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ORIGINAL RESEARCH

# Mixed Reality Learning Systems with Head-Mounted Displays in Higher Education: A Systematic Review

**Shi Liu**[1] · **Peyman Toreini**[1] · **Alexander Maedche**[1]

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**Abstract**
The advent of mixed reality (MR) technology has sparked emerging adoption of MR learning systems in higher education. In this systematic literature review, we examine the state of the art of MR systems in this field. We highlight the diverse applications and benefits of MR technology, including design features and specific fields of higher education addressed in existing studies. Despite its potential, our review also identifies research gaps, particularly regarding effective evaluation methods for learning outcomes. We identify the needs to provide advanced learning support and to better integrate established learning theories to guide more effective system design. Furthermore, we discover that leveraging biosignals to design biosignal-adaptive MR learning systems providing personalized learning support is currently underutilized. Through this systematic review, we aim to offer design implications for the application of MR in higher education, identify potential research gaps, and provide insights for future work in this rapidly evolving field.

**Keywords** Mixed reality · Human-computer interaction · Systematic literature review · Higher education

## 1 Introduction

Educational technology has witnessed rapid development, with researchers exploring innovative tools to enhance learning experiences (Perez & Torres-Delgado, 2023; Mitsuhara & Shishibori, 2015). Among these advancements, Mixed Reality (MR) using head-mounted displays (HMDs) has emerged as a new frontier, offering immersive experiences that merge the virtual and physical worlds (Speicher et al., 2019; Milgram & Fumio, 1994). Although

✉ Shi Liu
shi.liu@kit.edu

Peyman Toreini
peyman.toreini@kit.edu

Alexander Maedche
alexander.maedche@kit.edu

[1] Human-Centered Systems Lab (h-lab), Karlsruhe Institute of Technology, Karlsruhe, Germany

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not yet widely adopted across all educational contexts, HMD-based MR is increasingly recognized for its unique capabilities. Its application has been explored in diverse application fields, from virtual physics laboratories to immersive anatomy lessons (Grad et al., 2023; Laumann et al., 2024), often demonstrating benefits over traditional learning formats (Mohammadhossein et al., 2022; Su et al., 2025). Moreover, MR technology is considered foundational for the future of collaborative learning in the Metaverse (Mystakidis, 2022).

This growing interest arises from MR's unique affordances in addressing pedagogical challenges that are difficult to overcome with other immersive technologies. Unlike Virtual Reality (VR), which isolates learners from their physical environment, MR enables simultaneous interaction with real-world objects, making it particularly suitable for procedural skills training. For instance, a medical student can use an MR headset to practice a surgical procedure on a physical manikin while holographic anatomical models are overlaid directly onto it—a task that is challenging in the fully occluded environment of VR (Zhao et al., 2025). Moreover, MR's head-mounted, hands-free interaction provides a distinct advantage over Augmented Reality (AR) on mobile phones or tablets. Systems such as *SkillAR*, for example, can teach complex two-handed motor skills by delivering real-time holographic feedback on body and hand movements (Diller et al., 2025)—a task incompatible with mobile AR, which requires one hand to hold the device. These examples are not isolated cases but illustrate a broader class of learning tasks in which MR's capacity to merge the virtual and physical worlds offers distinct pedagogical potential.

Recognizing this potential, researchers have explored the use of MR technology across many fields of education (Lungu et al., 2021). In engineering education, MR supports the visualization of additive manufacturing by enabling students to interact with computer-aided design (CAD) models, thereby fostering a deeper understanding of engineering processes (Melo et al., 2024). The technology has also shown promise in vocational training, where realistic simulations of construction sites contribute to hands-on skill development and safer practice opportunities (Nguyen et al., 2021).

While existing studies have examined MR across different fields of education, they also span a wide range of education levels, from preschool to higher education. Within higher education, MR learning applications have shown promising results (Richards, 2023). However, knowledge about MR learning systems in this context remains fragmented. Other immersive technologies, such as VR, have already been the subject of systematic literature reviews (Hamilton et al., 2021; Radianti et al., 2020), yet the specific strengths, advantages, and design features of MR in higher education remain largely underexplored. Existing reviews on MR technology, such as those by Lungu et al. (2021) and Maas and Hughes (2020), often focus on different education levels (e.g., K-12 (Maas & Hughes, 2020)) or narrow domains such as language learning (Li & Wong, 2021) and medical education (Barteit et al., 2021).

Thus, a comprehensive understanding of MR learning systems specifically designed for higher education is still lacking. In the absence of a systematic overview, researchers and practitioners face challenges in building on prior work, identifying best practices, and synthesizing evidence on learning outcomes. By concentrating on higher education, our work provides a focused perspective that differs from broader surveys covering multiple educational levels or reviews restricted to single disciplines. To address this gap, we present a systematic literature review of the state-of-the-art research on MR learning systems in higher education. We aim to summarize existing knowledge and provide a clear overview by answering the following five research questions:

RQ1: Which types of head-mounted MR technologies have been applied in higher education across different fields?
RQ2: Which learning paradigms and theories have guided the design of MR learning systems in higher education?
RQ3: In which fields of higher education have MR learning systems been implemented and studied?
RQ4: What design features are commonly integrated into MR learning systems for higher education?
RQ5: What research methods and study designs have been used to evaluate the learning outcomes of MR learning systems?

In addressing these research questions, this paper contributes an integrative conceptual framework that synthesizes the state of the art of MR learning systems in higher education. The framework organizes existing evidence across five key dimensions–devices and technologies, learning paradigms and theories, fields of education, design features, and study design–offering a structured lens for understanding current developments. By doing so, we aim to provide a foundation that supports researchers, designers, and educators in leveraging MR learning systems for higher education.

## 2 Related Work

### 2.1 Mixed Reality Learning Systems

The term Mixed Reality (MR) was originally defined by Milgram and Fumio (1994) as a continuum spanning from AR to augmented virtuality. With the recent advancement of immersive technology and the wide adoption of the term, a shift and polarization of its definition has been observed (Speicher et al., 2019). In the scope of this literature review, we adopt the definition used by researchers including Yue et al. (2017) as well as Roo and Hachet (2017). In this interpretation, MR is defined as an advanced form of AR that enables interaction with virtual overlays, typically realized through HMDs. This definition of "strong AR", as reported in an overview by Speicher et al. (2019), has also been adopted by the industry, including companies such as Microsoft (2023). Compared to traditional AR experience with mobile phones or tablets, MR systems allow dynamic and interactive virtual elements to blend in the environments, instead of being static on-screen overlays on top of the physical surroundings. Therefore, this review focuses on MR learning systems implemented on HMDs. This definition distinguishes MR from other immersive technologies: VR systems, for instance, are excluded as they fully occlude the user's perception of the physical environment. Meanwhile, AR on mobile devices with 2D displays, such as smartphones or tablets, also falls outside our scope; these systems are typically limited to displaying virtual information and lack the capacity for direct spatial interaction between physical and virtual content.

MR has been explored across different fields of education. For instance, it has been applied in medical education to train specific anatomical techniques and surgical procedures, leading to effective knowledge retention (Moro et al., 2017). It has also been used in language learning to support the acquisition of sign languages by promoting motor learning (Shao et al., 2020). Other prominent applications of MR learning systems can be found in STEM education (Ibáñez & Delgado-Kloos, 2018). These systems have been shown to facilitate learners' understanding of complex content, reduce cognitive load, and increase motivation (Mohammadhossein et al., 2022). For example, Khan et al. (2019) evaluated an MR system designed to visualize abstract concepts in physics and found significant improvements in students' comprehension of the subject matter. In programming education, studies such as Hennerley et al. (2017) likewise demonstrated that MR systems can enhance students' motivation and conceptual understanding. Further benefits include the promotion of immersion and presence, both of which can positively influence learning outcomes (Mystakidis et al., 2022; Ryan et al., 2022). Moreover, MR can foster kinesthetic and motor learning by encouraging learners to integrate physical activities into their learning experience, thereby enhancing motivation (Iqbal et al., 2019). Similar benefits have also been identified in higher education contexts (Tang et al., 2020).

Nonetheless, despite the growing body of research on MR learning systems, a systematic overview of their design characteristics and outcomes is still lacking. Several studies have pointed out potential limitations and disadvantages. For example, Vovk et al. (2018) reported that MR learning systems may increase cognitive load. Likewise, a systematic review by Buchner et al. (2022) indicated that some studies observed undesirable cognitive overload, whereas others did not report such effects. Overall, these findings complicate earlier assumptions that MR is mostly beneficial for learning (Mohammadhossein et al., 2022). Therefore, a research gap remains in developing comprehensive understanding of MR learning systems across different contexts, including higher education, which to the best of our knowledge has not yet been addressed in educational technology research.

### 2.2 Learning Paradigms in Higher Education

In the field of educational research, various learning paradigms and theories have been proposed and applied to designing learning systems. Based on the classification of Schunk (2012), common learning paradigms include the following: behaviorism, cognitivism, and constructivism. The behaviorist learning paradigm has its roots in the well-established psychological theory of conditioning model (Thorndike, 1932). Here, learners are believed to passively receive the teaching from educators and need to be disciplined to better accept the knowledge, e.g., by forming habits, introducing sequential curricula, and giving instructions. One of the exemplary learning theories in the scope of behaviorism is the principle of reinforcement, which stresses the effectiveness of positive feedback and rewards for desired learning behavior and punishment for unwanted behavior (Skinner, 1961). With the further development of psychology and the increased criticism of behaviorism, cognitivism, and constructivism have gained popularity over the past decades. Both paradigms acknowledge learning as an active process executed by learners to foster knowledge. From a cognitivism perspective, learning involves different perceptual and cognitive processes that allow learners to acquire information, foster understanding, solve problems, and encode the information in the memory (Bruner, 1960; Shuell, 1986). Therefore, following cognitivism, the goal of designing an effective learning experience is to optimize the process with support, including providing social cognitive support (Benight & Bandura, 2004) or optimized instructions for information processing (Mayer, 1996). Lastly, constructivism underlines the active learning and knowledge-fostering process of learners. In the framework of constructivist learning, learners need to use their cognitive skills to construct new connections and structures of knowledge acquired in the external world and extend their knowledge base by interacting with the external environment (Schunk & Greene, 2017).

In higher education, these learning paradigms have been applied to create effective learning experiences and improve learning outcomes. For example, cognitivism has been highlighted in higher education with a focus on training the cognitive skills of students, including critical thinking, making abstracts, emotion regulation (Evans et al., 2010; Sprague, 1981). Meanwhile, the constructivist paradigm has been applied in higher education to promote active learning and creative thinking for students (O'Connor, 2022). Research has also been conducted to understand the impact of e-learning systems from a constructivist perspective in higher education (Bognar et al., 2015). A focus on constructivism in higher education is to strike a balance between providing effective guidance and providing self-directed learning opportunities to promote active learning (Kirschner et al., 2006). For the behaviorism paradigm, despite criticism over the past decades, its implications on designing learning systems can still be found in the practice of higher education (Weegar & Pacis, 2012).

Apart from these three major learning paradigms, we can identify various works that leveraged other learning paradigms or theories in their research. For example, experiential learning and inquiry-based learning have been applied to encourage learners to actively explore the learning content and seek answers to questions they propose during the learning process (Huang, 2019), (Maaß & Artigue 2013). These learning methods are sometimes seen as synonyms along with other terms including discovery learning, often considered as a specific example of constructivism (Kirschner et al., 2006). Furthermore, there is research that does not connect to any of the above-mentioned learning paradigms and follows alternative paradigms. Examples of these paradigms include simulation-based learning (Viglialoro et al., 2021), collaborative learning (Ali et al., 2019). Therefore, it is worth mentioning that there has not been an exhaustive list of learning paradigms and theories, as many are intertwined with each other and often defined from different perspectives. Due to the complexity of the topic, our work will not target providing a comprehensive classification of learning paradigms and theories. Instead, we will use the existing classification in existing literature reviews as a foundation and then develop a conceptual framework inductively.

## 3 Method

We conducted our systematic literature review based on the framework proposed by Kitchenham and Charters (2007), and we report our findings following the PRISMA 2020 guidelines (Page et al., 2021). The review process began with a preliminary scoping analysis to situate our work within the existing reviews and identify a clear research gap.

### 3.1 Scoping Analysis

First, aiming to better understand the related work and current research gaps in the state-of-the-art research, we used the following search string to find existing reviews focusing on learning systems, including MR as well as other Extended Reality (XR) technologies including VR and AR:

`("review") AND ("learning" OR "education") AND ("Extended Reality" OR "XR" OR "Augmented Reality" OR "AR" OR "Virtual Reality" OR "VR" OR "Mixed Reality" OR "MR")`

We used Scopus as our main database for this scoping analysis. In total, 354 reviews were identified using the search string. To narrow this to the most relevant publications within the educational technology research, we filtered the results to include only major research outlets. These venues were selected based on their Google Scholar ranking and h-index, resulting in a focus on the following key journals and conferences: *Computers & Education*, *Education and Information Technologies*, *British Journal of Educational Technology* (BJET), *International Journal of Educational Technology in Higher Education* (ETHE), *Educational Technology Research and Development* (ETR&D), *Journal of Interactive Learning Environments* (JILR), *Journal of Computer Assisted Language Learning* (JCAL), and *International Journal of Emerging Technologies in Learning*.

In these outlets, literature reviews on MR systems have been conducted (Rokhsaritalemi et al., 2020). However, our analysis revealed that they often have different focuses, such as revealing challenges (Moser et al., 2019), trends (Rokhsaritalemi et al., 2020), interaction techniques (Papadopoulos et al., 2021; Plopski et al., 2022), or specific application domains outside of education (De Guzman et al., 2019). After further examination, we identified seven highly relevant literature reviews from these outlets (summarized in Table 7 in Appendix).

Our analysis of the seven selected reviews indicates diverse adopted methodologies. Some leveraged established frameworks from the Information Systems (IS) community (Kitchenham & Charters, 2007), a research field that focuses on systems that collect and process information and analyzes their impacts on individuals, organizations and societies. Meanwhile, other reviews did not specify a particular methodology. Regarding research objectives, many reviews concentrate on specific fields of education—such as language learning (Li & Wong, 2021), surgical simulation (Lungu et al., 2021), or STEM (Ibáñez & Delgado-Kloos, 2018). Five of the seven reviews did not concentrate on a specific education level. Instead, their focus was primarily on the technology itself (Jensen & Konradsen, 2018) or a particular learning strategy like game-based learning (Yu et al., 2022). For the two reviews that did address the higher education context, one targeted VR technology (Radianti et al., 2020) and the other focused on AR within STEM education (Hidayat & Wardat, 2023). Other reviews, particularly from the Human-Computer Interaction (HCI) community, where researchers design and evaluate interactive systems using human-centered methods to fulfill user needs, have examined the use of specific sensors in immersive learning systems, such as eye-tracking (Shadiev & Li, 2023).

Therefore, we identified a clear research gap after the scoping analysis: none of the existing literature reviews provides a comprehensive investigation of MR learning systems specifically within the higher education context. Our study is designed to address this gap.

### 3.2 Conceptual Framework

Aiming to answer our research questions and systematically analyze the relevant literature, we propose a conceptual framework with multiple dimensions. The development process for each dimension is detailed below.

For the device and technology dimension (RQ1), we follow the work of Rolland and Fuchs (2000) and distinguish between *video see-through* devices and *optical see-through* devices. Video see-through devices present the physical surroundings as a video stream, which is rendered together with the virtual elements and presented in the display. Therefore, VR headsets are adopted as video see-through devices by integrating outward-facing cameras to capture the surroundings. Common video see-through devices used in the research include Oculus/Meta Quest, HTC Vive (Barteit et al., 2021). In contrast, optical see-through devices have a transparent display, allowing users to directly perceive the physical surroundings with naked eyes. The virtual content is then rendered on the transparent display to align with the physical surroundings. Exemplary devices in this category include Microsoft HoloLens (Barteit et al., 2021). A detailed explanation is provided in Table 1 in the Appendix.

For the learning paradigms and theories (RQ2), existing reviews have demonstrated the difficulty of creating an exhaustive taxonomy (Radianti et al., 2020). We therefore established a foundational framework based on the primary paradigms in educational research—*behaviorism*, *cognitivism*, and *constructivism*—as described by Schunk (2012). We acknowledge the following challenges of creating this taxonomy: First, there is an unclear relationship between the different learning paradigms. For example, experiential learning is sometimes seen as a synonym for exploratory learning, but often recognized as an independent paradigm of experientialism as well (Chen et al., 2024; Seaman et al., 2017). Second, other learning theories are also frequently referenced (Goldie, 2016). In some cases, they are treated as subcategories of the three paradigms, while in others they appear as independent approaches, such as self-regulated learning, active learning, collaborative learning, and gamification. Accordingly, the initial set of categories presented in Table 2 was designed to be extensible, allowing additional theories to be incorporated inductively during the review process.

For the fields of education dimension (RQ3), we adopted a bottom-up approach. Rather than using a predefined list, we categorized the disciplines during the data analysis, a common and effective method in educational technology reviews.

For the design features dimension (RQ4), we refer to the existing literature reviews of VR systems. In the two reviews focusing on higher education by Radianti et al. (2020) and Wohlgenannt et al. (2019), they have defined various design features including different interaction levels, instructions, user-generated content. Meanwhile, in the work of Won et al. (2023), design features are classified into sensory, actional, narrative, and social elements. To create a comprehensive overview, we therefore synthesized these varied approaches to form our initial analytical framework (see Table 3).

The study design dimension (RQ5) encompasses the overall research methodology, specific data collection techniques, and the outcomes measured. We classified the research methods as qualitative, quantitative, or mixed-methods, drawing on established classification (Edmonds & Kennedy, 2016; Creswell, 2009). We acknowledge the existence of concept-driven research methods, such as the approach proposed by Stolterman and Wiberg

(2010). However, our review focuses exclusively on empirical studies. Consequently, conceptual research was not included in the conceptual framework (see Table 4). To address the absence of a comprehensive overview of assessment tools for MR learning systems, we introduced a data collection sub-dimension (see Table 5). The initial list of methods was synthesized from prior work (Radianti et al., 2020; Cairns & Cox, 2008) and may be extended during the coding process based on the reviewed articles. In addition, the learning outcomes evaluated in each study (e.g., motivation, usability, knowledge gain) will be systematically coded as part of this process.

### 3.3 Search Strategy

Based on the guideline of Kitchenham and Charters (2007), we created a review protocol describing our search strategy, including the search strings, databases, and inclusion/exclusion criteria. We selected the following databases for identifying relevant literature: *ACM Digital Library*, *Web of Science*, *Scopus*, *IEEE Xplore*, *EBSCO Host*, and *ProQuest*. The selection of databases reflects our focus on educational technology and was informed by our initial scoping analysis. We applied the following search string to each database:

```
("head-mounted" OR "headset*" OR "glass*" OR "smartglass*" OR "goggle*" OR "HoloLens" OR "Magic Leap" OR "Quest")
AND ("Augmented Reality" OR "Mixed Reality" OR "Extended Reality" OR "XR" OR "AR" OR "MR" OR "immersive")
AND ("educat*" OR "learn*" OR "teach*")
```

The search string was designed to specify the MR technology and the educational context. To ensure the search results aligned with our focus on HMD-based systems, we added the keywords including "head-mounted" as well as common device names including "HoloLens". This approach of including device names has been established and applied in existing reviews on immersive learning systems (Radianti et al., 2020).

In addition to the search string, we defined several inclusion and exclusion criteria. First, only peer-reviewed articles were included to ensure methodological quality. Second, conceptual or technical papers without empirical studies were excluded. Third, articles had to be situated within a higher education context. Finally, we limited our search to articles published between 2013 and 2025. Even though both the concept of MR and pioneering HMD devices emerged a few decades ago (Milgram & Fumio, 1994), this timeframe captures the recent rapid development and application of modern MR devices. A complete summary of the inclusion and exclusion criteria can be found in Table 6.

### 3.4 Data Extraction

We identified an initial list of articles by applying our search string to the selected databases. The first and second authors then independently screened these articles in two phases: first by title and abstract, and then by full text for the remaining articles. Disagreements were resolved through discussion. Following this screening, we extracted data from the final articles into a concept matrix to provide a concept-centric overview of the topic (Webster & Watson, 2002). The complete matrix is available as supplementary material.

Our initial search across six databases identified 7,014 records. Scopus yielded the largest number of results (4000 articles), partly due to its overlap with other databases such as the

ACM Digital Library and IEEE Xplore. After removing 3,138 duplicates using the reference management tool Zotero,[1] 3876 unique articles remained. In the first screening phase, 3561 articles were excluded. Records were excluded if they were set in non-educational contexts, did not conform to our operational definition of MR, or focused on other educational levels (such as K-12). The remaining 315 records proceeded to the full-text review phase.

Of the 315 articles assessed at the full-text level, 80 were found to meet the criteria and thus included in the final review. To verify the higher education setting, we first searched the full text for the following keywords: "higher education", "university", or "college". If these keywords were absent, we examined the participant demographics. Studies conducted exclusively with university students were included, a method similar to that of Radianti et al. (2020). The entire literature selection process is illustrated in the PRISMA flowchart (Fig. 1).

[1] https://www.zotero.org/.

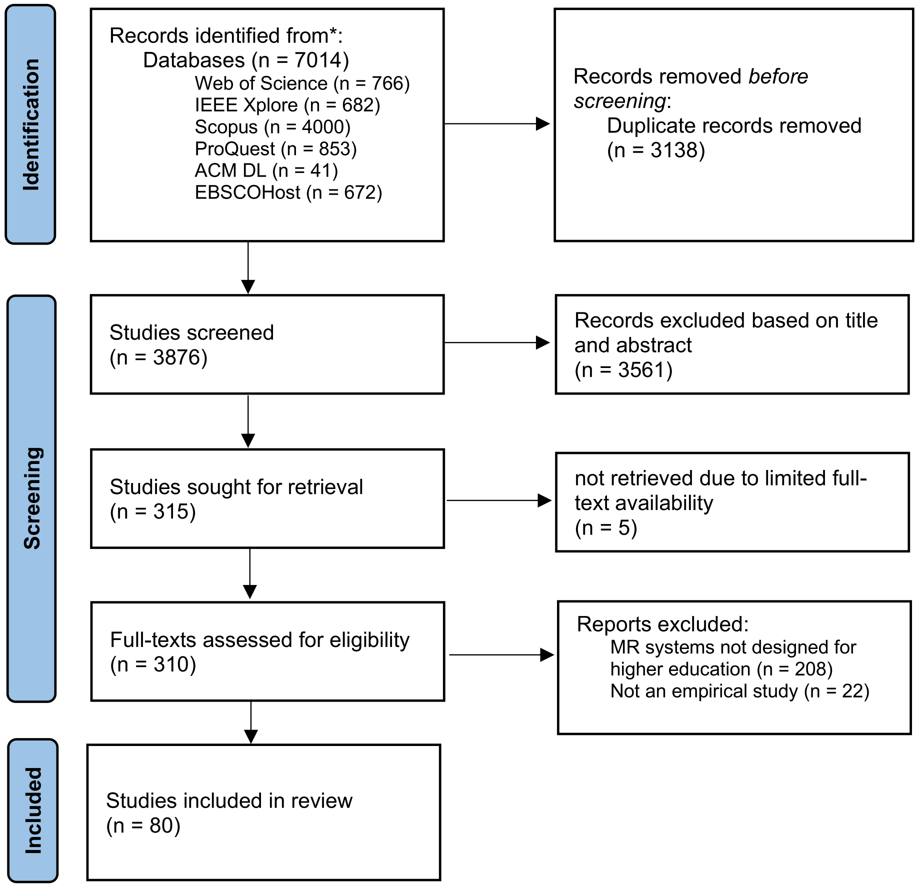


**Fig. 1** Flow chart of the data extraction process in the literature review

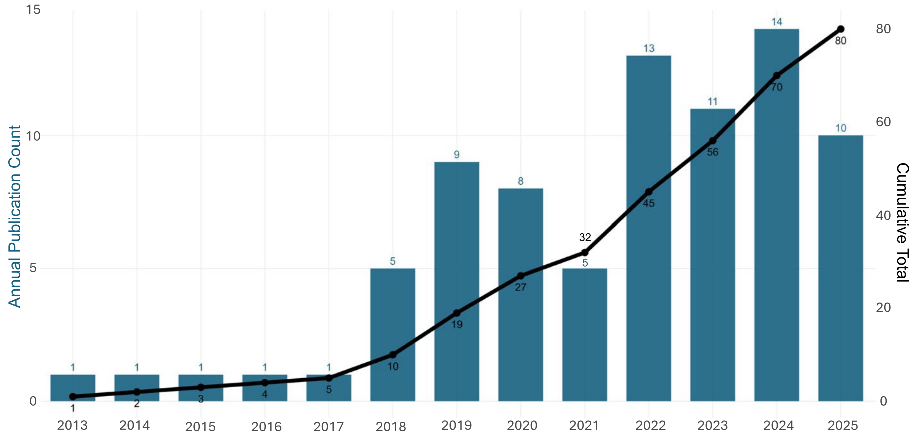


**Fig. 2** Annual and cumulative publication counts over time. The bar chart displays the annual counts of reviewed articles; the overlaid line graph shows the corresponding cumulative total

| Device and Technology | |
|---|---|
| Video See-through | Meta Quest 2/Pro *(5%)* |
| | Others *(5%)* |
| Optical See-through | HoloLens *(65%)* |
| | Google Glass *(9%)* |
| | Magic Leap *(10%)* |
| | Others *(6%)* |

| Paradigms and Theories |
|---|
| Experiential Learning *(9%)* |
| Embodied Learning *(5%)* |
| Simulated Learning *(15%)* |
| Case-based Learning *(8%)* |
| Collaborative Learning *(6%)* |
| Others *(57%)* |

| Fields of Education |
|---|
| Medical Education *(34%)* |
| Engineering *(15%)* |
| Physics *(8%)* |
| Learning Support *(11%)* |
| Computer Science *(6%)* |
| Others *(26%)* |

| Design Features | |
|---|---|
| Interaction Level | Passive Observation *(29%)* |
| | Basic Interaction *(38%)* |
| | High Interactivity *(33%)* |
| Social Interaction *(23%)* | |
| Contextual Instruction *(43%)* | |
| Feedback *(31%)* | |
| Embodied Movement *(11%)* | |
| Role-Playing *(11%)* | |

| Study Design | | | |
|---|---|---|---|
| Research Method | Qualitative *(10%)* | Type of Study | Lab Experiment *(89%)* |
| | Quantitative *(49%)* | | Field Study *(11%)* |
| | Mixed Methods *(41%)* | | |
| Measured Outcome | Usability *(41%)* | Data Collection | Interview *(25%)* |
| | Performance *(23%)* | | Survey *(78%)* |
| | Knowledge & Understanding *(25%)* | | Knowledge Test *(29%)* |
| | Satisfaction *(10%)* | | Interaction Log *(19%)* |
| | Engagement *(8%)* | | Biosignal Data *(6%)* |
| | Others *(50%)* | | |

**Fig. 3** A conceptual framework categorizing the reviewed literature across five key dimensions. Percentages indicate the distribution of the 80 selected articles

## 4 Results

We present here the descriptive analysis based on our research questions and the conceptual framework. Each subsection focuses on one particular dimension of the conceptual framework, which matches one specific research question. Fig. 3 shows the results in a morphological box based on the conceptual framework. Overall, the 80 reviewed articles were published from 2013 to 2025. Fig. 2 shows the distribution of published articles throughout the years. Since 2018, there has been a significant increase in the number of published articles, potentially due to the increased availability of widely used MR devices such as Microsoft HoloLens. A drop in publication numbers can be identified in 2021, possibly due to the global impact of the COVID-19 pandemic on research activities (Fig. 4).

## 4.1 MR Devices and Technology

Based on our conceptual framework, we categorize MR technology into two dimensions: video see-through and optical see-through devices. Each dimension comprises different devices, including Microsoft HoloLens and Meta Quest. The results indicate that most researchers employed optical see-through devices such as HoloLens to implement their learning systems. HoloLens has been the most popular option, with 52 articles (65%) reporting the use of either HoloLens 1 or 2. Other optical see-through devices, including Google Glass, were frequently adopted between 2014 and 2017, as well as Magic Leap used in eight articles.

The reviewed studies highlight several benefits of specific devices. For learning systems with high interactivity, HoloLens helps sustain the "spatial contiguity" of tasks through its sensors and high quality optical see-through (Laumann et al., 2024). For instance, Laumann et al. (2024) employed HoloLens to enhance the learning of optical polarization in a physics laboratory. In this context, it was crucial that the physical environment (optical equipment) remained clear, while the virtual overlays (instructions and sensor readings) were precisely aligned in the physical space. Consequently, HoloLens was identified as the most suitable device. Similarly, Magic Leap offers comparable qualities and has been used as an alternative in several studies (Gießer et al. 2023),(Zhao et al., 2025).

A second category of optical see-through devices supports only basic virtual information display without spatial awareness and high interactivity between virtual elements and the physical environment. Their key advantage lies in being lightweight and unobtrusive, making them suitable for tasks that merely require the display of instructions or additional information (Asaumi et al., 2025). Google Glass is a notable example. For instance, Zarraonandia et al. (2019) developed a feedback system that allowed teachers to receive synchronous student feedback displayed directly on the display. Since this scenario required a lightweight device that could be worn throughout a lecture, and the task only involved displaying feedback rather than interaction, Google Glass was considered the most appropriate solution.

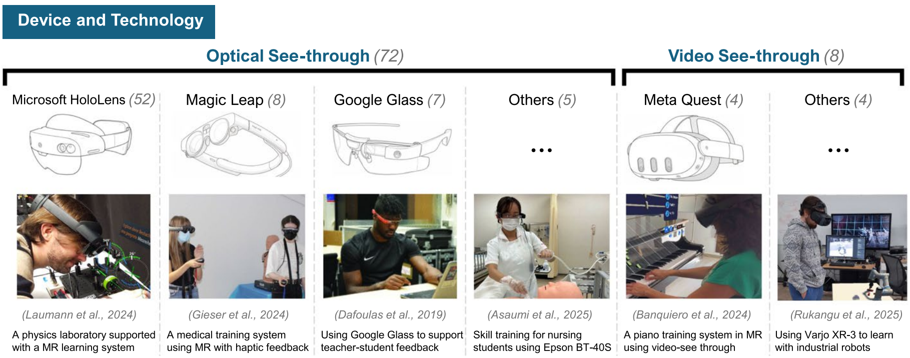


Fig. 4 An illustration of various MR devices and examples from the reviewed articles

Overall, the majority of studies employed optical see-through devices, while only eight used video see-through solutions. Of these, four adapted existing VR headsets such as Meta Quest 2 and Pro, using the integrated cameras to create MR experiences–an increasingly common approach in MR learning research (Ali et al., 2019). However, these studies also noted limitations of video see-through devices. For example, Banquiero et al. (2024) observed a "distorted" effect on Meta Quest devices that hindered effective piano training. By contrast, devices with more advanced sensors and cameras, such as the Varjo XR-3 used by Rukangu et al. (2025), produced more promising video see-through results without distortion of the physical environment. Yet, such devices often require a cable connection to an external PC, which can make the learning experience more cumbersome. The remaining four studies either did not explicitly mention the device model or built their own devices, such as the MR learning system presented by Yang and Liao (2014).

These findings illustrate the dominance of optical see-through devices over the past decade in the field of MR learning systems, with HoloLens to some extent representing MR technology. At the same time, ambiguities remain in the definition of MR, as noted in prior research (Speicher et al., 2019). While authors of some articles also described their systems as AR, others rejected the AR label (often associated with mobile phones or tablets) and instead referred to their works as MR learning systems (Fig. 5).

## 4.2 Learning Paradigms and Theories

In the identified articles, various learning paradigms and theories have been identified. Nonetheless, compared to the previously defined theories in our conceptual framework, few of those learning paradigms have been applied in the articles. More than half of the reviewed articles (43 out of 80) do not explicitly mention a specific learning paradigm or theory that guided their studies.

Because the hierarchies and definitions of learning paradigms are often ambiguous and overlapping, many articles only indirectly referenced their theoretical grounding. Among those that explicitly stated a paradigm, simulation-based learning was the most common, identified in 12 articles. Simulation-based learning is particularly applied in contexts involving risk or cost efficiency, such as medical training, engineering, or physics (Lateef, 2010; Chernikova et al., 2020). For example, Asaumi et al. (2025) implemented an MR learning system for surgical training, where endotracheal intubation was practiced in a controlled

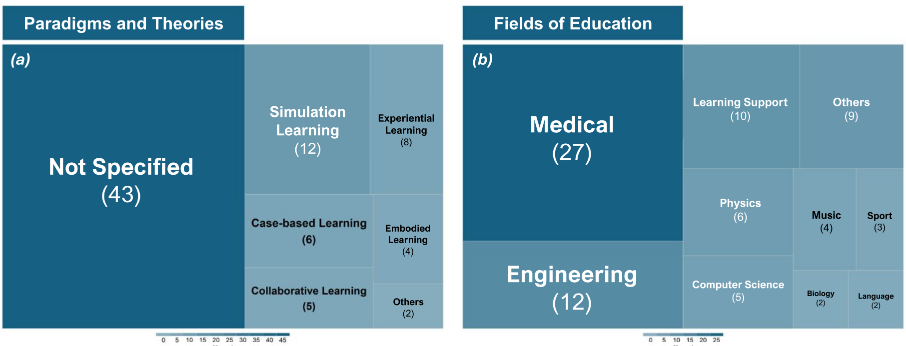


**Fig. 5** Treemaps illustrating the distribution of the reviewed articles. (**a**) Distribution by the learning paradigms and theories employed; (**b**) Distribution by fields of education

MR environment, leading to improved procedural accuracy. Similarly, MR-based tutorials that enhanced clinical instruction in medical education have been designed and evaluated with medical students (Connolly et al., 2024; Gieser et al., 2024). These works also confirm earlier evidence that simulation-based MR environments can foster performance and empathy in learners (Wunder et al., 2020; Nakazawa et al., 2023).

Experiential learning has also been explicitly employed. For example, a “multimodal drumming education tool” designed by Pinkl et al. (2024) leverages MR for embodied rhythm training through first-person action observation and motor engagement, aligning with both experiential and embodied learning paradigms. Similarly, MR-based anatomy teaching reported in Zhao et al. (2025) emphasizes hands-on interaction with 3D neuroanatomical models, allowing learners to actively experience spatial relations that are otherwise difficult to grasp.

Related paradigms found in the literature include case-based learning (Schoeb et al., 2020; Kapp et al., 2020) and embodied learning (Campo et al., 2023), which has gained renewed attention with recent systems such as *SkillAR* that deliver in-situ feedback for skill acquisition in physical training tasks (Diller et al., 2025). These developments extend traditional motor learning by integrating real-time multimodal sensing and context-aware feedback, deepening the link between MR technology and theories of embodied cognition.

Notably, among the typical paradigms discussed in educational theory (Schunk & Greene, 2017), neither behaviorism nor cognitivism was directly referenced, nor were their characteristics identifiable in the implicit designs of the reviewed works. By contrast, constructivist elements were recurrently emphasized, even when not explicitly labeled. For instance, several articles applied inquiry-based or problem-oriented approaches, such as *CuriosityXR*, which fosters exploratory engagement in context-aware MR environments (Vaze et al., 2024), or MR-supported physics experiments that encourage students to discover principles through guided exploration (Laumann et al., 2024). These approaches align with inquiry-based learning, itself considered a constructivist methodology (Maaß & Artigue 2013).

Taken together, these findings reveal that while explicit references to learning paradigms remain limited, simulation-based and experiential learning dominate the applied approaches, particularly in medical training and engineering. At the same time, recent developments demonstrate an increasing tendency toward embodied, exploratory, and inquiry-based methods that resonate with constructivist ideals, even when not explicitly stated. This trend suggests a growing consensus that MR technologies are particularly well suited to paradigms emphasizing interactivity, situated practice, and active learner engagement.

### 4.3 Fields of Education

All articles clearly stated the fields of education for their implemented MR learning systems. Not only are the fields very diverse, but some systems are designed to be field-dependent while others allow or are designed to be transferred in different fields of education.

Among the identified fields, medical education is the most common one. Of the 27 articles that focused on this topic, most of them support visualizing autonomy structure or transferring procedural knowledge with interactive instructions (Zhao et al., 2025; Kim et al., 2025). Nonetheless, these articles also show different approaches. For example, some have a more technological focus, such as comparing the impacts of different XR technologies (Serrano Vergel et al., 2020), while others focus on specific subdomains such as nursing education (Kim et al., 2020). Within this body of work, recent studies continue to broaden the scope and fidelity of clinical teaching with MR. For instance, remote bedside tutorials implemented with HoloLens 2 showed substantial gains in students' topic knowledge by broadcasting a tutor's point-of-view to a co-located class (Connolly et al., 2024). Other recent works cover the fields of vascular anastomosis simulation (Stoner et al., 2024), neuroanatomy seminars which students rated as more engaging than conventional sessions (Zhao et al., 2025), and nursing interventions in which AR smart glasses improved procedural skill scores and motivation in randomized or quasi-experimental designs (Kim et al., 2025). Among these articles, the design features are also heterogeneous, as some are single-user systems, while others have collaborative features such as telemonitoring (Rojas-Munõz et al., 2020).

In engineering and production, MR frequently supports interactive instructions, spatial reasoning, and design-for-manufacture. Extending earlier systems such as the digital fabrication system by Stemasov et al. (2023), more recent work uses MR to teach abstract engineering drawing with three-view projections, showing higher performance than desktop or mobile AR and improving interest and perceived intuitiveness (Yuan et al., 2024). Similarly, MR is leveraged to teach design for additive manufacturing and to scaffold complex design decisions in authentic workshop contexts (Melo et al., 2024). These studies showcase MR's value in connecting intangible representations (drawings, toolpaths) to the tangible workspace, providing effective visualization and scaffolding in the learning process.

Enhancing computer science education with MR has also been explored in existing literature. HCI researchers have introduced studies on collaborative robot programming (Radu et al., 2021) and MR-based pair-programming with conversational avatars (Manfredi et al., 2023). Furthermore, other articles extend MR into AI education for "non-technical students" (Schulz et al., 2024). In an exploratory study with business students, cross-device XR activities (mobile AR, MR, and VR) were perceived to make abstract concepts (e.g., k-means clustering) more concrete (Schulz et al., 2024). These findings suggest an expanding niche for MR as a conceptual bridge in computer science education beyond traditional learning formats.

MR is also gaining attention in domains where sensorimotor timing and embodied interaction are central, such as in music education. Banquiero et al. (2024) introduced an MR piano tutor which improved students' performance over a popular desktop benchmark while maintaining high presence and low adverse effects. Also in the field of music education, a multimodal MR tool for drumming improved rhythmic accuracy compared to video-based practice, underscoring that first-person MR embodiment and feedback can support complex motor learning (Pinkl et al., 2024). These add to prior work on violin gesture imitation using HoloLens avatars in higher music education (Campo et al., 2023).

Apart from the specific fields of education, a few reviewed articles focus on providing educational tools that can be applied in various fields. For these articles, we classify them as learning support. Some of these articles focus on providing authoring tools for lecturers. For example, Rajaram and Nebeling (2022) designed an immersive authoring tool to help instructors create interactive instructional systems without programming requirements. Meanwhile, Faridan et al. (2023) support remote collaboration with multi-device interaction using a tablet with an MR headset to create a co-present guidance experience. These learning support tools are diverse examples of how learning experience can be optimized with MR technology. Furthermore, gaze-aware feedback in MR uses eye-tracking to help learners improve attention management during the learning process and retrieve missed content (Liu et al., 2025). Other research explores context-aware mini-lessons with conversational AI to motivate inquiry and retention in self-directed learning (Vaze et al., 2024), as well as co-located MR classrooms at scale across courses (Chandran et al., 2024) (Fig. 6).

## 4.4 Design Features

The articles we reviewed propose different design features to support the learning experience. Based on the conceptual framework, we classified these features. During the screening process, we noticed that many MR learning systems presented in the articles are single-user systems, while others feature collaborative settings. Therefore, we first examine whether social interaction is present in the proposed systems. Out of the 80 articles, 18 include social interaction as a design feature. Some of these articles present a learning experience that involves tutoring or mentoring (Rojas-Munõz et al., 2020; Thanyadit et al., 2023), while others focus on a collaborative learning experience with peer students (Kim et al., 2022; Manfredi et al., 2023). For example, Connolly et al. (2024) showed how MR-enabled clinical tutorials can be delivered synchronously to groups of medical students, where tutors provide guidance in real time. As an example of peer collaboration, Radu et al. (2021) investigated the learning experiences and outcomes of a collaborative robot programming course supported with an MR learning system.

Interaction levels varied significantly across the reviewed systems. Twenty-three articles (29%) describe systems that offered only limited interactivity, restricting users to passive observation within the learning environment. The reasons for mainly providing a low level of interactivity in these systems are heterogeneous. For example, the guidance sys-

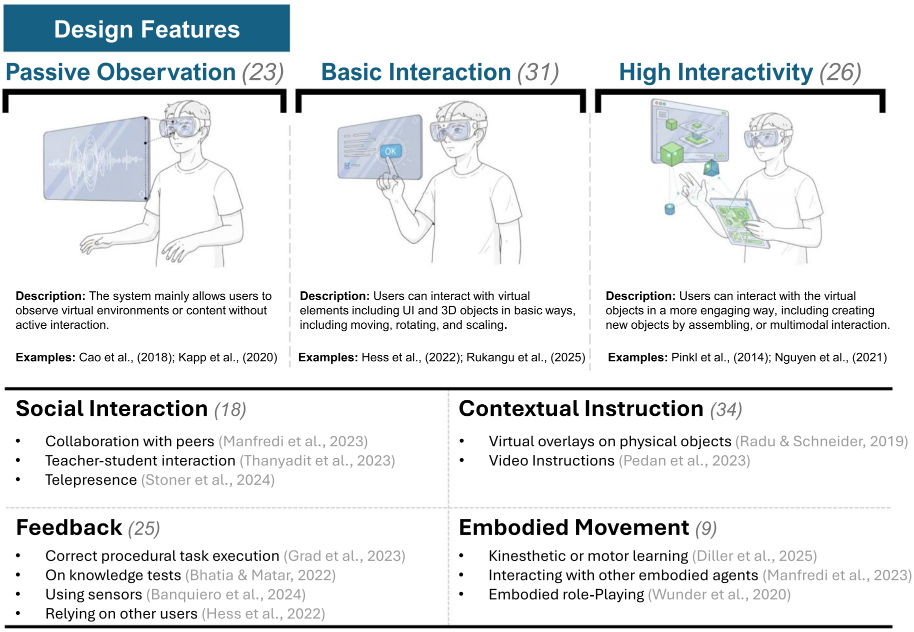


**Fig. 6** Different interaction levels and common design features identified in the reviewed articles

tem designed by Cao et al. (2018) aimed to guide users in completing different steps in an experiment. Therefore, users only need basic information overlay on how to conduct the experiment and interact with the physical object, instead of interacting with virtual elements in the MR system. Similarly, the MR experimental support system by Kapp et al. (2020) was mainly designed to visualize the parameters of the laboratory devices. Therefore, they only integrate passive observation in the system to fulfill the design requirement. In other cases, the lack of interaction is due to technical limitation. For example, Yu et al. (2019) designed an MR system that raised situation awareness of users in a museum visit. However, they were only able to evaluate the concept with a Google Cardboard prototype for better scaling, which limited the interactivity of the MR learning system.

Basic interaction is characterized by presenting an MR system that allows simple operations to move, scale, and rotate virtual objects or to interact with the user interface in MR. Thirty-one articles identified in the review provide such basic interaction. For most articles, this seems sufficient for the learning task, as it can effectively support interactive instruction (Huang, 2019), multi-device interaction (Yang & Liao, 2014) and simulation-based learning (Hess et al., 2022). Nonetheless, it has also been suggested that a higher level of interaction may further improve the system. For example, Banky and Blicblau (2017) discuss the possibility of enhancing the experimental experience with haptic feedback to minimize the use of physical experiment equipment. Among the reviewed articles, 26 of them achieved high interactivity in the system. Here, articles such as the one by Nguyen et al. (2021) leverage multi-modal interaction, including gaze and speech interaction. Besides, more articles integrate high interactivity to support additional interactive features such as annotation (Elor et al., 2022; Zoghi et al., 2018). Recent studies go further by investigating the impact of different modalities. For example, Yuan et al. (2024) evaluated head-mounted MR against desktop and mobile modalities, demonstrating how gesture-based interaction improved learners' spatial reasoning.

The most common design feature included in the reviewed articles is contextual instruction. Nearly half of the articles (34 out of 80) have some types of context-aware instruction to guide the learning experience. The contextual instructions often provide information on how to execute certain steps in the learning experience and deliver procedural knowledge. Some MR systems also utilized spatial information detected by the devices to deliver information more accurately. For example, Radu and Schneider (2019) implemented an MR learning system that interplays with the physical environment, by placing instructions and tooltips around the inquiry-based learning objects. Other systems adopted a simplified approach without spatial awareness, such as using video instructions in the work of Peden et al. (2016). Furthermore, contextual instructions have been applied into many fields of education. For example, Gieser et al. (2024) embedded MR-based contextual feedback in medical simulation labs, while Su et al. (2025) integrated MR with mobile devices in industrial ergonomics training to deliver task-relevant guidance directly aligned with real-world assembly contexts.

Another design feature that has been implemented in MR learning systems is user feedback. In 25 of the reviewed articles, feedback was part of the system design. Out of these articles, 20 of them provide feedback on whether the expected operation has been performed correctly by participants. For example, Grad et al. (2023) compared the performed anatomical actions with the predefined baseline to give feedback to users. Other feedback methods include integrating quiz questions to test users' understanding (Bhatia & Matar, 2022), Moreover, some collaborative systems rely on the tutor or the facilitator to give feedback to students, instead of generating feedback in the system (Hess et al., 2022). Recent works, however, increasingly rely on automated and adaptive feedback. For instance, Diller et al. (2025) introduced an MR framework providing omnipresent in-situ feedback for motor skills acquisition, showing measurable improvements in procedural learning. Similarly, Banquiero et al. (2024) presented a video see-through MR system that uses real-time visual feedback to increase task accuracy in complex environments. Haptic feedback using smart gloves has also been implemented by Gieser et al. (2024).

Other design features identified in the articles include agents as learning assistants (one article), embodied or motor learning (nine articles), and role-playing (nine articles). Some design features that are commonly found in Massive Open Online Courses (MOOCs) and gamified systems such as rewards and achievement are not found in the MR systems we reviewed.

### 4.5 Research Methods and Study Design

For the overarching research method, we excluded articles without an empirical evaluation. Therefore, all articles are classified to be one of the following three types of research: qualitative, quantitative, and mixed-methods research. Almost half of the articles (39 out of 80) adopted a quantitative approach to evaluate their systems, while eight articles opted for a qualitative evaluation and 33 followed a mixed approach.

For the data collection, interviews have been commonly used to collect qualitative data (20 articles). Apart from interviews, researchers have also used other methods to collect qualitative data for the evaluation. For example, in the work of Banky and Blicblau (2017), they recorded the session and coded the activities performed by users of MR systems and analyzed it with the Kikan-Shido framework (O'Keefe et al., 2006). For the quantitative and mixed-method research, most articles (62 out of 80) used surveys to collect data from participants. The survey items were designed to measure different outcomes, which will be discussed in the following paragraphs. Other data sources include biosignal data, e.g. eye-tracking and facial expression data (Nakazawa et al., 2023). For example, Liu et al. (2025) relied on gaze-tracking logs to evaluate attention allocation. Furthermore, 15 articles used interaction and log data, including task completion time, to measure different outcomes such as efficiency (Tang et al., 2020). For instance, Yuan et al. (2024) compared multimodal interaction logs across devices to investigate the acquisition of skills in learning engineering drawing. These approaches illustrate a growing methodological sophistication in analyzing learners' behavioral traces in MR environments.

In most studies (71 out of 80), the user evaluation has been conducted in controlled experiments, and in nine articles the authors evaluated their systems in the wild. The sample size of the studies also varies, with a mean sample size of 52.79 ($SD = 58.44$). In the articles, different dependent variables are measured to evaluate the learning system. A commonly measured outcome is usability, with 33 articles using different techniques to measure the usability of their proposed systems. Some including Magyar et al. (2020) used established measurement tools such as the system usability scale (SUS) to measure the usability, while others included a few questions in the survey to get an overall impression of the usability. Since MR systems have been researched to demonstrate the advantages of increasing motivation (Khan et al., 2019), supporting self-efficacy (Essmiller et al., 2020), reducing cognitive load (Mohammadhossein et al., 2022), these cognitive constructs have also been measured in a few studies. However, the total number of articles that directly measured these cognitive constructs remains relatively low: six articles measured cognitive load, six articles measured motivation, and seven articles measured self-efficacy. Similarly, even though engagement and immersion have been highlighted as a key factor in improving learning outcomes for MR learning systems (Dengel & Mägdefrau, 2018), only a few studies measured the engagement (six articles), presence (eight articles), and immersion (one article) level in the evaluation. For systems that involve collaborative learning experience, metrics including class dynamic, and collaborative contribution are also measured to evaluate how effective the MR system helps foster an efficient collaboration between users (Kim et al., 2022; Chandran et al., 2024).

Another commonly measured outcome is performance and knowledge. With 18 articles investigating the user performance and 20 measuring the knowledge acquisition or understanding. The constructs of performance, knowledge and understanding are defined and measured differently depending on the fields of education. For example, Campo et al. (2023) measured the performance of the violinists by recording the motion of playing the violin and comparing it with a standardized baseline. Similarly, Diller et al. (2025) used motion-tracking to quantify motor learning progression. In the study of Stemasov et al. (2023), performance was measured by the time and success rate of a personal fabrication task. Meanwhile, Gieser et al. (2024) followed a similar approach by measuring procedural accuracy using interaction logs collected with body sensors. Meanwhile, knowledge and understanding are commonly measured with knowledge tests and quizzes in surveys. In total, 15 articles implemented a knowledge test to analyze users' learning performance, and ten of them integrated the knowledge test into the survey. For example, Su et al. (2025) used an established knowledge acquisition test to measure whether their training system improved participants' awareness on neck-related health conditions. These examples illustrate a trend toward domain-specific, fine-grained performance and knowledge measures.

## 5 Discussion

### 5.1 Interpretation of Results

The results indicate that the application of MR learning systems in higher education is diverse across several dimensions, including technological choices, fields of education, system design features, and research methods. This multidimensional diversity highlights the flexibility of MR as a learning technology, but it also complicates efforts to draw consistent conclusions about its pedagogical effectiveness.

In terms of technology, optical see-through devices are more commonly adopted than video see-through systems. Their advantage lies in the ability to perceive the physical surroundings directly through a transparent display, whereas video see-through systems rely on video streams where latency and image quality may negatively affect the learning experience. At the same time, several studies have experimented with cross-device setups or developed systems compatible with different MR hardware, demonstrating the adaptability of these technologies to varied educational settings. However, the implications of these technological choices for actual learning outcomes remain underexplored.

For the fields of education, the articles identified in the review demonstrate the potential of MR in various fields. Apart from STEM education and medical education, which commonly adopt immersive technologies, disciplines such as music education have also been explored integrating MR systems in teaching and learning activities. In addition, some articles reported on the use of MR authoring tools and support mechanisms that operate independently of specific fields of education, further emphasizing the field-independent potential of MR in higher education. Taken together, these examples illustrate that the use of MR is not confined to traditionally technology-oriented disciplines but is increasingly relevant across a broad range of fields.

Moreover, the design features implemented in the reviewed articles are diverse as well. While some systems focus on delivering contextual instructions and allowing users to passively observe the training procedure, other systems are more immersive and strive for a higher level of interaction. A recurring design element is the provision of feedback and contextual instructions, but the effectiveness of these features in shaping learning outcomes is often overlooked in empirical evaluations. Compared to other digital learning formats, MR learning systems in higher education rarely incorporate learning assistants or gamified learning elements. This restrained approach may reflect a desire to avoid cognitive overload or distraction, yet it also suggests an underutilization of potentially effective design features. In general, through the reviewed articles, there is a lack of systematic investigation into how specific design features influence learning outcomes.

Finally, considerable variation exists in evaluation practices. Although all reviewed articles included empirical evaluation, the methodological rigor differed substantially. Usability was a common focus, but some measured it only through a single survey question, while others relied on standardized instruments. Similar inconsistencies were found in qualitative evaluations: while some articles employed a thematic analysis approach, others appeared to use the data only to form a general impression of users' opinions. A more comprehensive and standardized toolkit for evaluating MR learning systems could strengthen study design and enhance methodological rigor in future research.

## 5.2 Implications for Research and Practice

### 5.2.1 The Need for Advanced Learning Support as Design Feature

The state-of-the-art research in applying MR learning systems in higher education shows a variety of systems in terms of design features. First, the results of the review show various levels of interactivity among the MR systems. There are many systems with a high level of interaction, allowing users to immerse themselves in simulation-based learning (Wunder et al., 2020), real-time collaboration (Kim et al., 2022), human-robot interaction (Radu et al., 2021). However, this doesn't suggest that the systems with a lower level of interactivity are inferior. Sometimes the systems offer only limited interactivity and even only allow passive observation. While this to some extent doesn't exploit the unique advantages of MR technology to its maximum, it is sometimes intended. For instance, this would allow more flexibility to transfer the design and the system to other platforms, including mobile AR or VR, where the interactivity level can be limited due to the lack of sensors, as many articles including Dafoulas et al. (2019) propose a multi-device system. In this case, it is intended to limit the interactivity to make sure the system is compatible with different devices and technologies. Therefore, the level of interactivity should be decided based on the user requirements and the use case scenarios.

Furthermore, most design features included in the systems still focus on the level of interactivity and immersion. More effective and realistic visualization is the focus of articles across different fields. For example, the system implemented by Janeras et al. (2022) mainly supports the learners with a 3D visualization of the geo-information. During the learning process, guidance and adaptive support are often missing in such systems, the goal of improving the learning outcome relies solely on the benefits of the visualization. In many cases, visualization is beneficial to the increase of learning outcomes. However, the overall focus on the visualization might create a tunnel vision on utilizing MR for better learning support.

Among the reviewed articles, only a few integrated support mechanisms for students to better navigate through the learning experience. For example, providing feedback on the learning progress and outcome is regarded as an effective way to achieve self-regulation and reflection (Johnson & Davies, 2014). In our review, less than half of the articles provided an MR system that gives feedback to users. These systems mostly focus on checking if the task and procedure executed by the user match the predefined baseline. For example, Grad et al. (2023) examines if a dental operation of filling a tooth is performed well by comparing the performed result in MR with a 3D printed model. Other systems rely on the intervention of a human facilitator to give feedback. Therefore, feedback as learning support is not fully implemented in MR systems for higher education.

Apart from feedback, the potential of other learning support techniques has also been largely ignored. For example, note-taking and annotation techniques are only supported in three of the identified articles. However, these articles also did not evaluate the efficacy of the introduced learning support mechanism. Future research can investigate additional design features to provide more effective learning support. One method is to seek inspiration from other learning platforms, such as MOOCs. Research in MOOCs has revealed several learning elements as design features that improve learning outcomes. For example, Julia et al. (2021) categorized various learning elements in student-student interaction, student-content interaction, and student-teacher interaction dimensions. These dimensions open up the design possibilities of learning support techniques, including online quizzes, automated feedback, discussion forums. While not all design features in MOOCs may be suitable to transfer to MR learning systems, it is worth considering as references by researchers to provide better learning support and design features in MR learning systems.

### 5.2.2 Effective Evaluation Methods for Learning Outcomes

All articles included in the review have evaluated their systems with an empirical study. The study design and research methods also show heterogeneity. While many articles motivate the introduction of MR systems by improving learning motivation and engagement of the learners, only a few have systematically evaluated whether the intervention indeed helps to improve these outcomes for learners. Most studies only evaluate these constructs with one or two survey items instead of resorting to an established measurement tool. For example, even though improving motivation has been mentioned as a huge benefit of using MR learning systems, only three studies measured the motivation level of the participants. Only in the article of George et al. (2023), the authors used an established questionnaire of intrinsic motivation inventory (IMI) to measure the motivation level of learners (Ryan et al., 1983). A similar situation can be found for other cognitive constructs such as engagement and confidence. Similarly, immersion has been mentioned as one of the benefits of immersive learning experiences, such as using MR learning systems. Nonetheless, only the article of George et al. (2023) measured the immersion level of participants in their study. The evaluation problem has been previously highlighted by Nebeling et al. (2020), as they pointed out, the lack of effective evaluation methods dedicated to MR systems. Therefore, future research can be devoted to better understanding the effects and outcome of MR learning systems on various cognitive constructs with better evaluation methods, including leveraging biosignal data with different sensors.

Furthermore, some articles in the review focus on comparing the use of an MR system with other digital learning formats, such as VR and mobile AR (Kapp et al., 2020). These studies offer valuable insights into the impact of the choice of technology on the learning outcome. Nonetheless, the results of these studies might not be applicable in other fields of education. Therefore, aiming to better understand the unique advantages and characteristics of all XR technologies, more comparative studies and evaluation are needed. Specifically, comparing mobile AR and MR can be insightful for research and real-world applications, as mobile AR offers a more affordable and flexible learning option, while MR focuses on better fidelity and interactivity. Moreover, comparing VR and MR can also reveal design implications, as VR has the potential to offer a more immersive experience, while MR allows the perception of the physical environment. Understanding the nuances of the technology can help educators decide which technology to use for which specific fields and educational tasks.

Lastly, the goal of MR learning systems is first and foremost to improve the learning outcome of learners in the higher education context. The reviewed articles show different approaches for the evaluation of different variables, including qualitative, quantitative, and mixed-methods. However, specifically for the learning outcome, more articles use quantitative methods with surveys or knowledge tests. Here, only a few studies use standardized tests in educational research to test the performance or knowledge retention to measure the learning outcome, e.g., the use of Individual Procedure Score (IPS) for performance measurement in Rojas-Munõz et al. (2020). Instead, most studies design their own knowledge tests with a few relevant questions. Therefore, the results may suffer from validity concerns. Even for those with a clear evaluation strategy for learning outcomes, the evaluation is often conducted within a short time. Nonetheless, the learning outcome, especially in higher education, is often observed through long-term studies. Yet, longitude studies are missing in the identified studies. Furthermore, the sample size of different studies varies as well, as can be seen from the relatively great standard deviation regarding the sample size. It seems that a consensus on an appropriate sample size for evaluating MR learning systems has not been reached so far, which can be further explored in future research.

### 5.2.3 Explicit Integration of Learning Paradigms and Theories in MR Learning Systems

Investigating which learning paradigms and theories have been applied in MR learning systems is one of the research questions of our paper (RQ2). Yet, most articles don't explicitly specify their adopted learning paradigms, and the design decisions are usually not supported by a specific learning theory. Therefore, we suggest that the established learning paradigms are not well transferred into the practice of designing MR learning systems for higher education. Compared to other educational technology research, MR learning systems might benefit from adopting established learning theories and paradigms to guide their design decisions to ensure a better learning outcome. This opens up further interdisciplinary collaboration opportunities between researchers from the education community with HCI as well as IS researchers.

Even though many articles don't clearly outline a learning theory or paradigm for their research. It is also implied through the system design that an exploratory or inquiry-based approach has been adopted. For those works, concrete learning theories may guide the design and evaluation of these systems more effectively. Instead of assuming exploratory learning is most suitable for MR learning systems, researchers should also be aware of the risk that an exploratory design without efficient guidance and support can deteriorate the learning experience (Mayer, 2004). A good balance between exploration and instruction needs to be achieved in the system design and evaluated to make sure that the user doesn't get lost during the learning experience. While the evaluation of contextual instructions has been missing in the identified articles in this review, the effort of integrating contextual instruction has been seen in some articles. This attempt to strike a balance between encouraging active learning and providing users with sufficient guidance. This strategy has been highlighted in educational research, that pure exploratory learning may not work effectively as intended (Mayer, 2004). Furthermore, MR is a novel device for many users, which may introduce usability challenges. In this case, sufficient instruction as guidance is even more necessary. Nevertheless, it's not yet confirmed that a perfect balance between active learning and instruction has been guaranteed in state-of-the-art research. More than half of the articles don't explicitly design contextual instructions in their systems, and even the articles that integrated the instructions rarely measured the efficacy of their integrated instruction with a dedicated measurement tool.

Besides the commonly adopted self-directed learning approach that encourages users to explore the learning material independently, some articles allow different learning approaches such as collaboration, simulation-based learning, tutoring, etc. This shows the awareness of tailoring the technology to specific learning tasks and fields of education. Future research can further explore other learning paradigms such as behaviorism or cognitivism, which have also been identified as effective learning strategies in various fields (Schunk & Greene, 2017).

In the review process, we identified a total of 18 different fields of education for applying MR learning systems in higher education. This shows the potential of MR systems to adapt to different fields of education and support various topics. Nevertheless, medical training remains the most commonly researched field of education and the advantages of MR have been demonstrated well in these studies. In the field of medical training and laboratory training, established learning methods have been transferred well in MR learning systems, including operation training, simulation-based learning, etc. Nonetheless, in other fields, traditional learning techniques are often overlooked as design features, including note-taking, quizzes, and discussion opportunities. Future research can explore the feasibility of transferring existing effective methods to MR learning systems.

### 5.2.4 Designing Biosignal-Adaptive MR Learning Experiences

As the definition of MR suggests, MR learning systems provide more advanced and interactive experiences than traditional AR on mobile phones or tablets. This is largely due to the wide range of built-in sensors on MR headsets, including eye-tracking, motion-tracking, and hand-tracking. While some studies have begun to explore the use of these sensors to capture biosignals in educational contexts (Nguyen et al., 2021), most work continues to rely on them primarily for interaction purposes. A recent survey on eye-tracking in MR confirms this pattern, showing that the majority of studies use eye-tracking primarily for gaze-based interaction (Plopski et al., 2022). We argue that these sensing capabilities should not be treated as peripheral: beyond enabling additional interaction modalities, they offer rich opportunities for learning analytics and for designing adaptive learning experiences.

Evidence from desktop-based e-learning shows that biosignal data can be used to create adaptive systems that respond dynamically to learners' cognitive states (Hu & Kuo, 2017; Kennel, 2022). However, such systems typically require additional external sensors, making them difficult to scale. By contrast, MR headsets already integrate many of these sensing modalities, lowering the technical barrier to implementing biosignal-adaptive approaches. Beyond immersive learning, researchers have already demonstrated the feasibility of biosignal-adaptive systems that adjust interfaces in response to users' cognitive states (Doswell & Skinner, 2014; Schultz & Maedche, 2023). These examples suggest that MR learning systems are uniquely positioned to combine immersive interaction with continuous biosignal monitoring in ways that traditional desktop or mobile learning systems cannot.

The potential of biosignal-adaptive MR becomes clearer when considered alongside the design features identified in our review. Many existing MR learning systems emphasize contextual instructions and feedback, yet their effectiveness in shaping outcomes is often under-evaluated. Similarly, levels of interactivity vary widely: while some systems allow only passive observation, others integrate high interactivity through multimodal input such as gaze and speech (Yuan et al., 2024; Nguyen et al., 2021). In both cases, biosignal data could serve as an additional layer of adaptation. For example, attention patterns captured through gaze tracking could be used to tailor contextual instructions more precisely, while indicators of cognitive load could inform when feedback should be delivered or withheld Liu et al. (2025). This is particularly relevant for embodied learning tasks, which are common in MR environments and benefit from real-time responsiveness to learners' physical and cognitive states. The optimism toward biosignal-adaptive MR does not imply that other design features and evaluation methods lack value. Surveys, knowledge tests, and qualitative interviews remain indispensable for capturing learners' perceptions and outcomes across contexts. However, these methods typically provide retrospective or aggregated data, whereas biosignals enable real-time, in-situ understanding of users during the learning process. In this sense, biosignal-adaptive approaches complement rather than replace traditional designs, offering a path toward more responsive and personalized MR learning experiences.

## 5.3 Limitation

This systematic review has several limitations. First, our focus is on MR learning systems in higher education, and many of the identified articles explicitly highlight this target group in their design rationales. However, some reviewed articles did not clearly state that their systems were designed for higher education. These articles were nevertheless included, as their evaluations involved only university students. It remains unclear, though, whether the exclusive use of university students reflects a deliberate focus on higher education or merely a coincidental demographic choice without a dedicated target context. This ambiguity may introduce potential bias into the results.

Second, although our search strategy did not explicitly filter by language, the use of an English-language search string means that non-English articles would only be found if they included an English title and abstract. Consequently, relevant research published entirely in other languages was not captured by our search strategy. Nonetheless, we successfully retrieved 61 non-English articles with titles and abstracts translated in English. These articles were screened in the same process with other articles.

Furthermore, the results show a variety of different fields of education. However, due to the focus on higher education, we couldn't dive into each of these fields and discuss the characteristics of each field of education in detail. For example, each field has its unique subcategories, which may require different design solutions. This can only be explored with a dedicated literature review on the specific field. Therefore, future research can further explore MR learning systems in a specific field of education and compare the results with the findings of our work.

Lastly, our review follows mainly a qualitative approach, with descriptive analysis and a conceptual framework illustrating the result. Nonetheless, the review can be further extended with a quantitative approach in a meta-analysis. For example, we summarized measured outcomes and the study design of the articles. However, we didn't calculate and report the effect size of the measured outcomes among the articles. This insight can benefit further research and provide additional guidelines for designing MR learning systems.

## 6 Conclusion

This paper presents a systematic literature review of MR learning systems in the higher education sector. Our findings indicate that MR learning systems have been adopted across different fields of education. Through implementing different design features and learning elements, existing studies emphasize the integration of interactive and immersive experiences that enhance learning outcomes in higher education.

Despite the promising applications of MR in higher education, our review identified several areas that warrant further investigation. A primary need is the development of more comprehensive evaluation methods to assess the impact of MR systems on key cognitive and affective constructs, such as motivation, engagement, and immersion. Additionally, an area largely overlooked in current research is the incorporation of advanced cognitive and metacognitive support mechanisms, e.g., adaptive feedback, into the design of MR systems. Furthermore, the integration of established learning paradigms and theories can further guide the design and implementation of MR learning systems to deliver effective learning experiences.

Future research can also explore leveraging the integrated biosignal sensors in MR headsets to create user-adaptive learning environments. This approach holds potential for providing personalized learning support and enhancing the overall efficacy of MR-based instruction. Moreover, comparative studies between MR and other immersive technologies,

**Table 1** Types of HMDs for MR learning systems

| Technology | Explanation |
|---|---|
| Video See-through | The HMD blends the video stream of the surroundings captured by the device with the virtual elements, the blended content is then displayed on a screen in front of users' eyes |
| Optical See-through | The HMD has a transparent display that reflects the generated virtual elements in front of users' eyes. As a result, users can perceive the physical surroundings with the virtual overlay through the transparent display |

such as VR and mobile AR, are needed to elucidate the distinct advantages and optimal use cases for each modality. In conclusion, while MR technology holds significant potential for transforming higher education, future research can address the identified gaps and challenges to fully realize its advantages.

### 6.1 Supplementary materials

The supplementary material of this systematic literature review contains the following data: (a) An Excel spreadsheet with a table of the identified existing reviews from the scoping analysis, a concept matrix serving as a coding table for reviewed articles, and the search strings used across all databases during the search process. (b) Data analysis and visualization script with JASP. We gratefully acknowledge Brudy et al. (2019), whose clear and effective visualization style provided the inspiration for our figures. The data is openly accessible here: https://osf.io/duvqs/?view_only=6492fd17b9cb4af9a72c7d8681233438

**Table 2** Learning paradigms and theories

| Learning Paradigms | Explanation |
|---|---|
| Behaviorism | Behaviorism suggests that learning happens when behaviors are rewarded or punished. It emphasizes conditioning and reinforcement, focusing on the external manifestations of learning, not internal mental processes |
| Cognitivism | Cognitivism suggests that learning is driven by internal mental processes like thinking, memory, and problem-solving, highlighting the importance of understanding the information processing and cognitive process of learning |
| Constructivism | Constructivism proposes that learning is an active process where individuals build their understanding of the world through experiences and reflect on those experiences, emphasizing the role of personal meaning-making and active interaction in learning |

**Table 3** Design features of MR learning systems

| Design Features | Explanation |
|---|---|
| Passive observation | The system mainly allows users to observe virtual environments or educational content without active participation or interaction |
| Basic Interaction | Users can interact with virtual elements including UI elements and 3D objects in basic ways, including moving, rotating, and scaling the virtual objects |
| High interactivity | Users can interact with the virtual objects in a more engaging way, including creating new objects by assembling given objects |
| Social Interaction | Collaborative learning experiences that allow users to engage with peers or instructors in shared virtual spaces, encouraging communication and knowledge exchange during the learning experience |
| Contextual Instruction | Guidance and instructions during the use of the MR system to help students better understand and retain information |
| Feedback | The system gives feedback information on users' input and performance to help users reflect on their own learning strategies |
| Embodied movement | The system enables users to use their own body movements to interact with the learning content and make progress in learning |
| Rewards and achievement | Gamification elements that motivate users by presenting virtual rewards and acknowledgment of their learning progress |

**Table 4** Research methods

| Research Methods | Explanation |
|---|---|
| Qualitative Research | Research that evaluates subjective experiences and interactions. It emphasizes collecting and analyzing non-numerical data, such as interviews, observations, and textual analysis, to uncover underlying meanings, patterns, and insights (Edmonds & Kennedy, 2016) |
| Quantitative Research | Research that involves collecting and analyzing numerical data to deliver quantified results and trends. It emphasizes objective measurement, statistical analysis, and controlled experimentation to draw conclusions |
| Mixed-methods | Mixed-methods research combines elements of both qualitative and quantitative research methods to complement each other and allows researchers to conclude more comprehensively (Creswell, 2009) |

**Table 5** Data collection methods

| Data Collection | Explanation |
|---|---|
| Interview | A qualitative data collection method where researchers engage in conversation with participants to gather information about their experiences |
| Survey | Collecting data by asking participants questions about their opinions, behaviors, or demographic characteristics |
| Knowledge Test | An assessment of participants' understanding and learning progress of a given topic with multiple questions |
| Interaction Log | Log data of how participants interact with the presented MR learning system such as the time of each interaction, the user's actions or inputs, system responses, errors encountered, and any other relevant information related to the user-system interaction |
| Biosignal | Physiological signals or measurements generated by the human body, collected using biosignal sensors during the use of the MR system, including heart rate data, eye-tracking data, etc |

**Table 6** Inclusion and exclusion criteria of the literature review

| Inclusion Criteria | Exclusion Criteria |
|---|---|
| Peer-reviewed and published in journals or conferences | Non-peer-reviewed |
| With an empirical user evaluation | Pure conceptual papers |
| Full Papers | Short papers or work-in-progress papers |
| Published in 2013 - 2025 | Not applied in higher education context |

**Table 7** Summary of identified literature reviews on XR learning systems

| Authors | Keywords | Methodology | Databases | # Reviewed articles | Education Level |
|---|---|---|---|---|---|
| Won et al. (2023) | immersive VR, education, HMD, participant | not mentioned | Scopus, ProQuest, WoS, Google Scholar | 219 | All |
| Radianti et al. (2020) | VR, education, higher education | Webster and Watson (2002), Kitchenham and Charters (2007) | IEEE Xplore, ProQuest, Scopus, WoS | 38 | Higher Education |
| Ibáñez and Delgado-Kloos (2018) | AR, education, STEM | not mentioned | ACM DL, ERIC, IEEE Xplore, WoS, ScienceDirect, Scopus, Springer | 28 | All |
| Jensen and Konradsen (2018) | VR, HMD, education, training | not mentioned | Scopus, WoS, EBSCOHost, PubMed, IEEE Xplore, ERIC, PsycINFO, IBSS | 21 | All |
| Mystakidis et al. (2022) | AR, STEM, higher education | Petersen et al. (2015) | Scopus, Springer, WoS, ERIC, EBSCO, IEEE Xplore | 45 | Higher Education |
| Hidayat and Wardat (2023) | AR, STEM, education | Page et al. (2021) | ERIC, ScienceDirect, Scopus | 42 | All |
| Yu et al. (2022) | AR, game-based learning | Kitchenham and Charters (2007) | Google Scholar, ISI Web of Science, ProQuest, ProQuest Dissertation, PubMed, Engineering Village, IEEE Xplore | 46 | All |

## Detailed Method Description

See Tables 1, 2, 3, 4, 5, 6 and 7.

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**Data Availability** The data is openly accessible in an open data repository that can be accessed online: https://osf.io/duvqs/?view_only=6492fd17b9cb4af9a72c7d8681233438

## Declarations

**Conflict of interest** The authors have no Conflict of interest to declare that are relevant to the content of this article. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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