML, where methods often generalize across tasks and domains. For example, GPT-4 was tested on several benchmarks and exams [111]. Resource and access limitations, along with privacy concerns, hinder the application of advanced AI methods in learning and training environments. Similarly, conversational agents are underrepresented, with few papers discussing agents and none employing interactive, dynamic multi-turn agents (although one paper [143] did mention exploring this in the future). We anticipate the rise of generative AI will likely have a substantial impact on the field, in terms of multi-turn agents and otherwise. The lack of standardized coding practices and protocols is another gap. Most papers use domain-specific coding schemes, making replication difficult. Developing reliable methods for automating coding and creating standardized log formats would benefit the field.

Another finding is that training literature is sparse compared to learning literature. Physical training environments are underrepresented, and sensor data is rarely used in learning environments. Most papers use quantitative or qualitative analysis, with few employing mixed-methods approaches. Professional development environments and longitudinal analyses are also underrepresented.

Finally, little work focuses on the direct impact of methods on learners or trainees, or considers their input during development. Recently, particularly in education, researchers have adopted a more stakeholder-centric approach to

method development [33, 35] by incorporating *user-centered design* [2], i.e., focusing on users and their needs throughout the design process. Other stakeholder-centric approaches like *participatory design* [128] and *co-design* [113] are prevalent in learning sciences but not well-represented in our corpus.

While significant strides have been made in the field, numerous challenges and research gaps remain. The complexity of integrating multimodal data, scarcity of large and diverse datasets, and limitations in data alignment continue to hinder the development of robust and scalable models. The underrepresentation of more advanced AI methods, standardized coding practices, and stakeholder-centric approaches further limits the field's progress. Addressing these challenges will not only advance the state of multimodal learning and training research, but also enhance the utility and impact of educational technologies in diverse learning and training environments.

### 6.3 Future Research Directions

The results demonstrate that multimodal methods can be powerful in learning and training settings. However, persisting challenges and limitations highlight several research directions requiring further exploration. In the following subsections, we discuss directions that would provide the greatest benefit to the field.

*6.3.1 LLMs.* The recent boom in generative AI and multimodal LLMs creates tremendous opportunities for multimodal learning and training research. State-of-the-art models like GPT-4x [111] and Gemini [145] now offer multimodal capabilities and allow for prompt engineering approaches that can bypass the need for traditional model training (i.e., parameter updates) and large datasets [34]. Smaller, open-source models can also be trained via parameter-efficient methods to ease the computational overhead endemic to large transformer models [46]. We see both prompt engineering and multimodal conversational agents as two promising research directions.

Advances in multimodal transformers (especially those combining vision and text) have demonstrated these models' ability to perform multiple multimodal tasks. Examples include video-moment retrieval with step-captioning [163] and diagram generation via LLM planning [164]. Other work has built multimodal pipelines around LLMs by performing log-based discourse segmentation and using students' environment actions to contextualize students' discourse in the prompt [36, 133, 134]. Given the recent proliferation of multimodal LLMs in core AI research, we expect to see an increase in LLM integration with multimodal learning and training environments.

*6.3.2 Data Scarcity Mitigation.* Data scarcity is a major issue, causing multimodal learning and training methods to lag behind core AI approaches. Compiling large learning corpora could help, but challenges exist. Collecting multimodal data for large studies is more difficult than for unimodal ones, with a negative correlation between the number of modalities analyzed and sample size [131]. Ethical concerns, particularly regarding privacy and surveillance in educational datasets involving children, complicate data collection [42]. One solution is designing generalizable methods requiring limited data, such as zero and few-shot learning approaches, which have become prominent in core AI domains [76].

*6.3.3 Standardization.* Blanco et al. [45] emphasize the need for uniform coding standards for multimodal, temporal, and human-focused data. Current e-learning norms like xAPI [135] and LTI [1] are used in platforms like Canvas and Moodle but mainly for unimodal data and are limited by proprietary licenses. Adapting these frameworks for multimodal data is challenging, leading to minimal use in research.

Multimodal learning and training research merges AI, multimodal data, and educational contexts, requiring novel software. This has led to disparate approaches across research teams [161]. Creating uniform standards is crucial for the reliability of machine learning techniques and improving human-centric data analysis [44]. Adopting a unified log

format for multimodal data could reduce reliance on context-specific methods and improve generalizability. Researchers and engineers should also comply with existing standards and methodologies.

*6.3.4 Active Environments.* Environments where study participants are physically active provide an opportunity for researchers to accommodate motion-based modalities into their multimodal pipelines, e.g., via inertial measurement unit (IMU) sensors. This type of research was largely absent from our corpus, and we envision it being particularly useful for embodied learning and physical training research.

Embodied learning scenarios, where learners explore concepts through body movement, involve extensive multimodal data, capturing sensory inputs essential for movements, gestures, speech, gaze, interactions, and coordination [6]. Interaction analysis is common but challenging due to human analysts' cognitive limits and the fast-changing nature of embodied contexts [165]. Leveraging multimodal methods to support human analysts in such scenarios is promising. MMLA must address the complexities of 1) multimodal data collection from heterogeneous sensors, 2) data alignment, and 3) analysis to derive meaningful insights into learners' behaviors, providing educators with a comprehensive understanding of engagement and problem-solving [58].

Physical training environments, like rehabilitation therapy, weight lifting, running, and cycling, often use IMU sensors for human activity recognition (HAR). However, this is not typically done using multimodal data. Combining spatial modalities (like pose and gesture) with physiological modalities (such as blood pressure, body temperature, and electrodermal activity) could provide a more holistic interpretation of trainees' actions. Multimodality can decompose activities into sub-activities too nuanced to identify unimodally and add interpretability that IMU data alone cannot provide. For example, Xia et al. co-trained deep learning models using activities' images and IMU data, improving HAR generalizability [160]. While some physical training works in our corpus leveraged multimodality [51, 95], this was rare, and further research is needed to better inform physical training environments.

*6.3.5 Explainability.* Many AI and ML approaches use black-box algorithms with outputs that lack explainability, hindering teachers' and trainers' ability to guide students and fostering distrust in AI systems. Prior work has aimed to create more explainable systems using data visualization tools to make learning processes transparent [73, 152]. LLMs have potential for enhancing explainability through *Chain-of-Thought* prompting, which elicits reasoning chains from the model [34, 156]. Feedback from teachers and students shows they see potential for LLMs to improve learning outcomes, but explainability is crucial for their acceptance [33].

*6.3.6 Longitudinal Analyses.* The vast majority of studies in our corpus focus on using multimodality to either predict overall learning and training outcomes or identify features correlating with those outcomes; however, these approaches do not consider how students and trainees evolve over time. Conducting longitudinal studies and analyses would provide insight into how participants' behaviors and abilities develop as they progress in their learning or training. Longitudinal investigations have been successfully executed using unimodal and digital trace data [15], but less frequently within multimodal studies. The challenges of scalability and standardization of multimodal logs have restricted longitudinal MMLA research [161], affecting both research and software development in multimodal learning and training. There exists a void in the literature concerning longitudinal multimodal learner models encompassing a comprehensive view of learners' and trainees' evolution over time, making this an area ripe for further research exploration.

*6.3.7 Stakeholder Input and Impact.* Section 5 revealed a disconnect between researchers designing multimodal learning and training methods and the stakeholders these methods were intended to benefit. Few efforts incorporated user input in their method development pipelines or evaluated the impact of their methods on stakeholders' real-world

experiences. A larger emphasis on *design-based research* [7], i.e., iteratively designing and refining methods based on real-world research, would help bridge this gap. Additionally, employing *participatory design* (i.e., incorporating the input and participation of stakeholders into the design process) and *co-design* (i.e., giving stakeholders agency in processes leading to design decisions) [126] would help researchers develop multimodal methods better aligned with stakeholder experiences and outcomes.

### 6.4 Literature Review Limitations

We acknowledge the limitations of our literature review. While Google Scholar is widely used, it poses reproducibility challenges due to its opaqueness, non-determinism, and user-specific results. Although reconstructing our initial corpus *in its exact form* is unlikely, the authors are confident that the variability in Google Scholar searches does not prohibit the *overall* reproducibility of the corpus. This is because SerpAPI does not use individual user data when conducting web scrapes, as API calls are made via proxy and random headers.

Initially distilling our literature search corpus using citation graph pruning (see Section 3.2.1) is another potential limitation, as relevant papers may have been excluded due to minimal citations. However, since this paper reviews prominent methods in multimodal learning and training, the authors agreed that works not significantly citing other related papers (outgoing citations) or significantly cited by related papers (incoming citations) were outside our review's scope. For a detailed account of this review's limitations, see Appendix C.

## 7 CONCLUSIONS

In this paper, we conducted a comprehensive literature review of research methods in multimodal learning and training environments. We developed a novel approach, *citation graph pruning*, to distill our literature corpus. We presented a taxonomy and framework reflecting current advances, identifying and analyzing five modality groups (Natural Language, Vision, Sensors, Human-Centered, and Logs) through descriptive statistics, qualitative thematic analysis, and discussions on state-of-the-art findings, challenges, and research gaps. We derived three archetypes characterizing current research and identified the need for a new type of data fusion, *mid fusion*, which combines derived, observable features. We concluded with promising research directions and the limitations of our work. As multimodal learning and training analytics expand with generative AI, this review aims to inspire new methods and research.

## REFERENCES

[1] 1EdTech. 2019. Learning Tools Interoperability Core Specification 1.3 | IMS Global Learning Consortium — imsglobal.org. https://www.imsglobal.org/spec/lti/v1p3/. [Accessed 25-01-2024].

[2] Chadia Abras, Diane Maloney-Krichmar, Jenny Preece, et al. 2004. User-centered design. *Bainbridge, W. Encyclopedia of Human-Computer Interaction. Thousand Oaks: Sage Publications* 37, 4 (2004), 445–456.

[3] Michael Agyemang Adarkwah. 2021. The power of assessment feedback in teaching and learning: a narrative review and synthesis of the literature. *SN Social Sciences* 1, 3 (March 2021), 75. https://doi.org/10.1007/s43545-021-00086-w

[4] Haifa Alwahaby, Mutlu Cukurova, Zacharoula Papamitsiou, and Michail Giannakos. 2022. *The Evidence of Impact and Ethical Considerations of Multimodal Learning Analytics: A Systematic Literature Review.* Springer International Publishing, Cham, 289–325. https://doi.org/10.1007/978-3-031-08076-0_12

[5] Nese Alyuz, Eda Okur, Utku Genc, Sinem Aslan, Cagri Tanriover, and Asli Arslan Esme. 2017. An unobtrusive and multimodal approach for behavioral engagement detection of students. In *Proceedings of the 1st ACM SIGCHI International Workshop on Multimodal Interaction for Education.* ACM, Glasgow UK, 26–32. https://doi.org/10.1145/3139513.3139521

[6] Alejandro Andrade. 2017. Understanding student learning trajectories using multimodal learning analytics within an embodied-interaction learning environment. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference.* ACM, Vancouver British Columbia Canada, 70–79. https://doi.org/10.1145/3027385.3027429

[7] Matthew Armstrong, Cade Dopp, and Jesse Welsh. 2022. Design-based research. *N/A* N/A, N/A (2022), N/A.

[8] T. S. Ashwin and Ram Mohana Reddy Guddeti. 2020. Impact of inquiry interventions on students in e-learning and classroom environments using affective computing framework. *User Modeling and User-Adapted Interaction* 30, 5 (Nov. 2020), 759–801. https://doi.org/10.1007/s11257-019-09254-3

[9] Sinem Aslan, Nese Alyuz, Cagri Tanriover, Sinem E. Mete, Eda Okur, Sidney K. D'Mello, and Asli Arslan Esme. 2019. Investigating the Impact of a Real-time, Multimodal Student Engagement Analytics Technology in Authentic Classrooms. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, Glasgow Scotland Uk, 1–12. https://doi.org/10.1145/3290605.3300534

[10] David Azcona, I-Han Hsiao, and Alan F. Smeaton. 2018. Personalizing Computer Science Education by Leveraging Multimodal Learning Analytics. In *2018 IEEE Frontiers in Education Conference (FIE)*. IEEE, San Jose, CA, USA, 1–9. https://doi.org/10.1109/FIE.2018.8658596

[11] James Birt, Zane Stromberga, Michael Cowling, and Christian Moro. 2018. Mobile Mixed Reality for Experiential Learning and Simulation in Medical and Health Sciences Education. *Information* 9, 2 (Jan. 2018), 31. https://doi.org/10.3390/info9020031

[12] Paulo Blikstein. 2013. Multimodal learning analytics. In *Proceedings of the third international conference on learning analytics and knowledge*. Association for Computing Machinery, New York, NY, USA, 102–106.

[13] Paulo Blikstein and Marcelo Worsley. 2016. Multimodal learning analytics and education data mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics* 3, 2 (2016), 220–238.

[14] Ulrich Boser and Abel McDaniels. 2018. Addressing the Gap between Education Research and Practice: The Need for State Education Capacity Centers. *Center for American Progress* N/A, N/A (2018), N/A.

[15] Chris A. Boulton, Emily Hughes, Carmel Kent, Joanne R. Smith, and Hywel T. P. Williams. 2019. Student engagement and wellbeing over time at a higher education institution. *PLOS ONE* 14, 11 (11 2019), 1–20. https://doi.org/10.1371/journal.pone.0225770

[16] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (2006), 77.

[17] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems* 33 (2020), 1877–1901.

[18] Capital Normal University, Beijing, China, Xiaoyang Ma, Min Xu, Yao Dong, and Zhong Sun. 2021. Automatic Student Engagement in Online Learning Environment Based on Neural Turing Machine. *International Journal of Information and Education Technology* 11, 3 (2021), 107–111. https://doi.org/10.18178/ijiet.2021.11.3.1497

[19] Man Ching Esther Chan, Xavier Ochoa, and David Clarke. 2020. Multimodal Learning Analytics in a Laboratory Classroom. In *Machine Learning Paradigms*, Maria Virvou, Efthimios Alepis, George A. Tsihrintzis, and Lakhmi C. Jain (Eds.). Vol. 158. Springer International Publishing, Cham, 131–156. http://link.springer.com/10.1007/978-3-030-13743-4_8

[20] Wilson Chango, Rebeca Cerezo, and Cristóbal Romero. 2021. Multi-source and multimodal data fusion for predicting academic performance in blended learning university courses. *Computers & Electrical Engineering* 89 (Jan. 2021), 106908. https://doi.org/10.1016/j.compeleceng.2020.106908

[21] Wilson Chango, Rebeca Cerezo, Miguel Sanchez-Santillan, Roger Azevedo, and Cristóbal Romero. 2021. Improving prediction of students' performance in intelligent tutoring systems using attribute selection and ensembles of different multimodal data sources. *Journal of Computing in Higher Education* 33, 3 (Dec. 2021), 614–634. https://doi.org/10.1007/s12528-021-09298-8

[22] Wilson Chango, Juan A. Lara, Rebeca Cerezo, and Cristóbal Romero. 2022. A review on data fusion in multimodal learning analytics and educational data mining. *WIREs Data Mining and Knowledge Discovery* 12, 4 (2022), e1458. https://doi.org/10.1002/widm.1458 arXiv:https://wires.onlinelibrary.wiley.com/doi/pdf/10.1002/widm.1458

[23] Lujie Karen Chen. 2021. Affect, Support, and Personal Factors: Multimodal Causal Models of One-on-one Coaching. *Journal of Educational Data Mining* 13, 3 (2021), 36–68.

[24] Bonnie Chinh, Himanshu Zade, Abbas Ganji, and Cecilia Aragon. 2019. Ways of Qualitative Coding: A Case Study of Four Strategies for Resolving Disagreements. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI EA '19)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3290607.3312879

[25] Steven A. Cholewiak, Panos Ipeirotis, Victor Silva, and Arun Kannawadi. 2021. *SCHOLARLY: Simple access to Google Scholar authors and citation using Python*. N/A. https://doi.org/10.5281/zenodo.5764801

[26] Yi Han Victoria Chua, Justin Dauwels, and Seng Chee Tan. 2019. Technologies for automated analysis of co-located, real-life, physical learning spaces: Where are we now?. In *LAK19: 9th International Learning Analytics and Knowledge Conference*. ACM, Tempe AZ USA, 10. https://dl-acm-org.proxy.library.vanderbilt.edu/doi/10.1145/3303772.3303811

[27] Avery H. Closser, John A. Erickson, Hannah Smith, Ashvini Varatharaj, and Anthony F. Botelho. 2022. Blending learning analytics and embodied design to model students' comprehension of measurement using their actions, speech, and gestures. *International Journal of Child-Computer Interaction* 32 (June 2022), 100391. https://doi.org/10.1016/j.ijcci.2021.100391

[28] Keith Cochran, Clayton Cohn, Peter Hastings, Noriko Tomuro, and Simon Hughes. 2023. Using BERT to Identify Causal Structure in Students' Scientific Explanations. *International Journal of Artificial Intelligence in Education* N/A, N/A (2023), 1–39.

[29] Keith Cochran, Clayton Cohn, and Peter M. Hastings. 2023. Improving NLP Model Performance on Small Educational Data Sets Using Self-Augmentation. In *Proceedings of the 15th International Conference on Computer Supported Education, CSEDU 2023, Prague, Czech Republic, April 21-23, 2023, Volume 1*, Jelena Jovanovic, Irene-Angelica Chounta, James Uhomoibhi, and Bruce M. McLaren (Eds.). SCITEPRESS, N/A, 70–78. https://doi.org/10.5220/0011857200003470

[30] Keith Cochran, Clayton Cohn, Jean Francois Rouet, and Peter Hastings. 2023. Improving Automated Evaluation of Student Text Responses Using GPT-3.5 for Text Data Augmentation. In *International Conference on Artificial Intelligence in Education*. Springer, N/A, N/A, 217–228.

[31] Jacob Cohen. 1960. A coefficient of agreement for nominal scales. *Educational and psychological measurement* 20, 1 (1960), 37–46.

[32] Clayton Cohn. 2020. *BERT efficacy on scientific and medical datasets: a systematic literature review.* DePaul University, N/A.

[33] Clayton Cohn, Nicole Hutchins, and Gautam Biswas. 2024. Chain-of-Thought Prompting with Stakeholders-in-the-Loop for Evaluating Formative Assessments in STEM+Computing. (August 2024). Submitting to Education and Information Technologies..

[34] Clayton Cohn, Nicole Hutchins, Tuan Le, and Gautam Biswas. 2024. A Chain-of-Thought Prompting Approach with LLMs for Evaluating Students' Formative Assessment Responses in Science. *Proc. Conf. AAAI Artif. Intell.* 38, 21 (March 2024), 23182–23190.

[35] Clayton Cohn, Caitlin Snyder, Joyce Fonteles, Ashwin T S, Justin Montenegro, and Gautam Biswas. 2024. A Multimodal Approach to Support Teacher, Researcher, and AI Collaboration in STEM+C Learning Environments. (July 2024). Submitted to the British Journal of Educational Technology special section Hybrid Intelligence: Human-AI Co-evolution and Learning. Currently under review.

[36] Clayton Cohn, Caitlin Snyder, Justin Montenegro, and Gautam Biswas. 2024. Towards a human-in-the-loop LLM approach to collaborative discourse analysis. In *Artificial Intelligence in Education. Posters and Late Breaking Results, Workshops and Tutorials, Industry and Innovation Tracks, Practitioners, Doctoral Consortium and Blue Sky*. Springer Nature Switzerland, Cham, 11–19.

[37] Matt Cook, Zack Lischer-Katz, Nathan Hall, Juliet Hardesty, Jennifer Johnson, Robert McDonald, and Tara Carlisle. 2019. Challenges and strategies for educational virtual reality. *Information Technology and Libraries* 38, 4 (2019), 25–48.

[38] Hector Cornide-Reyes, René Noël, Fabián Riquelme, Matías Gajardo, Cristian Cechinel, Roberto Mac Lean, Carlos Becerra, Rodolfo Villarroel, and Roberto Munoz. 2019. Introducing Low-Cost Sensors into the Classroom Settings: Improving the Assessment in Agile Practices with Multimodal Learning Analytics. *Sensors* 19, 15 (July 2019), 3291. https://doi.org/10.3390/s19153291

[39] Lucrezia Crescenzi-Lanna. 2020. Multimodal Learning Analytics research with young children: A systematic review. *British Journal of Educational Technology* 51, 5 (2020), 1485–1504. https://doi.org/10.1111/bjet.12959

[40] Scott A Crossley, Kristopher Kyle, and Mihai Dascalu. 2019. The Tool for the Automatic Analysis of Cohesion 2.0: Integrating semantic similarity and text overlap. *Behavior research methods* 51 (2019), 14–27.

[41] Scott A Crossley, Kristopher Kyle, and Danielle S McNamara. 2016. The tool for the automatic analysis of text cohesion (TAACO): Automatic assessment of local, global, and text cohesion. *Behavior research methods* 48 (2016), 1227–1237.

[42] Mutlu Cukurova, Michail Giannakos, and Roberto Martinez-Maldonado. 2020. The promise and challenges of multimodal learning analytics. *British Journal of Educational Technology* 51, 5 (2020), 1441–1449.

[43] Mutlu Cukurova, Carmel Kent, and Rosemary Luckin. 2019. Artificial intelligence and multimodal data in the service of human decision-making: A case study in debate tutoring. *British Journal of Educational Technology* 50, 6 (Nov. 2019), 3032–3046. https://doi.org/10.1111/bjet.12829

[44] E. Davalos, U. Timalsina, Y. Zhang, J. Wu, J. Fonteles, and G. Biswas. 2023. ChimeraPy: A Scientific Distributed Streaming Framework for Real-time Multimodal Data Retrieval and Processing. In *2023 IEEE International Conference on Big Data (BigData)*. IEEE Computer Society, Los Alamitos, CA, USA, 201–206. https://doi.org/10.1109/BigData59044.2023.10386382

[45] Ángel del Blanco, Ángel Serrano, Manuel Freire, Iván Martínez-Ortiz, and Baltasar Fernández-Manjón. 2013. E-Learning standards and learning analytics. Can data collection be improved by using standard data models?. In *2013 IEEE Global Engineering Education Conference (EDUCON)*. IEEE, Berlin, Germany, 1255–1261. https://doi.org/10.1109/EduCon.2013.6530268

[46] Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. 2023. QLoRA: Efficient Finetuning of Quantized LLMs. *arXiv e-prints* N/A, N/A, Article arXiv:2305.14314 (May 2023), N/A pages. https://doi.org/10.48550/arXiv.2305.14314 arXiv:2305.14314 [cs.LG]

[47] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* N/A, N/A (2018), N/A.

[48] Daniele Di Mitri, Maren Scheffel, Hendrik Drachsler, Dirk Börner, Stefaan Ternier, and Marcus Specht. 2017. Learning pulse: a machine learning approach for predicting performance in self-regulated learning using multimodal data. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*. ACM, Vancouver British Columbia Canada, 188–197. https://doi.org/10.1145/3027385.3027447

[49] Daniele Di Mitri, Jan Schneider, and Hendrik Drachsler. 2022. Keep Me in the Loop: Real-Time Feedback with Multimodal Data. *International Journal of Artificial Intelligence in Education* 32, 4 (Dec. 2022), 1093–1118. https://doi.org/10.1007/s40593-021-00281-z

[50] Daniele Di Mitri, Jan Schneider, Marcus Specht, and Hendrik Drachsler. 2018. From signals to knowledge: A conceptual model for multimodal learning analytics. *Journal of Computer Assisted Learning* 34, 4 (2018), 338–349. https://doi.org/10.1111/jcal.12288

[51] Daniele Di Mitri, Jan Schneider, Kevin Trebing, Sasa Sopka, Marcus Specht, and Hendrik Drachsler. 2020. Real-Time Multimodal Feedback with the CPR Tutor. In *Artificial Intelligence in Education*, Ig Ibert Bittencourt, Mutlu Cukurova, Kasia Muldner, Rose Luckin, and Eva Millán (Eds.). Vol. 12163. Springer International Publishing, Cham, 141–152. http://link.springer.com/10.1007/978-3-030-52237-7_12

[52] Hendrik Drachsler and Jan Schneider. 2018. JCAL Special Issue on Multimodal Learning Analytics. *Journal of Computer Assisted Learning* 34, 4 (2018), 335–337. https://doi.org/10.1111/jcal.12291 arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcal.12291

[53] Vanessa Echeverria, Roberto Martinez-Maldonado, and Simon Buckingham Shum. 2019. Towards Collaboration Translucence: Giving Meaning to Multimodal Group Data. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, Glasgow Scotland Uk, 1–16. https://doi.org/10.1145/3290605.3300269

[54] Andrew Emerson, Elizabeth B. Cloude, Roger Azevedo, and James Lester. 2020. Multimodal learning analytics for game-based learning. *British Journal of Educational Technology* 51, 5 (Sept. 2020), 1505–1526. https://doi.org/10.1111/bjet.12992

[55] Andrew Emerson, Nathan Henderson, Jonathan Rowe, Wookhee Min, Seung Lee, James Minogue, and James Lester. 2020. Early Prediction of Visitor Engagement in Science Museums with Multimodal Learning Analytics. In *Proceedings of the 2020 International Conference on Multimodal Interaction*. ACM, Virtual Event Netherlands, 107–116. https://doi.org/10.1145/3382507.3418890

[56] Florian Eyben, Martin Wöllmer, and Björn Schuller. 2010. Opensmile: the munich versatile and fast open-source audio feature extractor. In *Proceedings of the 18th ACM international conference on Multimedia*. N/A, N/A, 1459–1462.

[57] Gloria Milena Fernandez-Nieto, Vanessa Echeverria, Simon Buckingham Shum, Katerina Mangaroska, Kirsty Kitto, Evelyn Palominos, Carmen Axisa, and Roberto Martinez-Maldonado. 2021. Storytelling With Learner Data: Guiding Student Reflection on Multimodal Team Data. *IEEE Transactions on Learning Technologies* 14, 5 (Oct. 2021), 695–708. https://doi.org/10.1109/TLT.2021.3131842

[58] Joyce Fonteles, Eduardo Davalos, T. S. Ashwin, Yike Zhang, Mengxi Zhou, Efrat Ayalon, Alicia Lane, Selena Steinberg, Gabriella Anton, Joshua Danish, Noel Enyedy, and Gautam Biswas. 2024. A First Step in Using Machine Learning Methods to Enhance Interaction Analysis for Embodied Learning Environments. In *Artificial Intelligence in Education*, Andrew M. Olney, Irene-Angelica Chounta, Zitao Liu, Olga C. Santos, and Ig Ibert Bittencourt (Eds.). Springer Nature Switzerland, Cham, 3–16.

[59] Joyce Horn Fonteles, Celestine E Akpanoko, Pamela J. Wisniewski, and Gautam Biswas. 2024. Promoting Equitable Learning Outcomes for Underserved Students in Open-Ended Learning Environments. In *Proceedings of the 23rd Annual ACM Interaction Design and Children Conference* (Delft, Netherlands) *(IDC '24)*. Association for Computing Machinery, New York, NY, USA, 307–321. https://doi.org/10.1145/3628516.3655753

[60] Society for Learning Analytics Research. N/A. Multimodal learning analytics across spaces (SOLAR crossmmla sig). https://www.solaresearch.org/community/sigs/crossmmla-sig/. [Accessed 07-02-2024].

[61] Society for Learning Analytics Research (SOLAR). N/A. What is Learning Analytics? https://www.solaresearch.org/about/what-is-learning-analytics/. [Accessed 07-02-2024].

[62] Fwa, Hua Leong and Lindsay Marshall. 2018. Investigating multimodal affect sensing in an Affective Tutoring System using unobtrusive sensors. *Psychology of Programming Interest Group* 29 (Oct. 2018), 78–85.

[63] Jing Gao, Peng Li, Zhikui Chen, and Jianing Zhang. 2020. A survey on deep learning for multimodal data fusion. *Neural Computation* 32, 5 (2020), 829–864.

[64] Michail Giannakos, Daniel Spikol, Daniele Di Mitri, Kshitij Sharma, Xavier Ochoa, and Rawad Hammad (Eds.). 2022. *The multimodal learning analytics handbook*. Springer International Publishing, Cham. https://doi.org/10.1007/978-3-031-08076-0

[65] Michail N. Giannakos, Kshitij Sharma, Ilias O. Pappas, Vassilis Kostakos, and Eduardo Velloso. 2019. Multimodal data as a means to understand the learning experience. *International Journal of Information Management* 48 (Oct. 2019), 108–119. https://doi.org/10.1016/j.ijinfomgt.2019.02.003

[66] Abhishek Gupta, Alagan Anpalagan, Ling Guan, and Ahmed Shaharyar Khwaja. 2021. Deep learning for object detection and scene perception in self-driving cars: Survey, challenges, and open issues. *Array* 10 (2021), 100057.

[67] Aric Hagberg, Pieter J. Swart, and Daniel A. Schult. 2008. Exploring network structure, dynamics, and function using NetworkX. *N/A* N/A, N/A (1 2008), N/A. https://www.osti.gov/biblio/960616

[68] John Hattie and Helen Timperley. 2007. The Power of Feedback. *Review of Educational Research* 77, 1 (2007), 81–112. https://doi.org/10.3102/003465430298487 arXiv:https://doi.org/10.3102/003465430298487

[69] Nathan L Henderson, Jonathan P Rowe, Bradford W Mott, and James C Lester. 2019. Sensor-based Data Fusion for Multimodal Affect Detection in Game-based Learning Environments. In *Proceedings of the EDM and Games Workshop at the 12th International Conference on Educational Data Mining*, Vol. 2592. International Educational Data Mining Society, Montreal, CA, 1–7.

[70] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation* 9, 8 (1997), 1735–1780.

[71] H Ulrich Hoppe. 2017. *Computational methods for the analysis of learning and knowledge building communities*. Society for Learning Analytics Research (SoLAR), Beaumont, Alberta, Canada, 23–33.

[72] Nicole Hutchins and Gautam Biswas. 2023. Using Teacher Dashboards to Customize Lesson Plans for a Problem-Based, Middle School STEM Curriculum. In *LAK23: 13th International Learning Analytics and Knowledge Conference* (Arlington, TX, USA) *(LAK2023)*. Association for Computing Machinery, New York, NY, USA, 324–332. https://doi.org/10.1145/3576050.3576100

[73] Nicole Marie Hutchins et al. 2022. *Co-Designing Teaching Augmentation Tools to Support the Integration of Problem-Based Learning in K-12 Science*. Ph. D. Dissertation. Vanderbilt University.

[74] Shiyan Jiang, Blaine E. Smith, and Ji Shen. 2021. Examining how different modes mediate adolescents' interactions during their collaborative multimodal composing processes. *Interactive Learning Environments* 29, 5 (July 2021), 807–820. https://doi.org/10.1080/10494820.2019.1612450

[75] Sanna Järvelä, Jonna Malmberg, Eetu Haataja, Marta Sobocinski, and Paul A. Kirschner. 2021. What multimodal data can tell us about the students' regulation of their learning process? *Learning and Instruction* 72 (April 2021), 101203. https://doi.org/10.1016/j.learninstruc.2019.04.004

[76] Suvarna Kadam and Vinay Vaidya. 2020. Review and analysis of zero, one and few shot learning approaches. In *Intelligent Systems Design and Applications: 18th International Conference on Intelligent Systems Design and Applications (ISDA 2018) held in Vellore, India, December 6-8, 2018, Volume 1*. Springer, N/A, N/A, 100–112.

[77] Barbara Kitchenham. 2004. Procedures for performing systematic reviews. *Keele, UK, Keele University* 33, 2004 (2004), 1–26.

[78] Kenneth R Koedinger, John R Anderson, William H Hadley, Mary A Mark, et al. 1997. Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education* 8, 1 (1997), 30–43.

[79] Marcus Kubsch, Daniela Caballero, and Pablo Uribe. 2022. Once More with Feeling: Emotions in Multimodal Learning Analytics. In *The Multimodal Learning Analytics Handbook*, Michail Giannakos, Daniel Spikol, Daniele Di Mitri, Kshitij Sharma, Xavier Ochoa, and Rawad Hammad (Eds.). Springer International Publishing, Cham, 261–285. https://link.springer.com/10.1007/978-3-031-08076-0_11

[80] Charlotte Larmuseau, Jan Cornelis, Luigi Lancieri, Piet Desmet, and Fien Depaepe. 2020. Multimodal learning analytics to investigate cognitive load during online problem solving. *British Journal of Educational Technology* 51, 5 (Sept. 2020), 1548–1562. https://doi.org/10.1111/bjet.12958

[81] Serena Lee-Cultura, Kshitij Sharma, Giulia Cosentino, Sofia Papavlasopoulou, and Michail Giannakos. 2021. Children's Play and Problem Solving in Motion-Based Educational Games: Synergies between Human Annotations and Multi-Modal Data. In *Interaction Design and Children*. ACM, Athens Greece, 408–420. https://doi.org/10.1145/3459990.3460702

[82] Serena Lee-Cultura, Kshitij Sharma, and Michail Giannakos. 2022. Children's play and problem-solving in motion-based learning technologies using a multi-modal mixed methods approach. *International Journal of Child-Computer Interaction* 31 (March 2022), 100355. https://doi.org/10.1016/j.ijcci.2021.100355

[83] Serena Lee-Cultura, Kshitij Sharma, Sofia Papavlasopoulou, and Michail Giannakos. 2020. Motion-Based Educational Games: Using Multi-Modal Data to Predict Player's Performance. In *2020 IEEE Conference on Games (CoG)*. IEEE, Osaka, Japan, 17–24. https://doi.org/10.1109/CoG47356.2020.9231892

[84] Krittaya Leelawong and Gautam Biswas. 2008. Designing learning by teaching agents: The Betty's Brain system. *International Journal of Artificial Intelligence in Education* 18, 3 (2008), 181–208.

[85] Ran Liu, John Stamper, Jodi Davenport, Scott Crossley, Danielle McNamara, Kalonji Nzinga, and Bruce Sherin. 2019. Learning linkages: Integrating data streams of multiple modalities and timescales. *Journal of Computer Assisted Learning* 35, 1 (Feb. 2019), 99–109. https://doi.org/10.1111/jcal.12315

[86] Ran Liu, John C Stamper, and Jodi Davenport. 2018. A Novel Method for the In-Depth Multimodal Analysis of Student Learning Trajectories in Intelligent Tutoring Systems. *Journal of Learning Analytics* 5, 1 (April 2018), 41–54. https://doi.org/10.18608/jla.2018.51.4

[87] Su Liu, Ye Chen, Hui Huang, Liang Xiao, and Xiaojun Hei. 2018. Towards Smart Educational Recommendations with Reinforcement Learning in Classroom. In *2018 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE)*. IEEE, Wollongong, NSW, 1079–1084. https://doi.org/10.1109/TALE.2018.8615217

[88] Edward Loper and Steven Bird. 2002. NLTK: The Natural Language Toolkit. https://doi.org/10.48550/ARXIV.CS/0205028

[89] María Ximena López, Francesco Strada, Andrea Bottino, and Carlo Fabricatore. 2021. Using Multimodal Learning Analytics to Explore Collaboration in a Sustainability Co-located Tabletop Game. In *15th European Conference on Game-Based Learning*. Academic Conferences LTD, Brighton, UK, 482–489.

[90] Yingbo Ma, Mehmet Celepkolu, and Kristy Elizabeth Boyer. 2022. Detecting Impasse During Collaborative Problem Solving with Multimodal Learning Analytics. In *LAK22: 12th International Learning Analytics and Knowledge Conference*. ACM, Online USA, 45–55. https://doi.org/10.1145/3506860.3506865

[91] Katerina Mangaroska, Kshitij Sharma, Dragan Gašević, and Michalis Giannakos. 2020. Multimodal Learning Analytics to Inform Learning Design: Lessons Learned from Computing Education. *Journal of Learning Analytics* 7, 3 (Dec. 2020), 79–97. https://doi.org/10.18608/jla.2020.73.7

[92] Kit Martin, Emily Q. Wang, Connor Bain, and Marcelo Worsley. 2019. Computationally Augmented Ethnography: Emotion Tracking and Learning in Museum Games. In *Advances in Quantitative Ethnography*, Brendan Eagan, Morten Misfeldt, and Amanda Siebert-Evenstone (Eds.). Vol. 1112. Springer International Publishing, Cham, 141–153. http://link.springer.com/10.1007/978-3-030-33232-7_12

[93] Roberto Martinez-Maldonado, Vanessa Echeverria, Gloria Fernandez Nieto, and Simon Buckingham Shum. 2020. From Data to Insights: A Layered Storytelling Approach for Multimodal Learning Analytics. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. ACM, Honolulu HI USA, 1–15. https://doi.org/10.1145/3313831.3376148

[94] Andino Maseleno, Noraisikin Sabani, Miftachul Huda, Roslee Bin Ahmad, Kamarul Azmi Jasmi, and Bushrah Basiron. 2018. Demystifying learning analytics in personalised learning. *International Journal of Engineering and Technology (UAE)* 7 (2018), 1124–1129.

[95] Khaleel Asyraaf Mat Sanusi, Daniele Di Mitri, Bibeg Limbu, and Roland Klemke. 2021. Table Tennis Tutor: Forehand Strokes Classification Based on Multimodal Data and Neural Networks. *Sensors* 21, 9 (April 2021), 3121. https://doi.org/10.3390/s21093121

[96] MDPI. 2021. New Trends on Multimodal Learning Analytics: Using Sensors to Understand and Improve Learning. https://www.mdpi.com/journal/sensors/special_issues/multimodal_learning_analytics_sensor. [Accessed 08-02-2024].

[97] Beloo Mehra. 2015. Bias in Qualitative Research: Voices from an Online Classroom. *The Qualitative Report* N/A, N/A (Jan 2015), N/A pages. https://doi.org/10.46743/2160-3715/2002.1986

[98] Daniele Di Mitri. 2019. Detecting Medical Simulation Errors with Machine learning and Multimodal Data. In *17th Conference on Artificial Intelligence in Medicine*. Springer International Publishing, Poznan, Poland, 1–6.

[99] Teresa Morell, Vicent Beltrán-Palanques, and Natalia Norte. 2022. A multimodal analysis of pair work engagement episodes: Implications for EMI lecturer training. *Journal of English for Academic Purposes* 58 (July 2022), 101124. https://doi.org/10.1016/j.jeap.2022.101124

[100] Su Mu, Meng Cui, and Xiaodi Huang. 2020. Multimodal Data Fusion in Learning Analytics: A Systematic Review. *Sensors* 20, 23 (2020), 6856. https://doi.org/10.3390/s20236856

[101] Jauwairia Nasir, Aditi Kothiyal, Barbara Bruno, and Pierre Dillenbourg. 2021. Many are the ways to learn identifying multi-modal behavioral profiles of collaborative learning in constructivist activities. *International Journal of Computer-Supported Collaborative Learning* 16, 4 (Dec. 2021), 485–523. https://doi.org/10.1007/s11412-021-09358-2

[102] Andy Nguyen, Sanna Järvelä, Carolyn Rosé, Hanna Järvenoja, and Jonna Malmberg. 2023. Examining socially shared regulation and shared physiological arousal events with multimodal learning analytics. *British Journal of Educational Technology* 54, 1 (Jan. 2023), 293–312. https://doi.org/10.1111/bjet.13280

[103] Helen Noble and Joanna Smith. 2015. Issues of validity and reliability in qualitative research. *Evidence Based Nursing* 18, 2 (Feb. 2015), 34–35. https://doi.org/10.1136/eb-2015-102054

[104] Rene Noel, Fabian Riquelme, Roberto Mac Lean, Erick Merino, Cristian Cechinel, Thiago S. Barcelos, Rodolfo Villarroel, and Roberto Munoz. 2018. Exploring Collaborative Writing of User Stories With Multimodal Learning Analytics: A Case Study on a Software Engineering Course. *IEEE Access* 6 (2018), 67783–67798. https://doi.org/10.1109/ACCESS.2018.2876801

[105] René Noël, Diego Miranda, Cristian Cechinel, Fabián Riquelme, Tiago Thompsen Primo, and Roberto Munoz. 2022. Visualizing Collaboration in Teamwork: A Multimodal Learning Analytics Platform for Non-Verbal Communication. *Applied Sciences* 12, 15 (July 2022), 7499. https://doi.org/10.3390/app12157499

[106] Xavier Ochoa and Federico Dominguez. 2020. Controlled evaluation of a multimodal system to improve oral presentation skills in a real learning setting. *British Journal of Educational Technology* 51, 5 (Sept. 2020), 1615–1630. https://doi.org/10.1111/bjet.12987

[107] Xavier Ochoa, Federico Domínguez, Bruno Guamán, Ricardo Maya, Gabriel Falcones, and Jaime Castells. 2018. The RAP system: automatic feedback of oral presentation skills using multimodal analysis and low-cost sensors. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge*. ACM, Sydney New South Wales Australia, 360–364. https://doi.org/10.1145/3170358.3170406

[108] Xavier Ochoa, AWDG Charles Lang, and George Siemens. 2017. Multimodal learning analytics. *The handbook of learning analytics* 1 (2017), 129–141.

[109] Journal of Learning Analytics. 2015. Special section on multimodal learning analytics. https://learning-analytics.info/index.php/JLA/announcement/view/102. [Accessed 08-02-2024].

[110] Jennifer K. Olsen, Kshitij Sharma, Nikol Rummel, and Vincent Aleven. 2020. Temporal analysis of multimodal data to predict collaborative learning outcomes. *British Journal of Educational Technology* 51, 5 (Sept. 2020), 1527–1547. https://doi.org/10.1111/bjet.12982

[111] OpenAI. 2023. GPT-4 Technical Report. *arXiv e-prints* N/A, N/A, Article arXiv:2303.08774 (March 2023), N/A pages. https://doi.org/10.48550/arXiv.2303.08774 arXiv:2303.08774 [cs.CL]

[112] Zacharoula Papamitsiou, Ilias O. Pappas, Kshitij Sharma, and Michail N. Giannakos. 2020. Utilizing Multimodal Data Through fsQCA to Explain Engagement in Adaptive Learning. *IEEE Transactions on Learning Technologies* 13, 4 (Oct. 2020), 689–703. https://doi.org/10.1109/TLT.2020.3020499

[113] William R. Penuel, Jeremy Roschelle, and Nicole Shechtman. 2007. Designing Formative Assessment Software With Teachers: An Analysis of the Co-Design Process. *Research and Practice in Technology Enhanced Learning* 02, 01 (2007), 51–74. https://doi.org/10.1142/S1793206807000300 arXiv:https://doi.org/10.1142/S1793206807000300

[114] Volha Petukhova, Tobias Mayer, Andrei Malchanau, and Harry Bunt. 2017. Virtual debate coach design: assessing multimodal argumentation performance. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction*. ACM, Glasgow UK, 41–50. https://doi.org/10.1145/3136755.3136775

[115] Volha Petukhova, Manoj Raju, and Harry Bunt. 2017. Multimodal Markers of Persuasive Speech: Designing a Virtual Debate Coach. In *Interspeech 2017*. ISCA, Stockholm, Sweden, 142–146. https://doi.org/10.21437/Interspeech.2017-98

[116] Phuong Pham and Jingtao Wang. 2017. AttentiveLearner2: A Multimodal Approach for Improving MOOC Learning on Mobile Devices. In *Artificial Intelligence in Education*, Elisabeth André, Ryan Baker, Xiangen Hu, Ma. Mercedes T. Rodrigo, and Benedict Du Boulay (Eds.). Vol. 10331. Springer International Publishing, Cham, 561–564. http://link.springer.com/10.1007/978-3-319-61425-0_64

[117] Phuong Pham and Jingtao Wang. 2018. Predicting Learners' Emotions in Mobile MOOC Learning via a Multimodal Intelligent Tutor. In *Intelligent Tutoring Systems*, Roger Nkambou, Roger Azevedo, and Julita Vassileva (Eds.). Vol. 10858. Springer International Publishing, Cham, 150–159. http://link.springer.com/10.1007/978-3-319-91464-0_15

[118] Stéphanie Philippe, Alexis D. Souchet, Petros Lameras, Panagiotis Petridis, Julien Caporal, Gildas Coldeboeuf, and Hadrien Duzan. 2020. Multimodal teaching, learning and training in virtual reality: a review and case study. *Virtual Reality & Intelligent Hardware* 2, 5 (Oct. 2020), 421–442. https://doi.org/10.1016/j.vrih.2020.07.008

[119] L.P. Prieto, K. Sharma, Ł. Kidzinski, M.J. Rodríguez-Triana, and P. Dillenbourg. 2018. Multimodal teaching analytics: Automated extraction of orchestration graphs from wearable sensor data. *Journal of Computer Assisted Learning* 34, 2 (April 2018), 193–203. https://doi.org/10.1111/jcal.12232

[120] Athanasios Psaltis, Konstantinos C. Apostolakis, Kosmas Dimitropoulos, and Petros Daras. 2018. Multimodal Student Engagement Recognition in Prosocial Games. *IEEE Transactions on Games* 10, 3 (Sept. 2018), 292–303. https://doi.org/10.1109/TCIAIG.2017.2743341

[121] Umar Bin Qushem. 2020. *Trends of Multimodal Learning Analytics: A Systematic Literature Review*. Ph. D. Dissertation. UNIVERSITY OF EASTERN FINLAND. https://erepo.uef.fi/bitstream/handle/123456789/23508/urn_nbn_fi_uef-20201250.pdf?sequence=1

[122] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog* 1, 8 (2019), 9.

[123] Joseph M Reilly, Milan Ravenell, and Bertrand Schneider. 2018. Exploring Collaboration Using Motion Sensors and Multi- Modal Learning Analytics. In *Proceedings of the 11th International Conference on Educational Data Mining*. International Educational Data Mining Society, Buffalo, NY, USA, 333–339.

[124] María Jesüs Rodríguez-Triana, Luis P Prieto, Alejandra Martínez-Monés, Juan I Asensio-Pérez, and Yannis Dimitriadis. 2018. The teacher in the loop: Customizing multimodal learning analytics for blended learning. In *Proceedings of the 8th international conference on learning analytics and knowledge*. Association for Computing Machinery, New York, NY, USA, 417–426.

[125] Thomas Rojat, Raphaël Puget, David Filliat, Javier Del Ser, Rodolphe Gelin, and Natalia Díaz-Rodríguez. 2021. Explainable artificial intelligence (xai) on timeseries data: A survey. *arXiv preprint arXiv:2104.00950* N/A, N/A (2021), N/A.

[126] Juan Pablo Sarmiento and Alyssa Friend Wise. 2022. Participatory and Co-Design of Learning Analytics: An Initial Review of the Literature. In *LAK22: 12th International Learning Analytics and Knowledge Conference* (Online, USA) *(LAK22)*. Association for Computing Machinery, New York,

NY, USA, 535–541. https://doi.org/10.1145/3506860.3506910

[127] Tjeerd AJ Schoonderwoerd, Wiard Jorritsma, Mark A Neerincx, and Karel Van Den Bosch. 2021. Human-centered XAI: Developing design patterns for explanations of clinical decision support systems. *International Journal of Human-Computer Studies* 154 (2021), 102684.

[128] Douglas Schuler and Aki Namioka. 1993. *Participatory design: Principles and practices*. CRC Press, N/A.

[129] SerpApi. N/A. Google Scholar API. https://serpapi.com/google-scholar-api. [Accessed 08-02-2024].

[130] Shashi Kant Shankar, Luis P. Prieto, María Jesús Rodríguez-Triana, and Adolfo Ruiz-Calleja. 2018. A Review of Multimodal Learning Analytics Architectures. In *2018 IEEE 18th International Conference on Advanced Learning Technologies (ICALT)*. IEEE, Piscataway, NJ, USA, 212–214. https://doi.org/10.1109/ICALT.2018.00057

[131] Kshitij Sharma and Michail Giannakos. 2020. Multimodal data capabilities for learning: What can multimodal data tell us about learning? *British Journal of Educational Technology* 51, 5 (2020), 1450–1484. https://doi.org/10.1111/bjet.12993 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/bjet.12993.

[132] Kshitij Sharma, Zacharoula Papamitsiou, Jennifer K. Olsen, and Michail Giannakos. 2020. Predicting learners' effortful behaviour in adaptive assessment using multimodal data. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*. ACM, Frankfurt Germany, 480–489. https://doi.org/10.1145/3375462.3375498

[133] Caitlin Snyder, Nicole Hutchins, Clayton Cohn, Joyce Fonteles, and Gautam Biswas. 2023. Using Collaborative Interactivity Metrics to analyze students' Problem-Solving Behaviors during STEM+C Computational Modeling Tasks. (2023). Submitted to Learning and Individual Differences. Currently under review.

[134] Caitlin Snyder, Nicole M Hutchins, Clayton Cohn, Joyce Horn Fonteles, and Gautam Biswas. 2024. Analyzing Students Collaborative Problem-Solving Behaviors in Synergistic STEM+C Learning. In *Proceedings of the 14th Learning Analytics and Knowledge Conference* (Kyoto, Japan) *(LAK '24)*. Association for Computing Machinery, New York, NY, USA, 540–550. https://doi.org/10.1145/3636555.3636912

[135] Rustici Software. 2024. xAPI.com — xapi.com. https://xapi.com/?utm_source=google&utm_medium=natural_search. [Accessed 25-01-2024].

[136] Daniel Spikol, Emanuele Ruffaldi, and Mutlu Cukurova. 2017. Using Multimodal Learning Analytics to Identify Aspects of Collaboration in Project-Based Learning. In *Making a Difference: Prioritizing Equity and Access in CSCL*, Vol. 1. International Society of the Learning Sciences, Philadelphia, PA USA, 263–270.

[137] Daniel Spikol, Emanuele Ruffaldi, Giacomo Dabisias, and Mutlu Cukurova. 2018. Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. *Journal of Computer Assisted Learning* 34, 4 (Aug. 2018), 366–377. https://doi.org/10.1111/jcal.12263

[138] Daniel Spikol, Emanuele Ruffaldi, Lorenzo Landolfi, and Mutlu Cukurova. 2017. Estimation of Success in Collaborative Learning Based on Multimodal Learning Analytics Features. In *2017 IEEE 17th International Conference on Advanced Learning Technologies (ICALT)*. IEEE, Timisoara, Romania, 269–273. https://doi.org/10.1109/ICALT.2017.122

[139] Penelope J. Standen, David J. Brown, Mohammad Taheri, Maria J. Galvez Trigo, Helen Boulton, Andrew Burton, Madeline J. Hallewell, James G. Lathe, Nicholas Shopland, Maria A. Blanco Gonzalez, Gosia M. Kwiatkowska, Elena Milli, Stefano Cobello, Annaleda Mazzucato, Marco Traversi, and Enrique Hortal. 2020. An evaluation of an adaptive learning system based on multimodal affect recognition for learners with intellectual disabilities. *British Journal of Educational Technology* 51, 5 (Sept. 2020), 1748–1765. https://doi.org/10.1111/bjet.13010

[140] Emma L Starr, Joseph M Reilly, and Bertrand Schneider. 2018. Toward Using Multi-Modal Learning Analytics to Support and Measure Collaboration in Co-Located Dyads. In *ICLS 2018*. International Society of the Learning Sciences, London, UK, 448–455.

[141] Steven A. Stolz. 2015. Embodied Learning. *Educational Philosophy and Theory* 47, 5 (2015), 474–487. https://doi.org/10.1080/00131857.2013.879694

[142] Ömer Sümer, Patricia Goldberg, Sidney D'Mello, Peter Gerjets, Ulrich Trautwein, and Enkelejda Kasneci. 2023. Multimodal Engagement Analysis From Facial Videos in the Classroom. *IEEE Transactions on Affective Computing* 14, 2 (April 2023), 1012–1027. https://doi.org/10.1109/TAFFC.2021.3127692

[143] Hiroki Tanaka, Hideki Negoro, Hidemi Iwasaka, and Satoshi Nakamura. 2017. Embodied conversational agents for multimodal automated social skills training in people with autism spectrum disorders. *PLOS ONE* 12, 8 (Aug. 2017), e0182151. https://doi.org/10.1371/journal.pone.0182151

[144] Sofia Tancredi, Rotem Abdu, Ramesh Balasubramaniam, and Dor Abrahamson. 2022. Intermodality in Multimodal Learning Analytics for Cognitive Theory Development: A Case from Embodied Design for Mathematics Learning. In *The Multimodal Learning Analytics Handbook*, Michail Giannakos, Daniel Spikol, Daniele Di Mitri, Kshitij Sharma, Xavier Ochoa, and Rawad Hammad (Eds.). Springer International Publishing, Cham, 133–158. https://link.springer.com/10.1007/978-3-031-08076-0_6

[145] Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al. 2023. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805* N/A, N/A (2023), N/A.

[146] David R. Thomas. 2006. A General Inductive Approach for Analyzing Qualitative Evaluation Data. *American Journal of Evaluation* 27, 2 (2006), 237–246. https://doi.org/10.1177/1098214005283748 arXiv:https://doi.org/10.1177/1098214005283748

[147] Thomas Thiebaud". 2020. Spacy FastLang. https://spacy.io/universe/project/spacy_fastlang. [Accessed 08-02-2024].

[148] Gabriella Tisza, Kshitij Sharma, Sofia Papavlasopoulou, Panos Markopoulos, and Michail Giannakos. 2022. Understanding Fun in Learning to Code: A Multi-Modal Data approach. In *Interaction Design and Children*. ACM, Braga Portugal, 274–287. https://doi.org/10.1145/3501712.3529716

[149] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models, 2023. *URL https://arxiv. org/abs/2307.09288* N/A, N/A (2023), N/A.

[150] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems* 30 (2017), N/A.

[151] Caleb Vatral, Gautam Biswas, Clayton Cohn, Eduardo Davalos, and Naveeduddin Mohammed. 2022. Using the DiCoT framework for integrated multimodal analysis in mixed-reality training environments. *Frontiers in artificial intelligence* 5 (2022), 941825.

[152] Caleb Vatral, Naveeduddin Mohammed, Gautam Biswas, Nicholas Roberts, and Benjamin Goldberg. 2023. A Comparative Analysis Interface to Streamline After-Action Review in Experiential Learning Environments. In *Proceedings of the 11th Annual Generalized Intelligent Framework for Tutoring (GIFT) Users Symposium (GIFTSym11)*. US Army Combat Capabilities Development Command–Soldier Center, N/A, N/A, 101.

[153] Bastian Venthur. 2010. GitHub - venthur/gscholar: Query Google Scholar with Python. https://github.com/venthur/gscholar. [Accessed 08-02-2024].

[154] Hana Vrzakova, Mary Jean Amon, Angela Stewart, Nicholas D. Duran, and Sidney K. D'Mello. 2020. Focused or stuck together: multimodal patterns reveal triads' performance in collaborative problem solving. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*. ACM, Frankfurt Germany, 295–304. https://doi.org/10.1145/3375462.3375467

[155] Milica Vujovic, Davinia Hernández-Leo, Simone Tassani, and Daniel Spikol. 2020. Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study. *British Journal of Educational Technology* 51, 5 (Sept. 2020), 1597–1614. https://doi.org/10.1111/bjet.12988

[156] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. 2022. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. *arXiv e-prints* N/A, N/A, Article arXiv:2201.11903 (Jan. 2022), N/A pages. https://doi.org/10.48550/arXiv.2201.11903 arXiv:2201.11903 [cs.CL]

[157] Marcelo Worsley. 2018. (Dis)engagement matters: identifying efficacious learning practices with multimodal learning analytics. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge*. ACM, Sydney New South Wales Australia, 365–369. https://doi.org/10.1145/3170358.3170420

[158] Marcelo Worsley and Paulo Blikstein. 2018. A Multimodal Analysis of Making. *International Journal of Artificial Intelligence in Education* 28, 3 (Sept. 2018), 385–419. https://doi.org/10.1007/s40593-017-0160-1

[159] Marcelo Worsley, Kevin Mendoza Tudares, Timothy Mwiti, Mitchell Zhen, and Marc Jiang. 2021. Multicraft: A Multimodal Interface for Supporting and Studying Learning in Minecraft. In *HCI in Games: Serious and Immersive Games*, Xiaowen Fang (Ed.). Vol. 12790. Springer International Publishing, Cham, 113–131. https://link.springer.com/10.1007/978-3-030-77414-1_10

[160] Kang Xia, Wenzhong Li, Shiwei Gan, and Sanglu Lu. 2024. TS2ACT: Few-Shot Human Activity Sensing with Cross-Modal Co-Learning. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 7, 4 (2024), 1–22.

[161] Lixiang Yan, Linxuan Zhao, Dragan Gasevic, and Roberto Martinez-Maldonado. 2022. Scalability, Sustainability, and Ethicality of Multimodal Learning Analytics. In *LAK22: 12th International Learning Analytics and Knowledge Conference* (Online, USA) *(LAK22)*. Association for Computing Machinery, New York, NY, USA, 13–23. https://doi.org/10.1145/3506860.3506862

[162] Xi Yang, Yeo-Jin Kim, Michelle Taub, Roger Azevedo, and Min Chi. 2020. PRIME: Block-Wise Missingness Handling for Multi-modalities in Intelligent Tutoring Systems. In *MultiMedia Modeling*, Yong Man Ro, Wen-Huang Cheng, Junmo Kim, Wei-Ta Chu, Peng Cui, Jung-Woo Choi, Min-Chun Hu, and Wesley De Neve (Eds.). Vol. 11962. Springer International Publishing, Cham, 63–75. http://link.springer.com/10.1007/978-3-030-37734-2_6

[163] Abhay Zala, Jaemin Cho, Satwik Kottur, Xilun Chen, Barlas Oguz, Yashar Mehdad, and Mohit Bansal. 2023. Hierarchical Video-Moment Retrieval and Step-Captioning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. N/A, N/A, 23056–23065.

[164] Abhay Zala, Han Lin, Jaemin Cho, and Mohit Bansal. 2023. DiagrammerGPT: Generating Open-Domain, Open-Platform Diagrams via LLM Planning. *arXiv preprint arXiv:2310.12128* N/A, N/A (2023), N/A.

[165] Mengxi Zhou, Joyce Fonteles, Joshua Danish, Eduardo Davalos, Selena Steinberg, Gautam Biswas, and Noel Enyedy. 2024. Exploring artificial intelligence supported interaction analysis. In *Proceedings of the 18th International Conference of the Learning Sciences - ICLS 2024*. International Society of the Learning Sciences, NY, USA, 2327–2328.

[166] John Zilvinskis, James Willis III, and Victor M. H. Borden. 2017. An Overview of Learning Analytics. *New Directions for Higher Education* 2017, 179 (2017), 9–17. https://doi.org/10.1002/he.20239 arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/he.20239

## A CORPUS TABLE

Table 5 enumerates the 73 papers in this literature review's corpus.

| UUID | First Author | Title | Year | Publication |
|---|---|---|---|---|
| 2456887548 [5] | Alyuz | An Unobtrusive And Multimodal Approach For Behavioral Engagement Detection Of Students | 2017 | MIE |
| 818492192 [6] | Andrade | Understanding Student Learning Trajectories Using Multimodal Learning Analytics Within An Embodied-Interaction Learning Environment | 2017 | LAK |
| 3637456466 [8] | Ashwin | Impact Of Inquiry Interventions On Students In E-Learning And Classroom Environments Using Affective Computing Framework | 2020 | UMUAI |
| 3448122334 [9] | Aslan | Investigating The Impact Of A Real-Time, Multimodal Student Engagement Analytics Technology In Authentic Classrooms | 2019 | CHI |
| 1886134458 [10] | Azcona | Personalizing Computer Science Education By Leveraging Multimodal Learning Analytics | 2018 | FIE |
| 3146393211 [11] | Birt | Mobile Mixed Reality For Experiential Learning And Simulation In Medical And Health Sciences Education | 2018 | Information |
| 1326191931 [19] | Chan | Multimodal Learning Analytics In A Laboratory Classroom | 2019 | MLPALA |
| 2936220551 [20] | Chango | Multi-Source And Multimodal Data Fusion For Predicting Academic Performance In Blended Learning University Courses | 2020 | CEE |
| 4277812050 [21] | Chango | Improving Prediction Of Students' Performance In Intelligent Tutoring Systems Using Attribute Selection And Ensembles Of Different Multimodal Data Sources | 2021 | JCHE |
| 1426267857 [23] | Chen | Affect, Support, And Personal Factors: Multimodal Causal Models Of One-On-One Coaching | 2021 | JEDM |
| 3809293172 [27] | Closser | Blending Learning Analytics And Embodied Design To Model Students' Comprehension Of Measurement Using Their Actions, Speech, And Gestures | 2021 | IJCCI |
| 4019205162 [38] | Cornide-Reyes | Introducing Low-Cost Sensors Into The Classroom Settings: Improving The Assessment In Agile Practices With Multimodal Learning Analytics | 2019 | Sensors |
| 1576545447 [43] | Cukurova | Artificial Intelligence And Multimodal Data In The Service Of Human Decision-Making: A Case Study In Debate Tutoring | 2019 | BJET |
| 1609706685 [48] | Di Mitri | Learning Pulse: A Machine Learning Approach For Predicting Performance In Self-Regulated Learning Using Multimodal Data | 2017 | LAK |

| | | | | |
|---|---|---|---|---|
| 2070224207 [98] | Di Mitri | Detecting Medical Simulation Errors With Machine Learning And Multimodal Data | 2019 | CAIM |
| 3009548670 [51] | Di Mitri | Real-Time Multimodal Feedback With The Cpr Tutor | 2020 | AIED |
| 1763513559 [49] | Di Mitri | Keep Me In The Loop: Real-Time Feedback With Multimodal Data | 2021 | IJAIED |
| 1296637108 [53] | Echeverria | Towards Collaboration Translucence: Giving Meaning To Multimodal Group Data | 2019 | CHI |
| 1581261659 [55] | Emerson | Early Prediction Of Visitor Engagement In Science Museums With Multimodal Learning Analytics | 2020 | ICMI |
| 1598166515 [54] | Emerson | Multimodal Learning Analytics For Game-Based Learning | 2020 | BJET |
| 4035649049 [57] | Fernández-Nieto | Storytelling With Learner Data: Guiding Student Reflection On Multimodal Team Data | 2021 | TLT |
| 483140962 [62] | Fwa | Investigating Multimodal Affect Sensing In An Affective Tutoring System Using Unobtrusive Sensors | 2018 | PPIG |
| 4278392816 [65] | Giannakos | Multimodal Data As A Means To Understand The Learning Experience | 2019 | IJIM |
| 853680639 [69] | Henderson | Sensor-Based Data Fusion For Multimodal Affect Detection In Game-Based Learning Environments | 2019 | EDM |
| 86191824 [74] | Jiang | Examining How Different Modes Mediate Adolescents' Interactions During Their Collaborative Multimodal Composing Processes | 2019 | ILE |
| 3398902089 [75] | Järvelä | What Multimodal Data Can Tell Us About The Students' Regulation Of Their Learning Process? | 2019 | LAI |
| 32184286 [79] | Kubsch | Once More With Feeling: Emotions In Multimodal Learning Analytics | 2022 | MMLA Handbook |
| 205660768 [80] | Larmuseau | Multimodal Learning Analytics To Investigate Cognitive Load During Online Problem Solving | 2020 | BJET |
| 1877483551 [83] | Lee-Cultura | Motion-Based Educational Games: Using Multi-Modal Data To Predict Player'S Performance | 2020 | COG |
| 3660066725 [81] | Lee-Cultura | Children'S Play And Problem Solving In Motion-Based Educational Games: Synergies Between Human Annotations And Multi-Modal Data | 2021 | IDC |
| 3856280479 [82] | Lee-Cultura | Children'S Play And Problem-Solving In Motion-Based Learning Technologies Using A Multi-Modal Mixed Methods Approach | 2021 | IJCCI |
| 804659204 [87] | Liu | Towards Smart Educational Recommendations With Reinforcement Learning In Classroom | 2018 | TALE |

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|---|---|---|---|---|
| 3783339081 [86] | Liu | A Novel Method For The In-Depth Multimodal Analysis Of Student Learning Trajectories In Intelligent Tutoring Systems | 2018 | JLA |
| 3796180663 [85] | Liu | Learning Linkages: Integrating Data Streams Of Multiple Modalities And Timescales | 2018 | JCAL |
| 518268671 [89] | López | Using Multimodal Learning Analytics To Explore Collaboration In A Sustainability Co-Located Tabletop Game | 2021 | ECGBL |
| 566043228 [18] | Ma | Automatic Student Engagement In Online Learning Environment Based On Neural Turing Machine | 2021 | IJIET |
| 3754172825 [90] | Ma | Detecting Impasse During Collaborative Problem Solving With Multimodal Learning Analytics | 2022 | LAK |
| 147203129 [91] | Mangaroska | Multimodal Learning Analytics To Inform Learning Design: Lessons Learned From Computing Education | 2020 | JLA |
| 1847468084 [92] | Martin | Computationally Augmented Ethnography: Emotion Tracking And Learning In Museum Games | 2019 | ICQE |
| 2879332689 [93] | Martinez-Maldonado | From Data To Insights: A Layered Storytelling Approach For Multimodal Learning Analytics | 2020 | CHI |
| 2155422499 [99] | Morell | A Multimodal Analysis Of Pair Work Engagement Episodes: Implications For Emi Lecturer Training | 2022 | JEAP |
| 2273914836 [101] | Nasir | Many Are The Ways To Learn Identifying Multi-Modal Behavioral Profiles Of Collaborative Learning In Constructivist Activities | 2022 | IJCSCL |
| 1469065963 [102] | Nguyen | Examining Socially Shared Regulation And Shared Physiological Arousal Events With Multimodal Learning Analytics | 2022 | BJET |
| 2345021698 [104] | Noël | Exploring Collaborative Writing Of User Stories With Multimodal Learning Analytics: A Case Study On A Software Engineering Course | 2018 | Access |
| 2609260641 [105] | Noël | Visualizing Collaboration In Teamwork: A Multimodal Learning Analytics Platform For Non-Verbal Communication | 2022 | DAMLE |
| 2497456347 [107] | Ochoa | The Rap System: Automatic Feedback Of Oral Presentation Skills Using Multimodal Analysis And Low-Cost Sensors | 2018 | LAK |
| 2634033325 [106] | Ochoa | Controlled Evaluation Of A Multimodal System To Improve Oral Presentation Skills In A Real Learning Setting | 2020 | BJET |

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|---|---|---|---|---|
| 3051560548 [110] | Olsen | Temporal Analysis Of Multimodal Data To Predict Collaborative Learning Outcomes | 2020 | BJET |
| 123412197 [112] | Papamitsiou | Utilizing Multimodal Data Through Fsqca To Explain Engagement In Adaptive Learning | 2020 | TLT |
| 85990093 [115] | Petukhova | Multimodal Markers Of Persuasive Speech : Designing A Virtual Debate Coach | 2017 | INTERSPEECH |
| 957160695 [114] | Petukhova | Virtual Debate Coach Design: Assessing Multimodal Argumentation Performance | 2017 | ICMI |
| 1374035721 [116] | Pham | Attentivelearner2: A Multimodal Approach For Improving Mooc Learning On Mobile Devices | 2017 | AIED |
| 2836996318 [117] | Pham | Predicting Learners' Emotions In Mobile Mooc Learning Via A Multimodal Intelligent Tutor | 2018 | ITS |
| 3135645357 [119] | Prieto | Multimodal Teaching Analytics: Automated Extraction Of Orchestration Graphs From Wearable Sensor Data | 2018 | JCAL |
| 3408664396 [120] | Psaltis | Multimodal Student Engagement Recognition In Prosocial Games | 2017 | T-CIAIG |
| 3308658121 [123] | Reilly | Exploring Collaboration Using Motion Sensors And Multi-Modal Learning Analytics | 2018 | EDM |
| 3625722965 [95] | Sanusi | Table Tennis Tutor: Forehand Strokes Classification Based On Multimodal Data And Neural Networks | 2021 | Sensors |
| 2000036002 [132] | Sharma | Predicting Learners' Effortful Behaviour In Adaptive Assessment Using Multimodal Data | 2020 | LAK |
| 1118315889 [136] | Spikol | Using Multimodal Learning Analytics To Identify Aspects Of Collaboration In Project-Based Learning | 2017 | CSCL |
| 3339002981 [138] | Spikol | Estimation Of Success In Collaborative Learning Based On Multimodal Learning Analytics Features | 2017 | ICALT |
| 1637690235 [137] | Spikol | Supervised Machine Learning In Multimodal Learning Analytics For Estimating Success In Project-Based Learning | 2018 | JCAL |
| 3796643912 [139] | Standen | An Evaluation Of An Adaptive Learning System Based On Multimodal Affect Recognition For Learners With Intellectual Disabilities | 2020 | BJET |
| 2181637610 [140] | Starr | Toward Using Multi-Modal Learning Analytics To Support And Measure Collaboration In Co-Located Dyads | 2018 | ICLS |
| 1315379489 [142] | Sümer | Multimodal Engagement Analysis From Facial Videos In The Classroom | 2021 | TAC |

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|---|---|---|---|---|
| 3093310941 [143] | Tanaka | Embodied Conversational Agents For Multimodal Automated Social Skills Training In People With Autism Spectrum Disorders | 2017 | PLOS |
| 1345598079 [144] | Tancredi | Intermodality In Multimodal Learning Analytics For Cognitive Theory Development: A Case From Embodied Design For Mathematics Learning | 2022 | MMLA Handbook |
| 433919853 [148] | Tisza | Understanding Fun In Learning To Code: A Multi-Modal Data Approach | 2022 | IDC |
| 1770989706 [154] | Vrzakova | Focused Or Stuck Together: Multimodal Patterns Reveal Triads' Performance In Collaborative Problem Solving | 2020 | LAK |
| 2055153191 [155] | Vujovic | Round Or Rectangular Tables For Collaborative Problem Solving? A Multimodal Learning Analytics Study | 2020 | BJET |
| 3095923626 [158] | Worsley | A Multimodal Analysis Of Making | 2017 | IJAIED |
| 3309250332 [157] | Worsley | (Dis)Engagement Matters: Identifying Efficacious Learning Practices With Multimodal Learning Analytics | 2018 | LAK |
| 666050348 [159] | Worsley | Multicraft: A Multimodal Interface For Supporting And Studying Learning In Minecraft | 2021 | HCII |
| 1019093033 [162] | Yang | Prime: Block-Wise Missingness Handling For Multi-Modalities In Intelligent Tutoring Systems | 2019 | MMM |

Table 5. Each of the 73 works in our corpus.

## B CORPUS DISTILLATION PROCEDURE

This appendix contains a detailed account of the steps we took to gather relevant works for our literature review and how we distilled the initial search results to the 73 papers in our final corpus.

### B.1 Literature Search

Our literature search consisted of 42 search strings defined, discussed, and agreed upon by the authors as being representative of the body of works this literature review would be conducted on. Instead of performing our queries manually, we opted to perform our queries programmatically via an API-based Google Scholar web scraping tool. There are several available tools for scraping Google Scholar, such as scholarly [25] and gscholar [153]. Ultimately, we employed SerpAPI [129], a third-party Google Scholar web scraping API, for its most essential feature: organic web results. Other API tools' results are not organic, i.e., a query made via the API and one manually queried in a browser-based environment will produce two different sets of results.

Queries were posed via API request to Google Scholar for papers published between 1/1/2017 and 10/22/2022 (the date of our literature search). 2017 was collectively agreed upon as being the best cutoff date for inclusion in our search due to the rapid technological advancements in the field over the past 5 years. Several papers prior to 2017 are discussed in Section 1, as they are seminal works; however, they are not considered for inclusion in our corpus.

For the literature search, this review's authors decided on 14 distinct search phrases, and each phrase was searched 3 times with a different spelling of the word *multimodal* — multimodal, multi-modal, and multi modal — prepended to it. The 14 search phrases are enumerated in Table 6.[2]

| | |
|---|---|
| education technology | explainable artificial intelligence |
| learning analytics | learning environments |
| learning environments literature review | learning environments survey |
| literature review | simulation environments |
| survey | training environments |
| training environments literature review | training environments survey |
| tutoring systems | xai |

Table 6. Search strings used for the initial literature search.

For each of the 42 search strings, the top 5 pages (100 publications) deemed most relevant by Google Scholar were collected. The top-5 cutoff was financially imposed because of our subsequent citation graph construction (see Appendix B.2.1). To build the citation graph, each individual paper's citation information is queried, but each query is capped at 20 citations per API call by SerpAPI. This means that a paper with 100 citations requires 5 additional API calls to gather all of its citation information. The number of API calls needed to construct the citation graph would be intractable if the initial search was left unbounded; therefore, the top-5 cutoff was put in place.

Our initial search yielded a total of 4,200 papers (14 unique search terms * 3 spellings of multimodal * 100 publications per search string). Our corpus reduction procedure is enumerated in Table 7 and discussed in the following subappendices. Throughout this appendix, each step of our corpus reduction procedure is identified via its Step ID in Table 7.

[2]The term "xai" was included in the search due to the authors' interest in exploring explainable AI methods applied to learning and training environments. Unfortunately, the field is still nascent, and no usable query results were returned with this search string.

| Step ID | Procedure | Removed | Remaining |
|---|---|---|---|
| 0 | Literature search | 0 | 4200 |
| 1 | Remove duplicates | 2079 | 2121 |
| 2 | Remove non-English | 1 | 2120 |
| 3 | Remove degree-0 nodes | 488 | 1632 |
| 4 | Remove disconnected components | 101 | 1531 |
| 5 | Iteratively remove degree-1 nodes | | |
| 5.1 | Iteration 1 | 373 | 1158 |
| 5.2 | Iteration 2 | 74 | 1084 |
| 5.3 | Iteration 3 | 19 | 1065 |
| 5.4 | Iteration 4 | 2 | 1063 |
| 6 | Remove titles with keywords | 204 | 859 |
| 7 | Title reads | 471 | 388 |
| 8 | Abstract reads | | |
| 8.1 | Remove inaccessible abstracts | 10 | 378 |
| 8.2 | First abstract round | 211 | 167 |
| 8.3 | Second abstract round | 40 | 127 |
| 9 | Full paper reads | | |
| 9.1 | First full paper round | 52 | 75 |
| 9.2 | Feature discretization and extraction | 2 | 73 |
| 9.3 | Second full paper round | 0 | 73 |
| 9.4 | Second feature extraction round | 0 | 73 |

Table 7. Our corpus reduction procedure. Step ID 0 is the literature search. Steps 1 and 2 used programmatic filtering via Python packages. Steps 3-5 were performed quantitatively via CGP (see Section 3). Step 6 uses human-in-the-loop regex filtering. Steps 7-9 were performed qualitatively via our quality control procedure. Each Step ID lists the number of papers removed and remaining.

Our initial corpus contained 2,079 duplicates, which were removed by hashing paper titles (Table 7, Step ID 1). If a paper had multiple versions (or other duplicates), we used the official source (e.g., journal or conference) of publication. We removed 1 non-English paper (Table 7, Step ID 2) due to pragmatism (English is the only language shared between all of this review's authors). Non-English papers were identified using spaCy FastLang [147], where any paper whose title was identified as having less than a 100% chance of being English was selected for manual review and potential exclusion. In total, our initial search yielded 2,120 unique English papers published within our search window.

### B.2 Study Selection

To reduce our corpus to a reviewable body of works, we employed both quantitative ans qualitative methods. After the initial search, we distilled the corpus quantitatively via CGP, which we discuss in Appendix B.2.1. Subsequent distillation was performed via qualitative means and is discussed in Appendix B.2.2.

*B.2.1 Citation Graph Pruning (Quantitative Corpus Reduction).* For visualization, analysis, and distillation purposes, we used NetworkX [67] to create and display a *citation graph* of the initial 2,120 works considered for inclusion in this review. The citation graph is a directed acyclic graph (DAG), where each node is a paper uniquely identifiable by its UUID (universally unique identifier) on Google Scholar, and each directed edge from A to B indicates paper A cites paper B. For the purposes of this paper, we consider the degree of each node (paper) $p$ to be the sum of both incoming and outgoing edges, i.e., papers citing $p$ and papers cited by $p$, respectively. We again used SerpAPI for collecting the list of works that cited each paper. The citation search did not need to be conducted in both directions, as any paper citing another paper in our corpus would already have been identified by the "cited by" list of the paper being cited. Citations by papers not included in our initial search (i.e., not in the DAG) were ignored. Initially, our DAG contained a 3-node cycle. This was due to papers by the same author citing each other during preprint. Once the cycle was identified, the cycle's edges were removed from the edge set. No nodes were removed as a result of correcting the cycle.

Once the DAG was constructed, we removed all 0-degree nodes (Table 7, Step ID 3; i.e., nodes with no edges coming in or going out). We felt it reasonable that if a paper did not cite (or was not cited by) any other papers in the field (as determined by our literature search), then the paper was either not relevant to the field or did not yield methods or findings referenced by subsequent works. Importantly, our approach strikes a balance between incoming and outgoing citations, as earlier works are unable to *cite* many works in the corpus, and later works are unable to *be cited by* many works in the corpus. For example, works from early 2017 may not have any outgoing edges simply due to being some of the earliest works in the corpus, which would have prevented them from citing papers that had not yet been published. However, these same papers had a greater opportunity to be cited by subsequent papers, which is why we felt it important to consider both incoming and outgoing edges. We expected earlier papers to have more incoming edges and later papers to have more outgoing edges, which was supported by our final corpus's relatively uniform distribution over publication years. Altogether, pruning 0-degree nodes from the DAG reduced our corpus by 488, dropping our corpus count to 1,632 works.

After removing 0-degree nodes, we examined the DAG's connectivity (Table 7, Step ID 4) to identify disconnected components deemed irrelevant to the field, which was necessary to account for overlapping terminology across domains. For example, a cursory look at our initial search results included several "multimodal training" papers related to deep learning (DL), where artificial neural networks (ANNs) are trained using data across multiple modalities but are not applied to multimodal learning or training environments. Our hypothesis, based on our search strings, was that the works relevant to this review would comprise the largest component of the DAG, leaving other smaller, disconnected components to be discarded as irrelevant because they lacked any edge to or from the DAG's primary component.

Evaluating the DAG's connectivity, we found one large component consisting of 1,531 nodes (papers) and 44 smaller, disconnected components of various sizes totaling 101 papers. The sizes of the disconnected components, their frequencies of occurrence in the DAG, and the total number of papers for each component size are listed in Table 8. All 101 papers were removed from the corpus by pruning the DAG's disconnected components, which left 1,531 papers represented by a single, connected graph.

Once we had our single component graph, we removed 1-degree nodes to further prune it. This created new 1-degree nodes, which were also removed. This process of removing 1-degree nodes was repeated four times (Table 7, Step ID 5) until the graph was stable (i.e., removing 1-degree nodes did not create any new 1-degree nodes). By iteratively removing 1-degree nodes, we felt we could effectively identify and remove works outside the scope of our literature review without losing works directly related to multimodal learning and training environments. This is because the field of multimodal learning and training environments spans several sub-fields across computer science, education,

psychology, etc., and the authors agreed it was unlikely papers with so few edges would be relevant to our review. We removed 373 nodes in the first iteration (Table 7, Step ID 5.1), 74 nodes in the second iteration (Table 7, Step ID 5.2), 19 nodes in the third iteration (Table 7, Step ID 5.3), and 2 nodes in the fourth and final iteration (Table 7, Step ID 5.4). Altogether, we removed 468 papers over four iterations, reducing our corpus from 1,531 papers to 1,063. The CGP pseudocode is presented in Section 3.2.1 (Algorithm 1). At this point we concluded our quantitative pruning procedure and began qualitatively reducing the corpus.

| Size | # | Papers |
|---|---|---|
| 2 | 35 | 70 |
| 3 | 6 | 18 |
| 4 | 2 | 8 |
| 5 | 1 | 5 |

Table 8. Disconnected DAG components by number of nodes in the component (size), frequency of occurrence (#), and total number of papers (papers). For instance, the first row indicates that there were 35 disconnected components of size 2 in the graph, totaling to 70 papers.

*B.2.2 Quality Control (Qualitative Corpus Reduction).* Manually examining the remaining 1,063 titles informed us that a large part of our corpus was still outside the scope of our review. First, we noticed there were still many papers related to training multimodal neural networks. We also noticed many works applying multimodal methods to the medical field, usually in terms of medical imaging. To remove papers pertaining to multimodal neural network training and multimodal medical applications, we programmatically identified 217 titles via regex keyword search (Table 7, Step ID 6) that contained at least one of the six following words: neural, deep, machine, medical, medicine, and healthcare. We then evaluated the selected titles by hand. Of the 217, 13 were kept in the corpus due to their potential relevance to our review. Papers employing deep learning methods in MMLA or applying multimodal methods to medical learning or training environments were within our scope, for example. Specific examples include removing one paper titled, "deep learning for object detection and scene perception in self-driving cars: survey, challenges, and open issues" [66]; and keeping one titled, "supervised machine learning in multimodal learning analytics for estimating success in project-based learning" [137]. The remaining 204 papers were removed from the corpus, reducing it to 859 potentially relevant works.

Next, we selected papers for exclusion based on consensus. Pursuant to Kitchenham [77], we initially excluded works based on reading papers' titles, then abstracts, and eventually full manuscripts. The first five authors of this review acted as reviewers (henceforth referred to as "the Reviewers") for the quality control procedure. For the title reads (Table 7, Step ID 7), four of the Reviewers read all 859 titles. For each title, each Reviewer independently determined whether the title was likely to fall inside the scope of the review. The results were tallied, and papers were then selected for inclusion/exclusion based on majority voting, i.e., papers with at least three votes "for" were automatically included, and papers with at least three votes "against" were automatically excluded. For the papers with a 2-2 tie, a fifth reviewer was used as a tie breaker. The Reviewers selected 347 papers for inclusion and 372 papers for exclusion. 140 papers were tied, and a fifth reviewer selected 41 of those for inclusion. In total, 388 papers were selected for inclusion after the title reads — 347 by majority vote, and 41 by tie-breaker.

Before conducting the abstract reads (Table 7, Step ID 8), several works were excluded due to their inaccessibility (Table 7, Step ID 8.1). While gathering the abstracts, we noticed not all papers were publicly available. Several were defined by invalid URLs or behind paywalls. Whenever a paper's abstract (or introduction, in the case of a book or book chapter) was unavailable via its SerpAPI URL, a Google search was conducted in order to obtain the abstract manually through websites such as ResearchGate and other academic repositories. When this failed, we relied on the Vanderbilt University Library's proxy to access papers behind paywalls. If we were unable to freely access a paper's abstract online

through Google search or via Vanderbilt's proxy, the paper was excluded from the corpus. Altogether, 10 papers were removed due to inaccessibility, leaving 378 papers for abstract reads.

The "abstracts" quality control procedure consisted of two rounds. Similar to the procedure for the title reads, each of the remaining 378 abstracts was first assigned to two Reviewers, and a majority voting scheme was employed (Table 7, Step ID 8.2). Papers were then selected for inclusion or exclusion based on a predefined set of exclusion criteria. The exclusion criteria for the abstracts is listed in Table 9. Exclusion criteria are cumulative, so each criterion applies to subsequent steps in our corpus reduction procedure. An exclusion criterion for the abstracts will similarly apply to full paper reads later on, for example.

| |
|---|
| 1. Paper does not deal with learning or training environments |
| 2. Paper's environment is VR-only |
| 3. Paper does not analyze multimodal data |
| 4. Paper does not apply multimodal analysis methods |
| 5. Paper is not original applied research |

Table 9. Exclusion criteria for the abstract reads. Each of the 378 abstracts was assigned to two different Reviewers. Each reviewer was instructed to exclude works based on this set of criteria.

Because this literature review focuses on multimodal methods applied to learning and training environments, any paper not dealing with a learning or training environment was not considered for this review. As mentioned in Section 1, virtual reality (VR) environments were also not considered for inclusion in our corpus due to issues with scaling this technology in classroom settings. If a paper does not analyze multimodal data, it is similarly out-of-scope for this review. Papers must also include systematic methods for analyzing the multimodal data, and those methods must be original, applied research. Papers that are literature reviews, pedagogical tools, theoretical foundations, doctoral consortiums, etc., may be used for reference in our Introduction and Background, but they are not considered for inclusion in the actual review corpus unless they additionally provide original, applied research via multimodal methods and analysis.

Of the 378 abstracts, Reviewers agreed to keep 96 papers (i.e., both Reviewers selected the work for inclusion) and discard 211 (i.e., both Reviewers selected the work for exclusion). 71 were selected for further review (i.e., one reviewer selected the work for inclusion and one reviewer selected the work for exclusion). To address the 71 abstracts that did not receive unanimous agreement among Reviewers, a second round of abstract reads was performed (Table 7, Step ID 8.3). This round consisted of each of the 71 abstracts without unanimous agreement receiving three additional reads: one read from each of the three Reviewers who did not read the abstract in the initial abstract round. Each of the 71 papers was subsequently included or excluded based on majority voting (i.e., papers were kept if and only if at least two out of the three second abstract round Reviewers elected to keep the abstract in the corpus). Of the 71 second abstract round papers, 31 were selected for inclusion, and 40 were removed from the corpus. With 96 papers selected for inclusion from the first round of abstract reads, and 31 papers selected from the second round, 127 papers in total were kept in the corpus for the next round of quality control: full paper reads.

The "full paper" quality control procedure also involved two rounds of review. To conduct full paper reads (Table 7, Step ID 9), the 127 papers kept from the abstract round were split into 5 approximately equal partitions and randomly assigned to the 5 Reviewers. Conducting full paper reads took several weeks, during which two additional exclusion criteria were defined. They are enumerated in Table 10.

Certain papers deal with learning or training environments but are outside the scope of this review because they are not informative with respect to learning or training. Consider a paper presenting a novel neural network architecture that uses a classroom dataset as a performance benchmark. While the classroom constitutes a learning environment,

the paper itself is not conducting research to inform learning or training, but rather is using a dataset collected from a learning environment to evaluate a core AI approach. We elected not to include these types of works in our review, as we aim to focus on multimodal methods that are explicitly used to inform learning or training. Additionally, a few papers we encountered did not have analysis methods that were well-defined enough for feature extraction (i.e., we were unsure of their exact methods for analyzing the data). This often included short workshop papers whose method details were unable to be determined without referencing external works.[3] Because these types of papers would be very difficult to reproduce on their own, we elected to exclude them from our review.

| |
|---|
| 1. Paper's results are not informative with respect to learning or training |
| 2. Paper's analysis methods are not able to be determined from the manuscript |

Table 10. Exclusion criteria for full paper reads. Each reviewer was instructed to recommend works for exclusion based on this set of criteria and the previously established exclusion criteria.

During the first round of full paper reads (Table 7, Step ID 9.1), Reviewers marked each paper as "immediate exclude," "immediate accept," "borderline exclude," or "borderline accept." Papers marked as "immediate exclude" were discussed by all 5 Reviewers and excluded only if all agreed. These were papers with easily identifiable reasons for exclusion based on our criteria (for instance, a proposed theoretical framework with no analysis or a doctoral consortium presenting ideas for future research). No papers were ever excluded from our corpus during full paper reads without unanimous agreement from all five Reviewers. Papers marked as "immediate accept" were kept in the corpus for the second full paper read round. Papers marked as "borderline exclude" or "borderline accept" were assigned to a separate reader for further review and were subsequently discussed. Similar to papers marked for immediate exclusion, borderline papers were excluded prior to the second full paper read round only if all Reviewers agreed. Altogether, 52 papers were excluded during the first round of full paper reads, which left 75 works remaining in the corpus.

### B.3 Feature Extraction

During the first full paper read round, several features were extracted from each paper (Table 7, Step ID 9.2). Features included identifying information (e.g., title, first author, publication year), and information related to the paper's methods (e.g., data collection mediums, modalities, and analysis methods). The extracted features and their descriptions are found in Table 11.[4]

After the first read, the Reviewers discussed their extracted features. To ensure alignment and understanding between the Reviewers with respect to the features, feature categories were discretized via inductive coding [146], where four Reviewers each extracted initial feature sets from 25% of the corpus's papers. For example, the initially extracted *data collection mediums* feature included instances of video camera, web camera, and Kinect camera, all of which were mapped to the "VIDEO" data collection medium. Once the Reviewers agreed on the discrete sets of features, papers were reread by their original Reviewers, and their features were extracted into the discrete sets. The initial feature-space is described below in Table 12. We call these features *circumscribing features* to delineate them relative to the identifying features (e.g., UUID, paper title, author, etc.) that were extracted for identification purposes but not used in our analysis.

[3]This does not include all workshop papers; only those whose analysis methods could not be determined from the manuscript.

[4]For the "Year" category, we used the date the manuscript was first publicly available (if listed, otherwise we used the publication date) in order to most accurately represent when the methods were performed. In some instances, the first date of online availability preceded the official publication date by over a year. Additionally, only data that was ultimately used in the paper's analysis was considered for the "Data Collection Mediums" category (i.e., if data was collected but never analyzed, we did not include it).

| Feature | Description |
|---|---|
| UUID | Universally unique identifier on Google Scholar |
| Title | Publication title |
| First Author | Publication's first author |
| Year | Year publication was first publicly available |
| Environment Type | Type of environment analyzed in the publication |
| Data Collection Mediums | Types of data collected from the environment |
| Modalities | List of the different modalities used during analysis |
| Analysis Methods | List of the analysis methods used in the publication |
| Fusion Type | List of data fusion types used in the publication |
| Publication Source | Publication journal, conference, workshop, etc. |

Table 11. Initial features extracted from each paper.

In total, two sets of circumscribing features were extracted from the corpus to gather the information needed to conduct our analysis (Table 7, Step IDs 9.2 and 9.4).

| Feature | Feature Set |
|---|---|
| Environment Type | learning, training |
| Data Collection Mediums | video, audio, screen recording, eye tracking, logs, physiological sensor, interview, survey, participant produced artifacts, researcher produced artifacts, motion, text |
| Modalities | affect, pose, gesture, activity, prosodic speech, transcribed speech, qualitative observation, logs, gaze, interview notes, survey, pulse, EDA, body temperature, blood pressure, EEG, fatigue, EMG, participant artifacts, researcher artifacts, audio spectrogram, text, pixel |
| Analysis Methods | Classification, regression, clustering, qualitative, statistical methods, network analysis, pattern extraction |
| Fusion Type | early, mid, late, hybrid, other |

Table 12. The first set of circumscribing features and their corresponding feature sets. For *Environment Type*, items in the feature set are mutually exclusive (i.e., an environment can either be a learning *or* training environment for the purposes of this paper, but it cannot be both). All other circumscribing features can consist of multiple items in the feature set (e.g., each paper in our corpus will contain multiple data collection mediums or modalities). Features are discussed individually in Section 2.2.

During feature discretization and extraction (Table 7, Step ID 9.2), additional papers were newly identified for possible exclusion pursuant to our aforementioned criteria. After discussing each paper selected for possible exclusion, 2 papers were removed from the corpus due to all five Reviewers agreeing that each paper violated at least one exclusion criterion. After the two removals, 73 papers remained in the corpus, all of whose features were extracted into discrete sets pursuant to Table 11 by the first full paper read round reviewer. At this point, a second and final quality control round was performed for full paper reads (Table 7, Step ID 9.3), where each of the 73 papers remaining in the corpus was assigned to a reviewer who had not yet read that particular paper. For this round, Reviewers were instructed to perform two tasks: identify any papers remaining in the corpus that violated any of the exclusion criteria (to discuss later for

possible exclusion), and perform a round of feature extraction (to determine inter-rater reliability, or IRR, with respect to the initial feature extraction via Cohen's $k$ [31]). For this round, no additional papers were identified for exclusion, resulting in a final corpus of 73 works. Each paper's discrete feature sets were ultimately determined via consensus coding [24] by the two Reviewers who read that particular paper (i.e., for each paper, both Reviewers needed to agree on the presence or absence of each item in each feature's feature set). For reference, Cohen's $k$ before consensus for the first round of feature extraction was $k = 0.873$.

Once our corpus was finalized, we performed one additional round of feature extraction (Table 7, Step ID 9.4) to allow for greater insight into the corpus via a more in depth analysis. The features we extracted are: Environment Setting, Domain of Study, Participant Interaction Structure, Didactic Nature, Level of Instruction or Training, Analysis Approach, and Analysis Results (the findings reported from each paper). All of these features are explained in Section 2.1 and presented again here in Table 13 for readability alongside their discrete values. The one exception is Analysis Results, which was not discretized due to the wide degree of variability across each paper's findings. Instead, we noted each paper's findings, and used them in our thematic analysis [16], which we describe in Section 3.4.

| Feature | Feature Set |
|---|---|
| Environment Setting | physical, virtual, blended, unspecified |
| Domain of Study | STEM, humanities, psychomotor skills, other, unspecified |
| Participant Interaction Structure | individual, multi-person |
| Didactic Nature | instructional, training, informal, unspecified |
| Level of Instruction or Training | K-12, university, professional development, unspecified |
| Analysis Approach | model-free, model-based |

Table 13. The second set of circumscribing features, all of which are multi-label, and their corresponding feature sets. Features are discussed individually in Section 2.2.

Similar to our initial round of feature extraction, we began with inductive coding, where four Reviewers first extracted the new circumscribing features for the same papers he or she performed inductive coding on during the previous round of feature extraction. We then discussed each paper's extracted features and formulated discrete sets for the new circumscribing features (with the exception of Analysis Results). Next, we conducted two rounds of full paper reads to extract the second set of circumscribing features. During the first round, Reviewers revisited the same papers they read during inductive coding and extracted the new circumscribing features pursuant to the agreed-upon feature sets devised during inductive coding. During the second round, Reviewers reread (and extracted the additional features from) the same set of papers they were the 2$^{nd}$ reviewer for during the initial round of feature extraction. At this point, for each paper, the two Reviewers who extracted that paper's additional features performed consensus coding to define that paper's final set of features. For reference, Cohen's $k = 0.71$ for the second round of feature extraction prior to consensus coding.

Each item in each of the circumscribing feature sets is described in Sections 2.2.1 (Environment Type), 2.2.2 (Data Collection Mediums), 2.2.3 (Modalities), 2.2.4 (Analysis Methods), 2.2.5 (Data Fusion), 2.2.6 (Environment Setting), 2.2.7 (Domain of Study), 2.2.8 (Participant Interaction Structure), 2.2.9 (Didactic Nature), 2.2.10 (Level of Instruction or Training), and 2.2.11 (Analysis Approach).

## C LITERATURE REVIEW LIMITATIONS

The limitations of this work involve the use of Google Scholar to conduct the literature search, the use of a citation graph for programmatic corpus reduction, and a lack of screening for peer reviewed papers. All are discussed below.

### C.1 Google Scholar.

While Google Scholar is widely used by researchers across both academia and industry, it poses a challenge for reproducibility. Like Google Search, Google Scholar is a proprietary search algorithm that is assumed to vary its results based on context. Factors such as the individual user conducting the search, the user's geolocation, the date the search is conducted, and the user's search history may all affect how Google Scholar collates search results. Google may also perform A/B testing in live environments to determine which version of its algorithm users deem more effective. The algorithm is also (presumably) continually evolving, and users are unable to know exactly which version of the algorithm was used to conduct a particular search. As such, there is little expectation that our initial corpus will be able to be reconstructed *in its exact form* without at least some degree of variability.

However, the authors are confident the degree of variability from different Google Scholar searches does not prohibit the *overall* reproducibility of the initial corpus. While SerpAPI's web scraping method is proprietary, its creators address several of our concerns in their documentation [129]. The API's search does not use information from any individual user's Google account when conducting the web scrape, as no Google account is attached to the SerpAPI account, API key, or API calls themselves. Instead, calls are made via proxy and random headers, as illustrated in Figure 8. When trying to reproduce the API's results via manual search, SerpAPI recommends using the URL in the API's JSON results in "incognito mode".

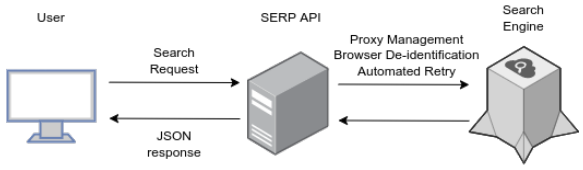


Fig. 8. Searching Google Scholar via SerpAPI.

Additionally, we reached out to SerpAPI directly and asked, "Does SerpAPI attach personal or identifying information when making request?", to which SerpAPI responded, "No, we don't add any personal information." SerpAPI also stated, "...others can reproduce your results by using Google Scholar website, if they use the same search criteria...", but we believe this to be an overstatement given Google's lack of transparency. While we cannot guarantee perfect reproducibility due to the aforementioned issues, we can state with a reasonable degree of confidence that our own individual search biases did not influence the initial search results (outside of the choosing of the search terms) due to how SerpAPI handles API calls to Google Scholar. For reference, this review's literature search was conducted by an author of this paper in Nashville, TN, USA.

### C.2 Citation Graph Pruning.

As discussed in Section 3.2.1, we initially distilled our corpus quantitatively via citation graph pruning. In doing so, it is possible we excluded relevant works from our corpus based on them only having cited or been cited by a minimal number of other works in our corpus. However, this paper is a literature review of the prominent methods researchers are applying to multimodal learning and training environments. As such, the authors agreed that if a work did not utilize a large degree of previous research (i.e., cite several other works in the corpus) or serve as a base from which a

large degree of other research has built upon (i.e., be cited by several other works in the corpus), then that work was, by definition, outside the scope of our review. Considering our corpus was still largely comprised (over 50%) of works later deemed to be outside the scope of this review after CGP, the authors are confident that few papers (if any) directly pertaining to multimodal learning and training environments were discarded as a result of CGP.

### C.3 Peer Review.

Due to the prevalence of papers being published to open, non-peer-reviewed platforms like arXiv in recent years (particularly in computer science), we did not screen for non-peer-reviewed works during study selection (i.e., we did not adopt a paper's not being peer-reviewed as an exclusion criterion). To the best of our knowledge, all papers in our corpus underwent formal peer-review, with one possible exception. There is one paper in the corpus that was submitted to a workshop that none of this review's authors are familiar with. We are, therefore, unsure of whether or not the paper underwent formal peer review. However, the workshop includes submission, notification, and camera ready dates, so we are confident that the workshop was at least refereed.