Towards Modeling Augmented Reading in a Phygital Learning System Using Learning Analytics Approaches

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Abstract

Augmented reading is increasingly situated in phygital learning systems where learners frequently transition between printed materials and digital devices. Yet, evaluating and modeling reading in these cross-media environments remains methodologically underspecified. Unlike traditional computer-based learning environments, interaction logs in phygital reading are inherently fragmented, i.e., the trace data is captured primarily during on-device actions, while a significant reading (or interactions) occurs off-device on paper, producing "partial traces" that are difficult to interpret. This paper synthesizes prior work to surface open questions for modeling augmented reading processes in XR–LLM systems. We emphasize two core bottlenecks: (1) reliable data logging that can operationalize augmented reading as temporally orchestrated states across paper and device, and (2) comprehension assessment approaches that remain feasible at scale in hybrid settings and can detect process-level disruptions such as conceptual roadblocks.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**.

Keywords

Phygital Learning System (PLS), Large Language Model (LLM), Optical Character Recognition (OCR), Academic Reading

1 Introduction

Reading is the foundational skill upon which academic achievement and lifelong learning are built. It is a complex process of meaning-making that evolves from the early elementary stage of "learning to read"(where decoding and fluency are paramount) to the critical "reading to learn" phase, where students learn to extract, integrate, and critique information from increasingly complex texts [5]. With the technological advancements and integration in learning environments, reading has moved from print to digital screens, and more recently, to environments augmented by Extended Reality (XR) and Generative AI (Gen-AI). While early research focused on the "screen inferiority effect", which involved comparative analysis of the comprehension outcomes between paper and digital displays [18, 36], the current era of augmented reading involves augmentation using Augmented Reality (AR) [8, 12, 24] and LLMs [41]. Technologies in-scope for this transition range from mobile AR applications that synchronize physical annotations with digital notes [24, 30], augment printed texts [33], etc. to mixed-reality assistants that provide on-demand summarization and definition overlays [16, 39]. Despite the proliferation of these systems, a critical bottleneck (in the context of education) remains, which is, the analysis of reading process for multi-artifact cross-media (Phygital) systems. Unlike the digital learning environments (also referred to as Computer-based learning environments; CBLEs [28]) where every scroll and click can be logged for the measurement of different constructs like cognitive load, affect, etc. [14], augmented reading in Phygital systems often results in a "partial trace" where the user interactions are split between a physical artifact (printed learning material) and a digital device. For instance, in a AR-based learning environment, the learner actions within the app (such as navigation, typing, etc.) can be logged as timestamped trace data, whereas the interaction with corresponding physical artifacts, like a paper card, is recorded as scanning actions [15]. Furthermore, the learning analytics approaches for AR-based systems primarily involves device-based data logging as the evaluation method, which again is affected by the hardware (like smartphones, head mounted displays, etc.) thereby curtailing the ability to model the learning process [37]. Consequently, this paper discusses open questions aimed at modeling of reading in XR-LLM phygital learning systems using Learning Analytics based approaches. We point to two key aspects, a) Reliable logging of data from such systems, and b) Assessment of comprehension form the data obtained from the user interactions.

2 Background

2.1 Medium effects on comprehension

Investigations into the impact of medium on comprehension yield a layered understanding [17, 18, 32]. While numerous studies suggest that reading performance is equivalent across mediums when time constraints are removed [18], meta-analyses frequently point to a "screen inferiority effect", particularly for informational texts [17] (also applicable for reading long form expository texts). Proponents of print media argue that paper supports better comprehension owing to its affordances namely, the physical, tactile, and spatiotemporal fixed cues that allow readers to build a coherent mental map of the text [21, 35]. These supports mechanisms fostering *deep reading*, which is characterized by sustained attention and linear processing, whereas screen environments often induce "F-shaped" scanning patterns, frequent task-switching, resulting in superficial strategies like *skimming* [18, 19]. Digital media however has the potential to provide unique affordances through the interface design [20, 38], which results in interactions to support active reading and comprehension. Recently, augmentation by Gen-AI are claimed to be useful for enhancing reading efficiency and strategic processing. Systems like *TreeReader* and *Marvista* demonstrate that LLM-based summarization and hierarchical restructuring can improve *deep reading* performance [7, 41]. Furthermore, intelligent texts utilizing

LLMs have been shown to lead to higher learning gains compared to static digital textbooks [10].

2.2 Reading in multi artifact cross-media systems

Reading in a multi artifact cross-media system can be operationalized as reading a printed textbook with a mobile device, often a common setting for academic reading contexts [29], which is often characterized as phygital learning system [28, 33]. These systems can be categorized into two types, based on the type of digital content the static text is augmented with.

(1) Conventional AR systems: These systems typically link predefined (or pre-programmed) multimedia onto paper-based texts primarily to aid users in visualization of information. Examples include AR textbooks following the *MagicBook* [3] interaction paradigm (which allows transitioning between 2D text and 3D virtual scenes [12, 13]), and recent examples of textbook application, like *Augmented Math* [9] that provides interactive animation through extracted content using computer vision technology.
(2) LLM integrated systems: These leverage generative AI to create dynamic, interactive experiences on demand. For example, *RealitySummary* utilizes LLMs to provide real-time summarization and question-answering with physical documents via the augmented interface [16]. Similarly, *ReaderQuizzer* generates just-in-time comprehension questions anchored to specific text sections to enhance engagement while reading [31].

2.3 Trace data in cross-media

The field of learning analytics has historically been concentrated within Computer-Based Learning Environments (CBLEs), where the digital systems are designed to capture interaction logs (trace data [14]. However, in hybrid reading environments that pair physical texts with digital device, this data stream is fundamentally fragmented. In such phygital systems, trace data is generated only when the learner explicitly interacts with the digital device (such as scanning an AR marker [15], querying an LLM in the mobile application [33]) leaving the primary activity of reading the physical text unobserved [19]. This results in the action logs characterized by "partial traces", where significant periods of cognitive processing occur while interacting with the paper. While multimodal approaches, including external video recording, think-aloud protocols, etc., have been utilized to bridge this gap, they are predominantly restricted to small-scale settings due to the resource constraints of human annotation and the technical complexity of synchronizing heterogeneous data streams [1, 25, 34]. Furthermore, accurately capturing the rapid, granular transitions between physical and digital contexts remains methodologically difficult without complex instrumentation that may alter natural reading behaviors [19].

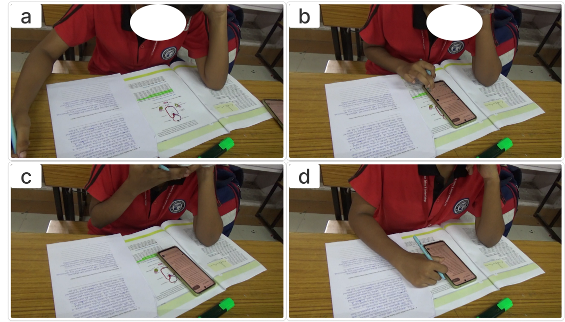

Figure 1: Video snippets elucidating Phygital reading, here a learner is switching between textbook, worksheet, and a mobile device for an academic reading task.

3 Issues with modeling reading process in XR-LLM based systems

3.1 Data logging techniques in XR based augmented reading systems

XR systems encompass a wide range of device configurations ranging from smartphones to head mounted displays (HMDs), which entails recording of high-frequency device sensor data, including accelerometer and gyroscope readings to track posture and physical movement [37] to explicit navigation, scanning markers, etc. [37] native to mobile applications. Despite this rich data potential, the hybrid nature of augmented reading introduces significant methodological ambiguities that researchers must address. Hence, there are these open questions that follow:

- **What counts as the reading process when reading spans paper and device?** In cross-media environments, reading cannot be defined merely as visual decoding of text on a screen. Instead, we propose an operational definition of the "augmented reading process" as the temporal orchestration of attention and cognitive strategies across physical and digital devices [25, 27]. This definition encompasses not only the linear processing of text but also the structural and alignment scanning required to coordinate physical artifacts with digital augmentations [26]. Researchers must categorize interactions as distinct behavioral states—such as persistent reading, scanning, and skimming—that account for the switching costs and multimodal integration inherent to AR [26].
- **How should the off-device reading should be interpreted?** A critical limitation of trace data in hybrid settings is the unobserved period that occurs when learners engage with the physical text without triggering digital sensors (see Figure 1. Standard trace-based analytics may yield "partial traces" that misrepresent these pauses as disengagement rather than deep processing [27]. Therefore, studies should interpret device logs as episodes rather than continuous reading records, or perhaps incorporate some implicit data

logging mechanisms that help in inferring off-device periods.
- **What trace signals are most informative in mobile AR settings, given known limitations of mobile-based data?** Mobile eye-tracking often suffers from lower precision due to small screens and variable viewing distances. However, alternative signals can serve as robust proxies for engagement. Specifically, device orientation and stability metrics (derived from gyroscopes) can distinguish between focused reading and fidgeting or disengagement [37]. Furthermore, synchronization events, such as the successful mapping of a digital note to a physical location via OCR, provide high-confidence markers of cognitive workflow continuity that are less susceptible to the noise of raw sensor data [15, 24].

3.2 Comprehension assessments for augmented reading systems

Current research employs a variety of instruments, ranging from traditional question-based assessments, such as multiple-choice questions (MCQ) for literal and inferential understanding [6] and open-ended retelling tasks [12, 42] to physiological approaches like eye-tracking that are useful in inferring constructs like cognitive load via fixation duration. Similarly, stealth assessments utilize Natural Language Processing (NLP) tools, such as Coh-Metrix [23] or the Constructed Response Analysis Tool (CRAT) [11], to automatically evaluate the linguistic quality of learner self-explanations without interrupting the reading flow [2, 22]. The key here is the adequate integration in the learning system, therefore the open research questions related to the comprehension assessments are:

- **Which comprehension assessment families remain feasible under cross-media augmented reading?** While eye-tracking is powerful, its feasibility is often limited to screen-based or HMD contexts, making it difficult to deploy in studies involving physical textbooks [18]. Consequently, constructed response tasks (e.g., short answers or summaries) remain a highly valid and feasible family of assessment for cross-media environments. Unlike MCQs, which may allow for guessing, constructed responses require active retrieval and integration of information [22], and recent advances in NLP enable these to be scored at scale with accuracy comparable to human raters [22].
- **How should assessment choice align with the stated goal of identifying "conceptual roadblocks"?** Conceptual roadblock is defined here as a point of cognitive disequilibrium where the learner encounters inconsistent or conflicting information and fails to resolve it [40]. To identify these, assessment choices must move beyond aggregate scores to capture process-level disruptions.

4 Conclusions

While trace data provides a non-intrusive window into learner behaviors, it remains fundamentally limited in cross-media environments by the "blind spots" that occur during reading intervals where no explicit digital interaction takes place [26]. These partial traces capture navigation and tool use but fail to record the cognitive processing occurring during off-screen engagement with physical texts [4]. Although multimodal approaches such as external video recording can capture these missing physical interactions, they impose a heavy burden of interpretation of nuanced embodied behaviors, such as gaze shifts or gestures, making them difficult to scale for large cohorts [1, 4]. Furthermore, physiological methods like eye-tracking, while offering high temporal resolution, face significant setup and hardware constraints that pose threats to the ecological validity [19].

The inquiry scope is further constrained by the prevalence of multiple device form factors, such as high-end Head-Mounted Displays (HMDs) or tablets [16], and heterogeneous learner populations (bringing in the factors attributed to individual differences)[19]. Consequently, these findings may not generalize to diverse educational contexts where environmental distractions and variable technical literacy significantly influence outcomes [6]. In conclusion, this paper argues that the primary bottleneck in advancing cross-media augmented reading systems is not technological capability, but evaluation-method uncertainty. To move forward, future research must prioritize the development of study designs that integrate sporadic or episodic logging with robust comprehension assessments, thereby capturing the full complexity of the augmented reading process in Phygital contexts.

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