

Augmented Reality Enhanced Analytics for Education: A Systematic Review

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Abstract

This systematic literature review of augmented reality (AR) applications utilizing enhanced analytics in education settings surveys publications from 2000 to 2025, specifically targeting AR use in primary, secondary, and higher-education sectors. With the growing use of AR in such settings, this review informs educators, application designers, and scholars on insights and evidence gained in current and past studies on the use of enhanced analytics in AR applications. There are relative advantages and challenges in using AR enhanced analytics in educational settings, with the potential to contribute to knowledge in understanding students' engagement, motivation, behaviour, learning experiences, and acquisition of skills. The synergy of AR and learning analytics (LA) is significant as it enables richer, unobtrusive, real-time insights into student learning processes, advancing research beyond traditional self-report measures. The review demonstrates that AR enhanced analytics expand measures of engagement and effectiveness, while also pointing to opportunities for broader extended reality (XR) integration and methodological standardization.

Notes for Practice

- This systematic review synthesizes evidence on augmented reality (AR) enhanced analytics by examining their reported uses, advantages, limitations, and effectiveness. Findings show that AR analytics provide actionable insights into student engagement, behaviour, and outcomes that help teachers make informed, real-time instructional decisions.
- AR enhanced analytics demonstrate strong potential to personalize learning by supporting disengaged students with adaptive scaffolds while extending challenges for motivated learners, thereby enhancing inclusivity and differentiated instruction across classrooms.
- The review also identifies methodological inconsistencies across studies and highlights opportunities for broader extended reality (XR) integration (virtual reality (VR) and mixed reality (MR)). Standardized reporting protocols are recommended to strengthen comparability, enable future meta-analyses, and extend AR analytics into richer multimodal and immersive learning contexts.

Keywords

Learning analytics, augmented reality, education, enhanced metrics.

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1. Introduction

1.1 Introducing Augmented Reality

Educational technologies are entering a new age of innovation with rapid growth in the use of new and emerging technologies. Augmented reality (AR) is a widely used technology in education. According to Rampolla and Kipper (2013), AR is disruptive in education, especially with the prevalence of mobile devices in classrooms. They provide an overview of AR applications, ranging from elementary science to medical training. AR education tools offer feedback to learners through analytics. Bacca Acosta and colleagues (2014) found that AR improves students' cognitive skills more effectively than traditional methods. K.-H. Cheng and Tsai (2013) argue that AR can engage both teachers and students in learning. This trend is supported by Sotiriou and Bogner (2008).

Educational AR analytics involve systematic collection, analysis, and interpretation of data from AR technologies used in learning environments. This data encompasses various AR interactions like student engagement with virtual objects, navigation in AR spaces, and responses to AR stimuli. Analyzing these interactions yields valuable insights for educational improvement. AR presents opportunities to enhance learning through access to learning analytics (LA), which can take various forms. AR applications employ extensive sensing capabilities, providing valuable information about student behaviour. Wu and colleagues (2013) explored AR's potential in education, showing how sensory inputs from AR environments could become valuable LA. AR activities can deliberately engage students and teachers, generating active analytics where the application enhances learning. AR experiences can offer real-time analytics insights during class to guide teaching. Addressing individual learning needs is possible through AR analytics, using evidence-based insights and data-driven decisions. Ibáñez and Delgado-Kloos (2018) demonstrated AR's adaptability to diverse learning styles, potentially aiding in identification of learning hurdles and enriching education. Instant automated feedback can assist teachers in tracking progress during the lesson. AR analytics can seize non-assessment-related insights like emotional well-being and engagement. Monitoring motor skills and behavioural trends allows for the identification of learning issues and potential disabilities beyond mere observation. Social interactions via AR avatars enable the observation and correction of behaviours. AR applications paired with analytics enable prompt identification and correction of behaviours. AR enhanced analytics encompass not only learning outcomes but also factors that influence the learning process.

AR usage in educational settings boosts attention, confidence, learning experience, student interest, and curiosity and helps students focus on key information (Acosta et al., 2019). It goes beyond assessing learning outcomes to delve into the nuances of the learning process itself. AR technologies significantly enhance emotional engagement and motivation, crucial for effective learning (Ibáñez & Delgado-Kloos, 2018). They also foster collaboration and social interaction among students, encouraging peer learning and group problem-solving, enriching the learning experience often overlooked by traditional analytics (Radu, 2014). Furthermore, AR aids in managing cognitive load during learning activities, presenting complex information interactively and in a digestible format, positively impacting cognitive processes (Ibáñez & Delgado-Kloos, 2018). AR significantly impacts skill development, problem-solving, and critical thinking, demonstrating utility in tracking and enhancing these skills over time (Tzortzoglou et al., 2023). Moreover, AR enhances accessibility and inclusivity in education, especially for students with special needs like dyslexia, highlighting its potential in providing comprehensive insights into diverse learning styles and challenges (Chen et al., 2017). Thus, AR enhanced analytics represent a multifaceted approach to education, going beyond traditional academic outcomes and offering a holistic view of the educational process.

1.2 AR Enhanced Analytics and LA

AR applications enhanced with LA could address the mentioned issues. LA involves measuring, collecting, analyzing, and reporting data on learners, teachers, and their contexts to understand and optimize learning and its environments (Sungkur et al., 2016).

LA allows analysis of data on learners within the environment, aiding teachers in identifying behaviour patterns, assessing learning processes and outcomes, enhancing the overall learning experience, and providing opportunities to reflect on user learning activities (Einhardt et al., 2016). LA aims to utilize educational data to offer feedback to learners and teachers within the system (Johnson et al., 2013).

The integration of LA with AR in education, as detailed in these studies, represents a significant advancement in educational technology. By combining AR's immersive and interactive capabilities with the data-driven insights of LA, educators have powerful tools to enhance learning experiences. This synergy offers a deeper understanding of student engagement, behaviour, and learning outcomes, enabling personalized and adaptive learning strategies. Notably, these technologies transform both content delivery and evaluation methods. This integrated approach meets contemporary educational needs, emphasizing technology's role in creating dynamic, responsive, and effective learning environments. Such developments are pivotal in shaping the future of education, making it more engaging and efficient and tailoring it to individual learner needs.

AR enhanced analytics collect data from devices like mobile displays and smart glasses to overlay virtual content onto the physical environment. This provides alternative methods to access and assess content, connects the classroom to digital spaces, and ensures inclusive learning access for students with disabilities (Carreon et al., 2020).

Studies demonstrate that AR integration in educational games enhances learning, engagement, motivation, and performance in authentic learning. Additionally, AR supports lifelong learning, including fostering conservation and sustainability habits (Pombo & Marques, 2020). Studies explore AR books' impact on reading comprehension, cognitive load, motivation, and attitudes. Moreover, students find AR in education enhances knowledge retention, cognition, collaboration, and social interactions (Pérez-López & Contero, 2013). We are at the frontier of teaching and learning innovation, offering students tools to engage physically and virtually with learning materials in unprecedented ways.

1.3 Features of AR Enhanced Analytics That Support Learning

AR in education, recognized as mixed reality (MR) and enhanced reality, offers compelling features for educational purposes. Its potential is notably amplified when integrated with various technologies, enhancing its utility. Wu and colleagues (2013) highlight key aspects making AR effective in education: presenting learning content in 3D; facilitating ubiquitous, collaborative, and situated learning experiences; and enhancing learners' presence, immediacy, and immersion. AR visualizes abstract concepts and bridges formal and informal learning environments. However, some features may not be exclusive to AR, as they are found in other systems like ubiquitous and mobile learning environments.

From an educational standpoint, the use of analytics within AR platforms, as discussed by Callaghan and colleagues (2014), presents an intriguing aspect. Custom measurements, funnels, and cohorts within AR analytics platforms enable educators to delve deeper into usage data, fostering a nuanced understanding of user engagement and retention (Callaghan et al., 2014). While AR technology enhances learning through immersive and interactive capabilities, AR analytics contribute specifically to understanding and improving the learning process. By leveraging AR analytics, educators gain insights beyond surface-level engagement, comprehending educational efficacy and learner behaviour. To fully utilize AR in education, exploring how AR, coupled with analytics, offers a comprehensive view of the learning process is essential, addressing content presentation, learner interactions, and outcomes.

1.4 Opportunities for AR Enhanced Analytics in Learning

As AR becomes more prevalent in education, it brings new opportunities and challenges to student learning and engagement. Key issues in the practical application of AR in education include (i) tracking student interactions with AR elements; (ii) identifying and modifying user behaviour; (iii) addressing lack of engagement and motivation with AR tools; (iv) managing indicators of anxiety, stress, or fatigue in students; (v) tracking completion of learning tasks; (vi) evaluating effectiveness of learning objectives and goals; and (vii) overcoming lack of expertise among teachers in implementing effective AR learning strategies. These challenges, primarily centred around understanding and enhancing the learning process through data generated by AR interactions, underscore the significance of AR analytics. AR analytics focus on capturing, analyzing, and interpreting data from students' engagement with AR environments. This analytical approach addresses challenges by providing insights into student behaviour, engagement levels, emotional states, and learning progress. It equips educators to monitor and adapt AR experiences to individual learners' needs, maximizing educational benefits. While AR technology enhances learning environments with interactive experiences, AR analytics are pivotal in addressing educational challenges by analyzing and improving the learning process. This dual focus on AR and AR analytics in education leverages their combined benefits for the effective fulfillment of learning objectives.

2. Related Work

In the realm of educational technology, particularly focusing on AR and LA in terms of the data collected and the dashboards, there is a growing interest in how AR applications can be optimized through analytics derived from user interactions in education, which remained restricted to video games. This interest is exemplified in studies like Roberto and colleagues (2019), which investigated an AR puzzle game application designed to capture a range of analytics, including usage patterns, crash data, and specific AR interactions like marker discovery time and user movements around AR components. Such analytics are vital for understanding application usage, performance, and popularity, aiding in the design and improvement of AR educational tools.

Further illustrating the diversity of AR applications in healthcare, Sullivan and colleagues (2000), Das and colleagues (2005), and Mott and colleagues (2008) have explored the use of AR and virtual reality (VR) technologies in pediatric healthcare, particularly for reducing anxiety in children during medical procedures. More recent studies like that of Vidal-Balea and colleagues (2021) have expanded this use to track patient activities and mood, showcasing the versatility of AR in different contexts.

Moreover, the application of AR analytics extends beyond healthcare into other areas such as emotional engagement and social interactions, as investigated by López-Faican and Jaen (2020) using the EmofindAR application. This study highlights the potential of AR in evaluating social skills and emotional intelligence in children. Similarly, in the cultural domain, Ohlei and colleagues (2020) demonstrated how AR analytics could provide insights into visitor behaviours in museum settings.

The integration of motion sensors in mobile devices for AR games, as explored by McKenzie and colleagues (2014), further exemplifies the potential of AR analytics in capturing physical activities and movements, contributing to a better understanding of user engagement and behaviour in educational contexts. This approach emphasizes the multifaceted nature of AR analytics, not only encompassing usage statistics but also providing insights into user behaviour, emotional responses, and physical activity, thereby offering a comprehensive view of the impact and effectiveness of AR applications in various settings.

AR applications have been used in previous studies on the success of pediatric healthcare in addressing and reducing anxiety in children using AR and VR technologies in hospitals, especially during pre-surgery (Sullivan et al., 2000) or as a novelty

distraction when drawing blood samples and managing pain (Das et al., 2005; Mott et al., 2008). Recently, exploratory studies have been conducted to measure patient step counts and present a visualized chart to physicians and caregivers that answers the patient's daily mood through a survey administered through the AR application (Vidal-Balea et al., 2021). In addition to being a distraction tool, AR seems to affect the emotional moods of a user through the sense of presence. Using the EmofindAR application, researchers determined that children generate powerful emotions when playing games, even more so when playing with fellow players (López-Faicán & Jaen, 2020). The ability to evaluate the levels of social interactions, communication skills, and emotional intelligence when children play is the motivating factor. Innovative use of AR analytics in a museum tour project by Ohlei and colleagues (2020) captured analytics while visitors interacted with exhibits during tours and provided additional insight on visitors' behaviours and also critical analytics such as activation and deactivation of AR markers and time (duration) of viewing of the particular exhibit. Using an anonymous ID for each visitor, the following analytics were also captured: user ID (useful for returning visitors), date, time, marker name, device type, event action, battery level, network used, institution name, tour name, language, ID, and consumed times, as well as any errors. Built-in motion sensors in mobile devices such as accelerometers, gyroscopes, and magnetometers able to capture data originating from game play and movement activities (McKenzie et al., 2014) used analytics captured from a Treasure Hunt-based mobile game and measured the duration of the game played; the number of treasure locations visited; the number of physical activities (PA), such as jumping, running, kicking, hopping, and fundamental movement skills (FMS) path activities; and the number of shortcuts taken by the children.

The findings of the research conducted with 38 grade 5 students between the ages of 9 and 11 years concluded that users' mood, level of physical activity, degree of social interaction, interest, and level of satisfaction are not affected by the mode of the game, which provides new insights into how young children interact with AR applications. However, the study does not cover the methodology for capturing user analytics, games results, and time between tasks, which would provide vital insight into user game play behaviour. Additionally, the use of audio capture and the application of voice semantic analysis would have provided more relevant results to showcase game-play motivation; this would have easily been added by activating the recording feature of the mobile devices. Face recognition analysis is another context that can be explored to capture facial semantics and expressions to further give insight into the level of motivation and interest when children use AR applications, which can also be simultaneously recorded from the front-facing camera of most smart mobile devices.

Based on these gaps, a distinction can be drawn between AR and AR enhanced analytics, which represent two interconnected but distinct aspects of technology application, particularly in education. AR itself is a technology that overlays digital information onto the real world, creating interactive and immersive experiences that can enhance learning by visualizing complex concepts in a tangible way. AR enhanced analytics, in contrast, refer to the systematic analysis of data generated from these AR interactions. This process involves tracking, analyzing, and interpreting how users engage with AR content, providing insights into their behaviour, learning patterns, and overall engagement. While AR transforms the user's real-world experience with digital enhancements, AR enhanced analytics focus on extracting and utilizing data from these experiences to optimize the AR application's effectiveness and personalize the learning experience.

2.1 Purpose of Review

There are numerous systematic reviews on AR applications in educational contexts, focusing on the uses, potential benefits, difficulties, and effectiveness of this emerging technology. Several studies address and report the results obtained through quantitative, qualitative, and mixed-methods research to investigate the benefits, difficulties, and effectiveness of AR environments in various learning subjects (Pellas et al., 2019). AR appears to have the potential to influence students' engagement and participation, as well as to assist knowledge transfer, skill acquisition, and embodied learning experience within a well-structured learning context (Pellas et al., 2019). The purpose of this systematic review of the literature is to investigate the use of AR enhanced analytics by integrating data collection and data analytics into AR applications in a classroom environment. The study also surveys the use of data visualization techniques using AR applications which provide opportunities to present this information to teachers and even to learners in ways that support the learning process.

2.2 Research Questions

Current knowledge suggests that the use of AR technologies promotes and supports student participation during the transition phase from kindergarten to primary school for students between 5 and 6 years of age. Using the Forest Classroom experience (Singh et al., 2023), a physical room can provide a calming environment for disengaged and restless students. An opportunity was identified to use AR experiences to collect and present LA to improve existing data collection and data analytics to provide better teacher reflection mechanisms.

We are now able to identify the research questions to assist our study survey. The overarching research question is "To what extent can AR enhanced analytics data be collected, analyzed, and visually presented to give insights into students' progress and engagement in the classroom and support teachers in enabling learning and student welfare?"

With the following key questions, we present a systematic review of the literature on AR enhanced analytics used in educational settings.

RQ1: What are the uses, advantages, limitations, and effectiveness of AR enhanced analytics in learning?

RQ2: What are the evaluation methods, instruments, and measurable metrics of AR enhanced analytics in learning?

The purpose of this systematic review of the literature is to investigate the use of teaching analytics by integrating data collection and data analytics into AR applications in a classroom environment. The study also surveys the use of data visualization techniques using AR applications which provide opportunities to present this information to teachers and even to learners in ways that support the learning process.

3. Method

3.1 Theoretical Framework for AR Enhanced Analytics

Various established learning theories and frameworks relevant to AR in education settings have been thoroughly considered to contextualize AR enhanced analytics within broader educational technology paradigms. Firstly, constructivist learning theory underscores the role of extended reality (XR) technologies by facilitating active, student-centred exploration, allowing learners to build knowledge through immersive, interactive experiences (Vygotsky, 1978; Papakostas et al., 2023). Secondly, experiential learning theory emphasizes the power of XR to deliver concrete experiences, promoting active experimentation and reflective observation, thus enhancing retention and higher-order cognitive skills (Kolb, 2014; Dewey, 1986). Thirdly, theories of situated and embodied learning highlight XR's capability to immerse learners in authentic contexts, encouraging meaningful knowledge transfer and embodied engagement through physical interactions (Lave & Wenger, 1991; Wilson, 2002). Additionally, cognitive theories such as Mayer's cognitive theory of multimedia learning (CTML) and cognitive load theory (CLT) further explain how thoughtfully designed XR experiences leverage multiple sensory modalities, optimizing cognitive processes and reducing unnecessary mental load (Mayer, 2005; Sweller, 1988).

Building on these theories, the conceptual model proposed by Kazanidis and colleagues (2021)—AR LA—explicitly integrates AR technology with LA to systematically measure learner interactions, enabling personalized feedback and interventions (Kazanidis et al., 2021). This comprehensive model highlights the interconnectedness of AR experiences, analytics-driven insights, and educational outcomes, ensuring that immersive technologies not only engage students but also demonstrably enhance their learning (Kazanidis et al., 2021; Papakostas et al., 2023). Collectively, these theoretical frameworks and conceptual models firmly ground AR enhanced analytics within established educational paradigms, providing robust support for the integration of AR technologies, analytics, and educational outcomes.

For this review, we considered the systematic review guidelines proposed by Kitchenham (2004): (i) selecting journals from reputable sources, (ii) defining inclusion and exclusion criteria, (iii) defining the categories for the analysis, and (iv) conducting the review of the studies selected using methods of data extraction (content analysis), data synthesis, and coding.

3.2 Prior Systematic Reviews

It is essential for systematic reviews to present valuable interpretations of previous research studies and present unbiased and balanced findings in a way that provides benefits to support further research and identify new potential research directions (Kitchenham, 2004). Relevant systematic reviews were searched from SCOPUS and Web of Science (WOS) databases with the search string ((analytics) AND (education) AND (“augmented reality”) OR (“virtual reality”) OR (“mixed reality”)) AND (“systematic review”)). Utilising SCOPUS's “Reviews only” filter, 178 results were returned, and WOS returned 95 results. The last search was conducted on 11 May 2025. After removing duplicates, 25 reviews were considered relevant and the remaining reviews were manually classified into (i) systematic reviews (12), (ii) meta-analysis reviews (7), and (iii) scoping reviews (6), as shown in Table 8 and Figure 1.

Only three had studies that included evaluations that recorded user interactions on AR mobile devices. More specifically, they collected user data using functionality that is present in smart mobile devices, e.g., logging data associated with tapping the mobile device interface, locating the device's physical movement in the environment, use of any device-based biosensors (e.g., to measure skin temperature; heartbeat; and electrical activity in the brain, detected by electroencephalography using small metal discs (electrodes) attached to the head/scalp), audio and video recordings, gesture sensing, and eye-tracking, enabling the collection, analysis, and presentation of insightful analytics. Traditional data collection methods to consider are (a) questionnaires, (b) interviews, (c) surveys, (d) observation, (e) focus groups, and (f) writing essays (Bacca Acosta et al., 2014). It was noted that very few systematic reviews mentioned the capture of data logging analytics using mobile devices used for AR in the education context. The few studies that captured AR analytics from mobile devices consisted of basic user information, device's geolocation, and simple feedback capture using online surveys. It can be seen as a challenge to consider including AR-related analytics, which can be collected, analyzed, and presented to users in real time to make informed decisions on tasks or for evaluation purposes. With the vast amount of data ready to be captured and analyzed, the advantages do outweigh the limitations, but one aspect will be the need to place additional cognitive load on the user of an AR application. Hence, it is inevitable that the convergence of AR and analytics will be further explored through a review of the existing literature. For this review, we considered the systematic review guidelines proposed by Kitchenham (2004) that (i) comprised selection of journals

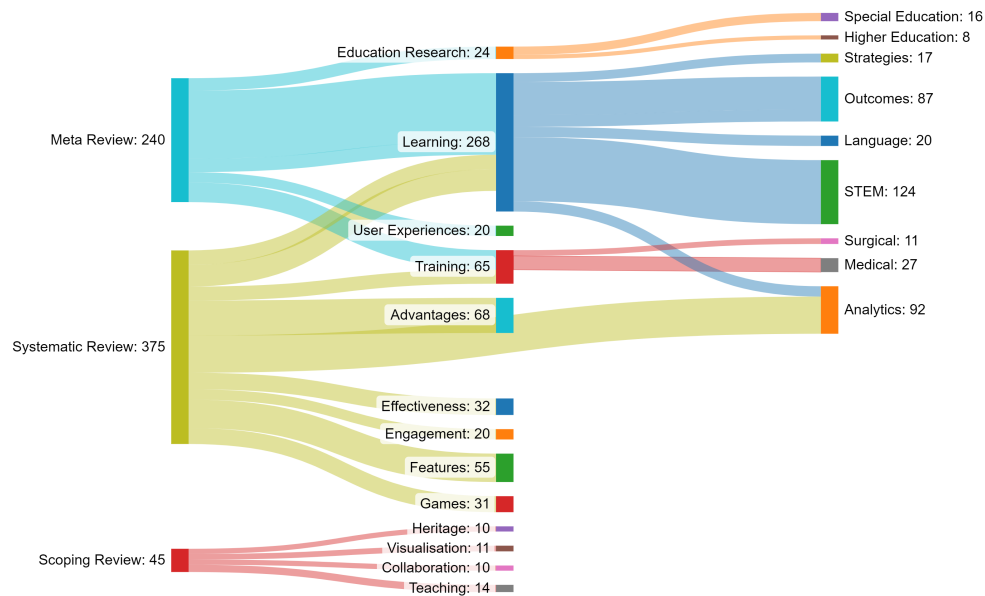


Figure 1. Analysis topics of prior meta reviews, systematic reviews, and scoping reviews.

from reputable sources; (ii) defined the inclusion and exclusion criteria; (iii) defined the categories for the analysis; and (iv) reviewed the studies selected using methods of data extraction (content analysis), data synthesis, and coding.

The following are the subsections presented according to the statement of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Moher et al., 2009): methodology, compiling of analysis of results, discussion of findings, and future trends and conclusion.

3.3 Search Strategy

3.3.1 Search String

A search string is constructed from the keywords in the research questions to ensure that the most relevant search results are obtained. Table 1 shows the three main groups of keywords: (i) analytics, (ii) augmented reality, and (iii) education, with alternative keywords used in related research domains. The keywords were combined with Boolean operators AND and OR to generate the search string as follows: (((“learning analytics”) OR (“analytics”) OR (“augmented analytics”) OR (“data analytics”) OR (“immersive analytics”)) AND ((education) OR (classroom) OR (school)) AND (“augmented reality”) OR (“virtual reality”) OR (“mixed reality”))).

Table 1. Formulating the search string.

Group A	Group B	Group C
Analytics	Augmented Reality	Education
Learning Analytics	Mixed Reality	Classroom
Data Analytics	Virtual Reality	School
Immersive Analytics		Students
Augmented Analytics		

3.3.2 Selecting Journals from Electronic Databases

Using the generated search string, an exhaustive search was performed to collate relevant peer-reviewed journals from January 2000 to May 2025. The following eight well-known online research databases, which index journal papers in the education and technology domains, were identified: JSTOR, SCOPUS, EBSC, ERIC, Web of Science (SSCI), IEEE Explorer, ACM Digital Library, and ProQuest. The search from the electronic databases separately returned 1673 results (see Table 2). The last search was performed on 11 May 2025. The Google Scholar research repository was also searched with the above query,

returning more than 17,000 results, mainly comprising grey literature from various sources. These were then manually searched to identify relevant papers from reputable journals, yielding 130 results. These were added to the prospective research papers to consider.

Table 2. *Electronic databases and retrieved journals.*

JSTOR	116
SCOPUS	210
EBSCO	158
ERIC	527
Web of Science (SSCI)	100
IEEE Explorer	140
ACM Digital Library	263
ProQuest	29
Google Scholar	130
TOTAL	1673

The journals in the systematic review process were managed and streamlined using the web-based software Covidence (<https://www.covidence.org>), including adding reviewers, importing the studies, searching and removing duplicates, facilitating the screening process, implementing the inclusion and exclusion criteria, doing a full-text review, quality assessment, data extraction, and finally exporting the data. The added feature of Covidence to automatically populate the PRISMA flow diagram is shown in Figure 2.

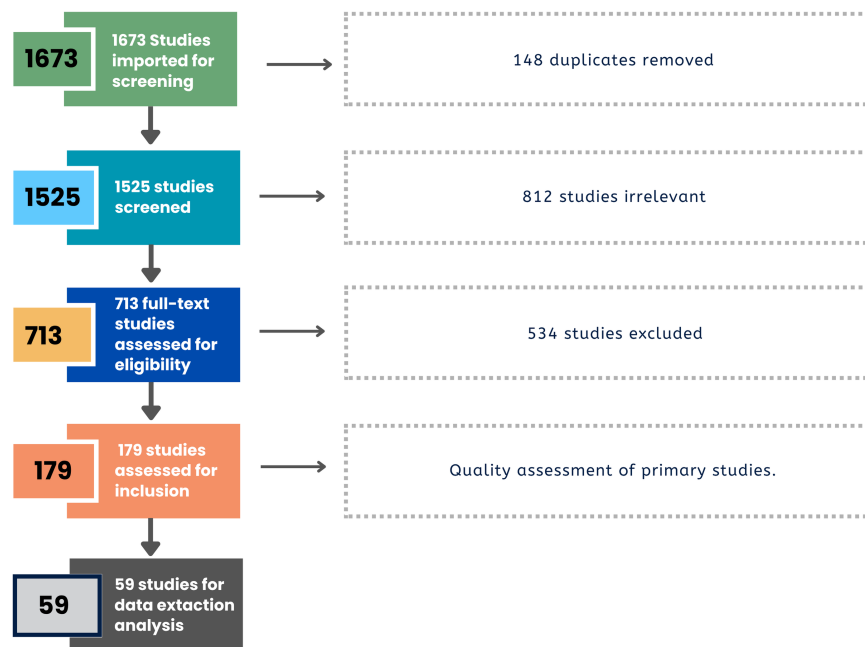


Figure 2. *PRISMA flow diagram.*

Of the 1673 studies, 148 duplicates were deleted. The title and abstract were reviewed and it was determined whether the study was relevant for AR in the education context, and the inclusion and exclusion criteria were applied. Only peer-reviewed journals were considered, and studies that were not exclusively focused on the field of AR were excluded at this stage, such as those including VR and MR. Studies related to medical research and those related to business, industry, and manufacturing were also excluded. Studies with a focus on artificial intelligence (AI), machine learning (ML), and Internet of Things (IoT) and specific to future trends were also excluded. Those without experimental evaluation data in education settings were also excluded. This process resulted in 179 primary studies that were subjected to a full-text review and quality assessment.

The following set of inclusion criteria was used for the review: (1) studies that were peer reviewed and published in a journal/conference proceeding, (2) studies published between 2000 and 2025, (3) studies concerning the use of AR in education settings (primary, secondary, higher education), (4) studies on AR apps and prototypes in education settings, and (5) studies that

were available in full text and in the English language. The following set of exclusion criteria was used to determine those that would not be covered in the review: (1) non-research studies (i.e., papers without bibliographic information such as publication name, volume, issue numbers); (2) studies that were not AR related; (3) medical research–related studies (those using AR in medical training were acceptable, however); (4) studies applying AR in business/industry/manufacturing, including those with a focus on AI, ML, and IoT; and (5) those studies focusing on future trends.

3.3.3 Quality Assessment of Primary Studies

A quality assessment (QA) of each study was performed using the following questions, which ensured quality of content and relevance and made sure the study was within the scope of the research questions. The questions were yes (1)/no (0) questions. The score for each study was summarized and tabulated, and it was observed that almost all studies rated “yes” for QA4 as these studies focused on student learning in classrooms or outdoors and concluded that various metrics do benefit and add value to the student learning experience. Therefore, studies that scored a “yes” for the remaining three questions were selected and shortlisted. Forty-seven studies were shortlisted, with 12 additional studies identified by manual search that were presented at prominent conferences in the areas of AR, MR, and education technology. A final total of 59 studies were subjected to a comprehensive data extraction analysis to answer the four research questions:

QA1: Are there methods described in the study capturing analytics from the AR experiences or interactions?

QA2: Does the study present any form of analytics captured from AR experiences or interactions?

QA3: Has the data captured contributed to any learning measure or metrics?

QA4: Do learning metrics add value to student or classroom learning?

The NVivo (version 12) content analysis tool was used to process and analyze the vast amount of qualitative literature in the shortlisted review studies. This computer software package has many advantages and can significantly improve the quality of research. Qualitative data analysis has become easier and yields more professional results. Software reduces a large number of manual tasks and gives the researcher more time to discover trends, recognize themes, and draw conclusions (Wong, 2008). Easily importing full-text documents into the software and using nodes, coding facilities allow further analysis with concepts, categories, and themes, employing numerical data to present visual figures, concepts maps, and sketches. All NVivo documents sourced are rich-text PDFs, with another key component being nodes. The nodes are places to further subclassify and store in themes or “codes,” the terminology used in NVivo. It is important to note the difference between a code and a node in NVivo parlance. A node is a physical location where you store the groups of ideas to be coded. Thus, coding (putting things into codes) is a process—a way to label certain aspects of the data and to sort information into distinct categories. On the other hand, the node holds all the information that has been coded into a certain category.

3.3.4 Categories for the Analysis and Data Coding

Using the NVivo content analysis functionality, the research trends of the review article’s literature were extracted and grouped according to the nodes and codes defined. The nodes are defined as categories of the referencing theme, such as uses, advantages, limitations, effectiveness, and affordances, as in the review studies. The codes are the subcategories that correspond to each research question. With the vast amount of analysis to be performed, the use of nodes and codes allows the grouping of studies according to the shared characteristics for review as shown in Table 3.

Table 3. *The list of nodes and codes for the analysis classified by the research questions (RQs).*

RQ1	Reported advantages, limitations, and effectiveness of AR enhanced analytics
RQ2	Type of evaluation methods, instruments of measures, and metrics of AR enhanced analytics

4. Results

For this review, we considered the systematic review guidelines proposed by Kitchenham (2004): (i) selection of journals from reputable sources; (ii) defining of inclusion and exclusion criteria; (iii) defining the categories for the analysis; and (iv) review of the studies selected using methods of data extraction (content analysis), data synthesis, and coding. The results of the review of the 59 studies according to the research questions that are being addressed are presented in this section. Table 4 shows the studies analyzed by journal with year of publication and Table 5 shows the studies analyzed by evaluation of user age groups.

Table 4. Studies analyzed by journal and year of publication.

<i>Physics Education</i>	3	2018, 2020, 2020
<i>ACM International</i>	5	2018, 2018, 2018, 2019, 2020
<i>Personal Ubiquitous Computing</i>	2	2009, 2017
<i>Journal of Computer Assisted Learning</i>	4	2009, 2017, 2023, 2025
<i>Journal of Visual Languages & Computing</i>	1	2016
<i>Journal of Education Technology</i>	2	2018, 2019
<i>Journal of Educational Computing Research</i>	1	2019
<i>Journal of Ambient Intelligence and Humanized Computing</i>	1	2020
<i>IEEE Transactions</i>	4	2014, 2020, 2020, 2021
<i>Interactive Learning Environments</i>	3	2016, 2018, 2025
<i>Contemporary Educational Technology</i>	1	2023
<i>International Journal of Instruction</i>	2	2019, 2022
<i>International Association for Development of the Information Society</i>	1	2018
<i>Educational Technology Research and Development</i>	2	2016, 2016
<i>Education Sciences</i>	3	2018, 2020, 2024
<i>Multimodal Technologies and Interaction</i>	1	2023
<i>E-Learning and Digital Media</i>	2	2023, 2024
<i>Computer & Graphics</i>	3	2021, 2022, 2024
<i>Contemporary Educational Technology</i>	3	2022, 2023, 2025
<i>British Journal of Educational Technology</i>	5	2013, 2020, 2022, 2024, 2025
<i>Studies in Health Technology & Informatics</i>	1	2020
<i>Interactive Learning Environments</i>	4	2017, 2020, 2022, 2023
<i>Frontiers in Education</i>	1	2024
<i>International Journal of Child-Computer Interaction</i>	1	2025
<i>Novel & Intelligent Digital Systems</i>	1	2023
<i>International Learning Analytics Knowledge</i>	1	2025
<i>Sensors</i>	1	2021

Table 5. Studies analyzed by evaluation of user age groups.

Higher-Education Students	25	Manuel et al. (2017), Zarranonandia et al. (2013), Callaghan et al. (2014), Ball and Johnsen (2017), Bos et al. (2019), ElSayed et al. (2016), Harley et al. (2016), Lytridis et al. (2018), Nicola and Stoicu-Tivadar (2020), Ogata (2013), Pombo and Marques (2018), Santos et al. (2019), Shao et al. (2020), Squires (2018), Vergel et al. (2020), Yau et al. (2020), C.-I. Cheng (2023), Geng and Yamada (2023), Ivarson et al. (2024), Amirbekova et al. (2024), Senthil Pandi et al. (2024), Li et al. (2025), and Bigonah et al. (2024)
Secondary School Students	12	Holstein et al. (2018), Vidal et al. (2018), Altmeyer et al. (2020), Arvanitis et al. (2007), Cai et al. (2016), Pombo and Marques (2018), Yau et al. (2020), Ens et al. (2021), Saucier et al. (2022), Arzmann et al. (2025), and Bigonah et al. (2024)
Primary School Students	12	Holstein et al. (2018), Rodríguez et al. (2020), Vidal-Balea et al. (2021), Chang et al. (2014), Geng and Yamada (2023), Olea-Ibarra et al. (2025), Tzortzoglou et al. (2023), Na et al. (2025), Na and Sung (2025), Singh et al. (2021, 2023), and Senthil Pandi et al. (2024)
Experts/Professionals	7	Whitlock et al. (2019), Antoniou et al. (2017), Saucier et al. (2022), Trajkova and Cafaro (2018), Papakostas et al. (2023), and Li et al. (2025)
Preschool/Kindergarten Children	3	Vidal-Balea et al. (2021), Olea-Ibarra et al. (2025), and Amirbekova et al. (2024)

4.1 RQ1: What Are the Uses, Advantages, Limitations, Effectiveness, and Affordances of Using AR Enhanced Analytics versus Conventional AR Use in Learning?

The following codes corresponded to the nodes of the research question in Table 6.

Table 6. NVivo extracted codes for RQ1.

(A) Uses	(B) Advantages	(C) Limitations	(D) Effectiveness	(E) Affordances
(A1) Visualize Information	(B1) Measure Interactions	(C1) Cognitive Overload	(D1) Tracking Interactions	(E1) Sensory
(A2) Knowledge Acquisition	(B2) Measure Learning Outcomes	(C2) Device Data Capture	(D2) Context Awareness	(E2) Spatial Portability
(A3) Manipulate Objects	(B3) Measure Cognitive Load	(C3) Unfamiliarity	(D3) Behaviour Monitor	(E3) 3D Visual Overlay
(A4) Explore Locations	(B4) Effectiveness in Data Logging	(C4) Difficult to Use (Usability)	(D4) Multimodal	(E4) Projection of Contextual Information
(A5) Instructional Medium	(B5) Measure Movements	(C5) Content Creation	(D5) Better Learning Outcome Measure	(E5) Interaction
(A6) Gamified Learning	(B6) Locate Spatial Information	(C6) Unstable	(D6) Feedback Communication	
(A7) Lab Equipment Use	(B7) Easy Deployment	(C7) Data Interpretation	(D7) Clear Presentation	
	(B8) Low Cost	(C8) Acceptance	(D8) Variation of Use	
	(B9) Numerical Accuracy	(C9) Persistence Location	(D9) Communication Medium	
	(B10) Measure Safety			
	(B11) Measure Eye Gaze			
	(B12) Body Posture Recognition			
	(B13) Facial Emotions			
	(B14) Measuring Accessibility for the Disabled			
	(B15) Audio Input Analysis			

4.1.1 Uses of AR Enhanced Analytics

The reported uses of AR enhanced analytics in education are detailed in Table 9. Each study can report more than one use and so studies can fall into more than one subcategory. The benefits of AR analytics can be categorized as follows:

(A1) Visualize information: The study “Situated Analytics” by ElSayed and colleagues (2016) combines visual analytics and AR techniques to offer real-time interaction methods for analytical reasoning in physical spaces. It explores how digital information presented visually can be connected to physical objects by developing and evaluating a shopping application. This application demonstrates how AR-based analytics assist users in managing complex data associated with physical artifacts, enabling users to view information from their perspective. The study highlights the effectiveness of integrating visual information with AR, as evidenced by improved task completion, reduced error rates, and enhanced user preferences compared to manual task performance.

(A2) Acquire knowledge: A study by Altmeyer and colleagues (2020) aimed to teach students voltage and current concepts using AR alongside hands-on physics experiments. They developed a tablet-based AR app showing real-time measurement data above electric circuit components during lab work. The study found that the AR app aided conceptual knowledge acquisition more effectively than traditional physics lab lessons. Even in inquiry-based learning, AR supported conceptual knowledge acquisition, especially in challenging areas. Displaying real-time device measures in AR resulted in slightly better conceptual knowledge gains than with traditional methods.

(A3) Manipulate objects: In a study by Chang and colleagues (2014), an ARFlora system was developed to aid students in constructivist learning about plants. They could manipulate virtual objects to observe plant growth. Unlike typical AR systems, this one emphasized hands-on operation and observing virtual object changes. Input devices included a webcam, mechanical clock, and microphone, with an Arduino platform converting analog signals. The webcam captured AR marker info, the clock and Arduino controlled time changes, and the microphone simulated CO₂ release. A monitor displayed virtual object changes. An animated virtual clock was designed for realistic time control. After the activity, students completed a learning motivation questionnaire. The experimental group, using AR technology, showed higher motivation than the control group did, indicating AR's effectiveness in plant study engagement.

(A4) Explore locations: The AR app (MetaGuide) in the study by Harley and colleagues (2016) used Google Earth's geolocation to locate historical venues. It enabled users to view old and current representations, enhancing understanding of historical differences. User emotions like enjoyment and boredom were measured at specific locations. The study assessed using the AR app to promote positive emotions and learning outcomes in both laboratory and outdoor settings.

(A5) Instructional medium: In a study by Lytridis and colleagues (2018), ARTutor, an AR mobile app, enables students to access augmented books created with an AR authoring tool. ARTutor overlays digital assets on trigger images, offering interaction via finger gestures like tapping to start or stop videos, pinch-to-zoom to resize images, and horizontal sliding to rotate 3D models. Voice commands enhance interaction, aiding students with disabilities. Evaluation analytics focus on functionality and system errors, undergoing further testing for usability and educational effectiveness.

(A6) Gamified learning: Integrating mobile devices, AR, and game-based learning in education extends learning beyond traditional classrooms into natural environments. Pombo and Marques (2020) assesses educational value through user feedback and AR game case study logs. Users aged 10 to 15 engaged with the AR game app, highlighting motivational aspects like treasure hunting, point collection, mobile device use outdoors, and AR features. The study found that the EduPARK app encompassed educational value dimensions including learning, motivation, participation, authenticity, lifelong learning, and sustainability habits.

(A7) Lab equipment use: In a study by Altmeyer and colleagues (2020), real-time data capture was used to record voltage readings during laboratory experiments in science education. The AR learning environment included custom-designed experimental components with built-in measurement nodes that transmitted data to a mobile application in real time. A tablet displayed this data alongside corresponding components, following the spatial contiguity principle of multimedia instruction. This design principle reduced learners' cognitive load and encouraged generative processing, facilitating conceptual knowledge acquisition. Real-time measurement data, represented as digits and virtual needle deflections, was displayed above components as learners manipulated the voltage. This AR-based representation of measurement data proved effective in supporting physical experimentation and science learning.

4.1.2 Advantages of AR Enhanced Analytics

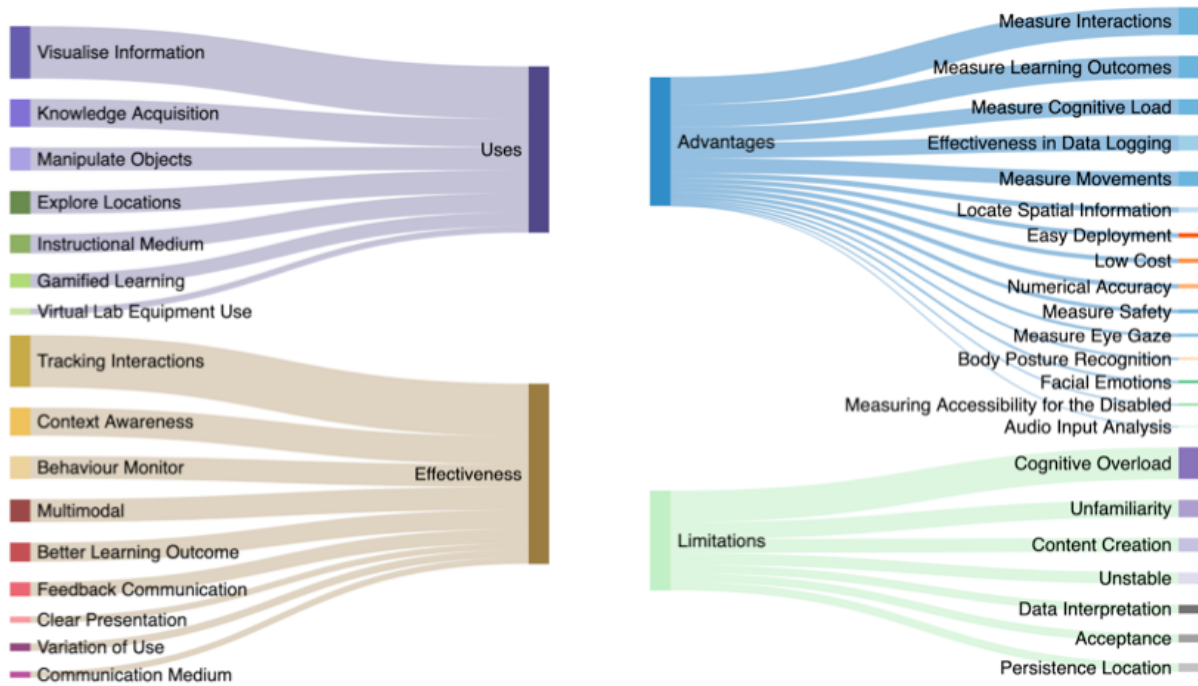


Figure 3. Uses/advantages/limitations/effectiveness of AR enhanced analytics.

The numerous reported advantages of AR enhanced analytics in education are detailed in Table 10 and Figure 3 in the literature review from various research studies. Since one study can report more than one advantage, each study can meet more than one subcategory. From the results, it can be seen that the major advantages reported in the studies are as follows:

(B1) Measure interactions: A study by Casarin and colleagues (2019) introduces a UMI3D-based interaction analytics system aimed at simplifying the assessment and categorization of XR devices and interaction techniques. This system, designed as an open cloud platform for researchers, is still under development and focuses on common 3D interaction tasks: object selection, translation, and rotation. The ultimate goal is to generate dashboards presenting statistical analyses results, offering a comprehensive comparison of device performance in task interactions. AR enhanced analytics offer significant benefits, including detailed tracking of learner interactions and personalized learning pathways, enhancing student engagement and motivation (C.-I. Cheng, 2023; Singh et al., 2023). Additionally, the integration of gamified elements and multimodal analytics effectively improves students’ cognitive, emotional, and behavioural engagement in educational activities (Ivarson et al., 2024; Arzmann et al., 2024).

(B2) Measure learning outcomes: Examining the fusion of AR with wearable devices like Google Glass, a study by Leue and colleagues (2014) delves into creating an enriched learning atmosphere within art galleries. Employing the Generic Learning Outcomes (GLO) framework, it investigates how Google Glass amplifies visitors’ learning experiences. The study’s qualitative findings highlight substantial enhancements in participants’ comprehension of art, facilitated by the AR app’s provision of supplementary information on paintings, artists, and related pieces. This research underscores the transformative potential of wearable technologies in refining and personalizing museum visits.

(B3) Measure cognitive load: A mixed-methods study by Squires (2018) employed Task Load Index (TLX) Cognitive Load Assessment and an AR app to overlay mapping information in online instructional design courses. It aimed to determine whether AR positively impacts associative information processing and working memory between two groups: those without iOS devices and those with mobile iOS devices. Participants used their AR-enabled devices to point at learning content and answer knowledge transfer feedback questions. Embedded software analytics recorded responses, timing, unique device IDs, and time spent on each question. Qualitative data suggested that AR-only users were more engaged and remembered content more positively. Information processing analytics used Google Analytics APIs to capture user interactions.

(B4) Effectiveness in data logging: A study by Holstein and colleagues (2018) aims to understand K–12 teachers’ real-time information needs in personalized classrooms and identify key needs that real-time analytics could address. It

explores the potential of wearable technologies to enhance teacher awareness while maintaining focus on the classroom. Using HoloLens design mock-ups, each student has an indicator display above their head, with two class-level analytics displays at the front of the class. One shows skills practised by many but mastered by few, while the other displays recent errors made by many students. Teachers can “deep-dive” into specific student analytics screens by clicking on an indicator. Another prototype involves “Replay Enactments,” replaying logged data from students’ interactions to provide real-time analytics and visualizations to teachers via AR headsets.

(B5) Measure movements: The study by Aoki and colleagues (2020) presents a system that uses a stereo-type depth camera to measure 3D dynamic motion and display the trajectory of moving objects in real-time AR. This system aims to intuitively demonstrate physical dynamics, which can be challenging to depict on 2D surfaces and requires spatial recognition for comprehension. Learners can easily observe 3D motion using tablet devices. Improvements include the capability to measure fast movements like falling objects. Currently, the system offers a 3D object-tracking feature, enabling trajectory observation from any direction and visualization of velocity and acceleration as AR on tablet devices. Its portability allows for classroom use in WiFi-equipped lecture rooms, facilitating the visualization of experimental results and enhancing beginners’ understanding of physical dynamics.

(B6) Locate spatial information: CrowdAR, introduced by Savenije and colleagues (2020), employs spatial AR techniques to overlay virtual information onto users’ real environments. It utilizes real-time interactive crowd simulation to visually study crowd motion behaviour. The simulation output is projected onto an AR table and objects placed on it. By employing a depth camera, physical object contours are detected, allowing colour-coded crowd movement simulation data to be projected onto the table. Real-time data manipulation is enabled by the depth camera’s detection of user hand and arm movements, corresponding to simulated crowd movement around the objects on the table.

(B14) Measure accessibility for the disabled: The research conducted by Arvanitis and colleagues (2007) aims to enhance the visual perception of learners with physical disabilities through novel content representation and education service delivery. The CONNECT AR interactive learning environment assists users in contextualizing and reinforcing their learning in various settings, including schools, science centres, and homes. The study focuses on a user-centred evaluation of human factors and pedagogical aspects of the CONNECT project, particularly examining wearability and its effects on physically disabled students. Quantitative scores collected from disabled and able-bodied users concentrate on comfort dimensions such as emotions, attachment, harm, movement, and anxiety, along with vision symptoms like visual discomfort, eye dryness, irritation, difficulty focusing, visual fatigue, headache, dizziness, nausea, and general tiredness. The study concludes by indicating the importance of inclusion in novel technology-enhanced learning approaches for science education. No measurable analytics were presented in the paper; however, there is a key indication that work should examine the importance of considering special needs education in the design of such technologies by looking at (1) alternative ways to influence the education beyond the mere use of computers, (2) contributions to the improvement of students’ lives, (3) how technology can overcome the boundaries of disability, (4) how to alleviate isolation, (5) how to increase self-esteem, and (6) how to support integration.

4.1.3 Limitations of AR Enhanced Analytics

The limitations of AR enhanced analytics in education are detailed in Table 11, compiled from various research studies. Each study may report multiple limitations, covering several subcategories. The predominant limitations identified in the studies include the following:

(C1) Cognitive overload: In a study by Squires (2018), the impact of information overlays on cognitive load and working memory in education was explored. Findings indicated positive effects on learning in the AR group, with participants showing improved content retention compared to the control group. A key limitation is the increased cognitive load and complexity associated with immersive AR environments, potentially leading to learner distraction or affective overload (Olea-Ibarra et al., 2025). Additionally, technological constraints, usability challenges, and methodological inconsistencies in analytics approaches limit broader implementation and interpretation across diverse educational contexts (Senthil Pandi et al., 2024).

(C3) Unfamiliarity: In an experiment by Antoniou and colleagues (2017) with medical students, it was reported that virtual button data was often obstructed by other virtual elements, making manipulation and use challenging.

Additional limitations identified include technological constraints (hardware limitations, battery life, connectivity), usability challenges (interface complexity, learner confusion), and inconsistent measurement approaches across studies. Such limitations highlight critical areas for future research to improve AR implementations in educational contexts.

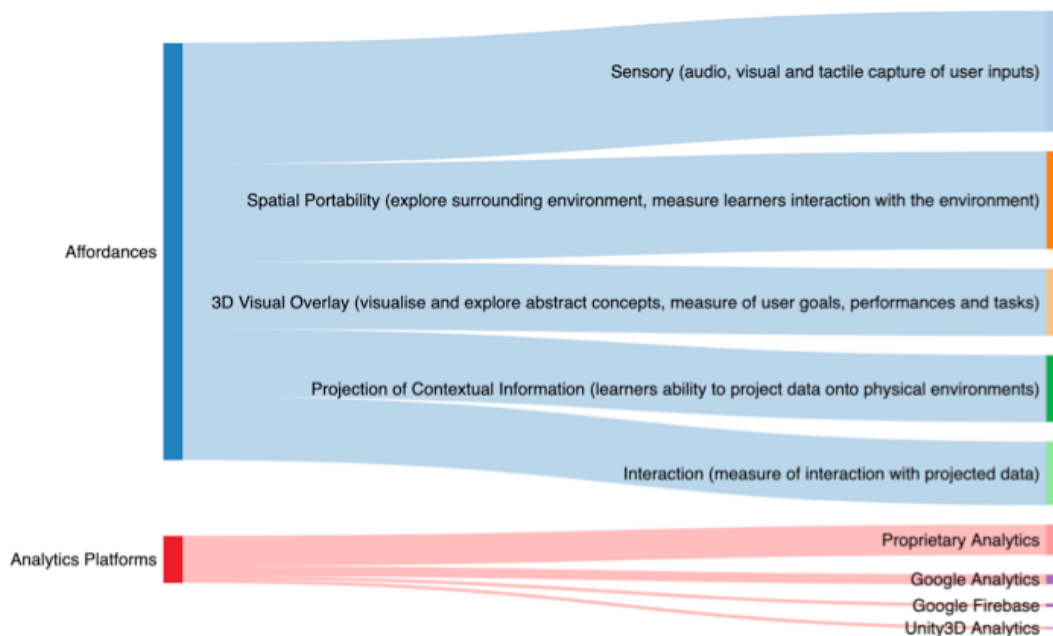


Figure 4. *Affordances/platform used in AR enhanced analytics.*

4.1.4 Effectiveness of AR Enhanced Analytics

The reported effectiveness of AR enhanced analytics in education is summarized in Table 12. The factors affecting effectiveness are “tracking interaction” (38), with “context awareness” (19) and “behaviour monitor” (15), capturing “multimodal interactions” (14) and ensuring “better learning outcome measures” (13).

(D5) Better learning outcome measures: Empirical evidence demonstrates that AR enhanced analytics significantly improve educational outcomes, particularly in skill development, problem-solving abilities, and knowledge retention, by providing rich, contextual learning experiences (Na et al., 2025; Bigonah et al., 2024). Studies consistently show that thoughtfully designed AR interventions, supported by robust analytics, effectively enhance student learning, performance, and engagement across educational levels (Amirbekova et al., 2024; Tzortzoglou et al., 2023).

(D6) Feedback communication: An AR-based feedback system named ALF (Augmented Lectures Feedback System) was developed by Zarraonandia and colleagues (2019) to enhance classroom communication. ALF, utilized by teachers wearing AR glasses, displayed virtual symbols above students’ heads to depict their understanding in real time or responses to questions. Students selected their status and responded via mobile phones. The study, conducted in real classrooms, showed promising results, indicating potential for improved communication and class adaptation. Inspired by successful classroom response systems (CRSs) and digital back channels, ALF facilitated anonymous student contributions, fostering increased participation and engagement. The study highlights the significance of anonymous student input in boosting engagement. Overall, it suggests that AR could enhance current classroom communication systems, facilitating smoother feedback delivery from students to teachers.

4.1.5 Affordances of AR Enhanced Analytics

Table 13 and Figure 4 detail reported affordances of AR enhanced analytics in education gathered from the literature review research studies. Since one study can report more than one affordance, each study can meet more than one subcategory. From the results, the major affordances reported in the studies are “sensory” (10), “spatial portability” (8), “3D visual overlay” (7), “projection of contextual information” (11), and “interaction” (14).

(E1) Sensory: Another innovative method of AR interaction involves voice activation on mobile devices, allowing students to ask questions when they trigger an AR marker on their textbooks. In addition to visualizing 3D models in the AR experience, research explores the use of voice commands to detect student questions. The development of ARTutor by Lytridis and colleagues (2018) facilitates interaction with augmentations through both haptic and verbal means. Voice commands not only enable hands-free operation but also serve as an accessibility feature, allowing students with disabilities to manipulate augmentations. Another notable feature of ARTutor is its capability to perform content

searches within educational material, reinforcing self-study and independent learning by providing relevant information based on student queries. Although not explicitly discussed in the literature, with ARTutor built on a web-based platform, AR analytics can be easily captured and retrieved for analysis using system log files that indicate when AR markers are triggered by users. AR analytics for mobile game-based learning were used to assess player engagement and learning in a study by Vidal and colleagues (2018). “Igpaw Intramuros” is a virtual tour game encouraging players to explore historical markers within the walled city of Intramuros in Manila, Philippines, to learn about their historical significance. The AR game logs analytics whenever players reach specific points in the game, such as during in-game quizzes. This allows for tracking the ratio of players attempting quizzes versus those passing them, facilitating the measurement of the educational content’s learnability within the game.

(E2) Spatial portability: The paper by Arvanitis and colleagues (2007) focuses on human factors and pedagogical effectiveness in using AR technology for special needs learners, impacting technology redesign, implementation, and deployment. Dilek and Erol (2018) demonstrated AR’s capability in real-time position detection during physics experiments, using Apple’s ARKit to fuse camera sensor data with motion sensor data. This interactive method aids students in understanding position-time graphs. Holstein and colleagues (2018) addressed the need for real-time classroom orchestration tools, presenting a prototype study using AR-enabled head-mounted devices (HMDs) like Microsoft HoloLens. This system provides teachers with a class dashboard, individual student indicators, and class-level analytics for personalized learning support in K–12 classrooms. One screen reveals commonly practised skills mastered by few, while another identifies recent errors made by many students. Through deep-dive screens accessed by teachers clicking on indicators, they can observe students’ progress and solution paths during personalized lessons. AR-enabled analytics offer live insights from classroom usage data. However, the study notes a lack of empirical knowledge on the impact of real-time analytics on teacher-student interactions and student learning. Another AR application, developed by Vidal-Balea and colleagues (2021), aims to motivate pediatric patients and increase their physical activity through AR games in hospital environments. Hospitalization often increases stress levels, particularly among children, leading to aggressive behaviours, isolation, and recovery difficulties. Reducing anxiety is crucial for helping children relax during medical procedures. The AR app enhances engagement and motivation, preventing boredom and encouraging longer usage. Usage analytics collected by the app are visualized and managed through a web platform, displaying playing time, steps, and daily mood survey responses in simple charts. The patient analytics page includes personal information alongside charts showing step count, movement, and the evolution of daily mood survey responses. The AR app captures mood analytics, physical activity motivation, and collaboration in AR games among pediatric patients.

(E4) Projection of contextual information: Laine and colleagues (2016) introduced the Science Spots AR (SSAR) learning platform, merging storytelling, gaming, context awareness, and AR to engage learners in understanding scientific concepts such as geometry and kinetics. By leveraging AR enhanced analytics capture from mobile device sensors, context-aware learning experiences have been enabled, complementing classroom pedagogy by integrating contextual elements into the learning process. This context-aware learning space can detect and respond to changes in the learner’s context, offering learning content tailored to their situation (Laine et al., 2016). The authors suggest incorporating various context-aware analytics capabilities into typical AR applications, including (a) temperature, (b) illumination, (c) humidity, (d) GPS location, (e) acceleration, (f) height (jumping), (g) speed/acceleration (running/walking), (h) orientation (compass), and (i) heart rate monitor. These context-aware AR analytics can be used in gamified challenges for students, focusing on science themes.

(E5) Interaction: The study by Chang and colleagues (2014) used AR technology to create ARFlora, a learning system aiding students in observing plant growth changes within the classroom. Using AR markers, students manipulate virtual objects like sunlight to observe real-time effects on plant growth. Compared with an experimental group using video-based learning, ARFlora demonstrated equal effectiveness in student learning outcomes, with a noted advantage in knowledge retention and motivation to learn about plants. The ARFlora system incorporated student interaction via an attached microphone, translating sounds of respiration and breathing to trigger actions and feedback. Additionally, students manipulated a mechanical clock to simulate variations in time of day. AR analytics captured from microphone and clock manipulations enhanced student engagement in the learning process. The EduPARK AR-based Treasure Hunt game, developed by Pombo and Marques (2020), uses AR analytics to assess its impact across various educational dimensions: (a) learning value, (b) intrinsic motivation, (c) engagement, (d) authentic learning, (e) lifelong learning, and (f) conservation and sustainability habits. In the game, users explore the park using an AR app with embedded game design mechanics, presented in a treasure hunt format with a friendly mascot offering hints and feedback. Players accumulate points by correctly answering challenges, striving to achieve the best performance, which fosters motivation in learning. Automatic user interaction analytics capture mechanisms gather various data, including (a) final score (points gathered through correct answers and points gained through collecting rewards), (b) game time, (c) number of

questions answered correctly and incorrectly, and (d) number of treasures collected. While AR is increasingly used in education to engage students, measuring its impact often relies on questionnaires, surveys, and observations, which lack objectivity and veracity. Rodríguez and colleagues (2020) highlight the importance of identifying student emotions for measuring impact. The study proposes, develops, and tests an LA scheme using the density-based spatial clustering of applications with noise algorithm and time series analysis, employing the Emotiv EPOC brain-computer interface device to collect emotional metrics. Using an AR-Sandbox device, the study demonstrates emotional characterization in five trend components: (1) interest, (2) focus, (3) engagement, (4) stress, and (5) relaxation. External sensors like brain-interface devices offer insights into emotional aspects of learning, promising directions for exploring student learning outcomes through analytics capture capabilities.

Analytics derived from student interactions facilitate the creation of an adaptive learning experience through a technology-mediated instructional framework that adjusts the learning path, pace, and mediated content (Moskal et al., 2017). The Instructional Design and Educational Technology Augmented Reality Transmedia Storytelling (IDET ARTS) application developed by Squires (2019) incorporates an adaptive analytic data collection model. This model enables tracking of user behavioural analytics within the IDET ARTS platform, including participant behaviour, AR content viewed at learning sites, time-on-task, and average session duration of use.

4.2 RQ2: What Are the Evaluation Methods, Instruments, and Measurable Metrics of AR Enhanced Analytics in Learning?

To collect user data effectively using smart mobile devices, various functionalities can be leveraged. This includes logging data associated with tapping the mobile device interface, tracking the device's physical movement in the environment, utilizing device-based biosensors (e.g., measuring skin temperature, heartbeat, and brain activity using electroencephalography), recording audio and video, sensing gestures, and tracking eye movements for insightful analytics. Some studies have used these data-logging mechanisms for assessment, analysis, and feedback purposes within an AR-enabled education context. However, incorporating AR-related analytics that can be collected, analyzed, and presented to users in real time poses challenges. While the vast amount of data offers advantages, it also adds cognitive load to users of AR applications. Therefore, further exploration of the convergence of AR and analytics through a review of existing literature is necessary. For such a review, systematic review guidelines proposed by Kitchenham (2004) were considered. This involves selecting reputable journals, defining inclusion and exclusion criteria, establishing categories for analysis, and conducting the review through methods such as content analysis, data synthesis, and coding of the selected studies.

The reported evaluation methods of AR enhanced analytics in education are detailed in Table 14 and were gathered from the literature review research studies. Since one study can report more than one evaluation method, each study can meet more than one subcategory. From the results, it can be seen that the major evaluation methods reported in the studies are “device-based data logging” (13), “questionnaires/survey forms,” (19) and “user interviews” (19).

4.3 Evaluation Methods in AR Enhanced Analytics

Device-Based Data Logging. Evaluation methods predominantly include real-time multimodal analytics, sequential pattern analysis, and comparative analyses, offering deeper insights into learning processes and behavioural patterns (Geng & Yamada, 2023). Despite advancements, most current studies still depend significantly on traditional qualitative methods (post-activity surveys and interviews), highlighting opportunities for more real-time data-driven methods.

4.4 Instruments of Measure in AR Enhanced Analytics

Instruments. The reported instruments of measure of AR enhanced analytics in education detailed in Table 15 were gathered from the literature review research studies. Since one study can report more than one instrument of measure, each study can meet more than one subcategory. From the results, it can be seen that the major instruments of measure reported in the studies are “mobile phone” (22), “sensors,” (9) and the use of “VR/AR glasses” (5).

4.5 Analytics Platforms Used in AR Enhanced Analytics

The reported analytics platforms used for AR enhanced analytics in education detailed in Table 16 were gathered from the literature review research studies. Since one study can report *only one* analytics platform, there are 40 studies which did not mention or use any analytics platform. From the results, it can be seen that the major analytics platform reported in the studies are “proprietary analytics software” (9) and “Google Analytics” (3).

4.6 Measurable Metrics in AR Enhanced Analytics

The reported measurable metrics of AR enhanced analytics in education detailed in Table 17 were gathered from the literature review research studies. Since one study can report more than one measurable metric, each study can meet more than one

subcategory. From the results, it can be seen that the major metrics measured in the studies are “task time” (20), “number of sessions,” (11) and “number of active users” (7).

Task Time. Commonly measured metrics include task performance, learner interaction frequency, cognitive load indicators, engagement levels, emotional responses, and behavioural patterns (Arztmann et al., 2025; Olea-Ibarra et al., 2025). These metrics enable robust, detailed assessments of AR activities, facilitating accurate evaluation and targeted, personalized educational interventions.

5. Discussion

5.1 Limitations and Inconsistencies in AR Enhanced Analytics Research

A critical analysis of methodologies and measurement tools across the reviewed studies reveals several important considerations regarding AR enhanced analytics in educational contexts. Firstly, studies assessing cognitive load in AR environments predominantly employed self-reported instruments like the NASA Task Load Index (TLX) and subjective questionnaires. Although widely used, these self-report measures can introduce potential biases due to learners’ varied interpretations of perceived cognitive load and emotional responses, thus affecting their reliability and validity in AR contexts (Squires, 2018; Geng & Yamada, 2023). Few studies complemented self-reports with objective physiological measures, such as eye-tracking or EEG, which could provide more precise and unbiased insights into learners’ cognitive states (Na & Sung, 2025; Li et al., 2025). Furthermore, inconsistencies emerge when comparing methodologies across studies. For instance, while some research suggests that AR significantly reduces cognitive load by clearly integrating multimodal elements (Geng & Yamada, 2023), others report that highly immersive AR experiences may inadvertently increase cognitive demands, leading to cognitive overload (Olea-Ibarra et al., 2025). Such contradictions highlight the need for standardizing methodological practices and encouraging mixed-methods approaches to enhance reliability and triangulation of findings. Additionally, analysis of behavioural engagement frequently relied on interaction logs and time-on-task metrics; however, limited methodological transparency regarding analytics data collection, feature extraction, and interpretation hampers cross-study comparability and generalizability (Arztmann et al., 2025). To overcome these limitations, future research should explicitly report methodological decisions, clearly articulate data processing strategies, and adopt multimodal analytics that integrate self-report, physiological, and behavioural data. By addressing these methodological weaknesses, the validity and robustness of AR enhanced analytics research can be significantly improved, providing educators and developers with clearer, more actionable insights. Methodological inconsistencies between AR studies limit the comparability of the findings, where some report gains through detailed interaction logs, while others rely heavily on post-surveys, making synthesis difficult. Although a formal meta-analysis was not feasible due to varied designs, this diversity directs the need for standardized reporting. Future research could adopt LA-specific extensions of PRISMA, requiring consistent disclosure of effect sizes, data sources, and analytic methods. Such protocols would improve transparency, allow meaningful meta-analyses, and strengthen the reliability of conclusions in immersive LA.

5.2 RQ1: What Are the Uses, Advantages, Limitations, and Effectiveness of AR Enhanced Analytics in Learning?

AR enhanced analytics are used in education for various purposes, including visualizing complex information, facilitating knowledge acquisition, manipulating virtual objects, and providing immersive experiences. These tools serve as instructional media and platforms for gamified learning, increasingly in laboratory settings. Advantages of AR in education include measuring student interactions, assessing learning outcomes, gauging cognitive load, and enhancing data logging efficacy. AR also supports measuring physical movements and spatial comprehension while being relatively low cost and easy to deploy. Studies demonstrate AR’s diverse uses and advantages in education. For instance, Wu and colleagues (2013) explored how AR facilitates learning by visualizing complex information and enhancing student interaction. Ibáñez and Delgado-Kloos (2018) highlighted AR’s role in laboratory settings, providing hands-on experience without associated costs or risks. Limitations, such as potential cognitive overload and the need for technical support, were discussed by Akçayır and Akçayır (2017), emphasizing the importance of balancing interactivity with usability.

Uses: AR enhanced analytics serve as valuable tools for informing teachers’ decision-making and enhancing instructional delivery, thereby improving lesson effectiveness and student engagement. These analytics also assist students in acquiring knowledge by providing interactive displays during practical lessons, resulting in higher conceptual understanding. Furthermore, the ability to measure analytics related to object manipulation during learning is crucial for gathering interaction data and stimulating learning experiences. AR enhanced analytics extend beyond the classroom, offering directions and navigation information to users exploring various locations. As an instructional medium, AR enhanced analytics enable the creation of virtual simulations, providing learners with hands-on experiences in a safe and controlled environment. Additionally, gamified learning using AR allows students to venture beyond traditional classroom settings to natural spaces, where they can engage with game mechanics and design to learn about the environment in novel and

exciting ways. Moreover, AR enhanced analytics hold promise in teaching laboratory equipment by virtually presenting data and allowing real-time manipulation, providing step-by-step instructions, and offering feedback for proper handling, thereby enhancing the learning experience in educational settings.

Advantages: AR enhanced analytics offer precise and convenient measures of student interactions on mobile devices, using device sensors to identify significant learning outcomes and body movement. Additionally, they can assess cognitive loads using brainwave- and eye-tracking devices. Providing location and spatial information through AR enhances learning experiences by contextualizing students' preferences to their surroundings, aiding navigation in unfamiliar environments safely online. These capabilities promote interactive and immersive learning experiences. Moreover, facial emotion and audio input analysis in education settings through AR enhanced analytics yield valuable insights for personalized experiences, mental health monitoring, improved educational outcomes, and enhanced retail environments. Analyzing students' emotion levels during class using AR enhanced analytics provides teachers with valuable insights into their engagement levels.

Low cost and easy to deploy: With no specialized hardware required and no additional physical infrastructure needed, analytics can be collected, processed, and analyzed with low cost. Being easy to deploy with minimum training for the teachers and not requiring extensive technical knowledge make AR enhanced analytics a cost-effective method to gather insightful metrics of students in classrooms.

5.2.1 Integration and Synthesis of AR Affordances, Analytics Types, and Learning Outcomes

This review synthesizes the multiple dimensions of AR enhanced analytics through an integrative approach on how AR affordances, types of analytics, and learning outcomes interrelate. AR technologies offer various affordances, such as visual immersion, interactive manipulation, and real-time contextualization, each distinctly influencing learner engagement, cognitive load, and skill development (Papakostas et al., 2023; Tzortzoglou et al., 2023). To effectively capture the interactions among these elements, a comprehensive matrix was constructed, systematically cross-referencing AR affordances with specific types of analytics (interaction logs, multimodal analytics, self-reports) and corresponding educational outcomes (motivation, cognitive skills, content mastery). For example, visual immersion affordances combined with multimodal analytics (eye-tracking, physiological measures) commonly enhanced student engagement and reduced cognitive load, whereas highly interactive AR affordances analyzed through detailed interaction logs correlated with improved knowledge retention and higher-order thinking skills (Kazanidis et al., 2021; Geng & Yamada, 2023; Arzmann et al., 2025).

Conversely, limitations such as cognitive overload were frequently associated with overly complex AR tasks, as evidenced by certain self-report analytics (Olea-Ibarra et al., 2025). The matrix further revealed recurring patterns indicating that effectively balanced AR designs, leveraging multiple affordances and analytics types, consistently yielded optimal educational outcomes. Thus, successful AR enhanced analytics implementations require alignment among interactive design, analytics methods, and pedagogical objectives. To consider the importance of mixed-methods analytics approaches, a combination of objective interaction data with subjective self-report and physiological measures is used, thus providing richer insights and enhancing validity. Such structured synthesis contributes significantly to a clearer understanding of how immersive AR environments can be purposefully designed, analytically evaluated, and pedagogically optimized in educational settings.

5.2.2 AR Enhanced Analytics within the Broader XR Continuum

This review primarily emphasizes AR in education; however, the findings also hold significant implications across the broader XR continuum, encompassing VR and MR. VR provides fully immersive environments, isolating users from physical surroundings, while MR integrates virtual content seamlessly within the physical world, allowing dynamic interaction with both digital and real elements. Many analytics strategies identified in AR research, such as multimodal analytics, interaction logs, and cognitive load measures, are similarly applicable to VR and MR contexts. For instance, multimodal analytics that combine physiological data (e.g., eye-tracking and EEG) with interaction logs could effectively evaluate learner engagement in fully immersive VR scenarios. Likewise, MR's capability to merge real and virtual objects extends the potential of AR-driven analytics by providing richer interaction data and enhanced contextual authenticity. Therefore, AR analytics frameworks (e.g., Kazanidis et al., 2021) could be adapted to evaluate learning outcomes and interactions within VR and MR environments. Future research can explicitly compare these XR technologies, identifying unique affordances and limitations to provide educators with comprehensive, evidence-based guidelines for choosing the most effective XR modality for specific pedagogical objectives. AR enhanced analytics approaches such as interaction logging, multimodal data capture, and cognitive load assessment offer insights that can inform both VR and MR learning environments. In VR, where immersion is total, similar analytics could track learner engagement and problem-solving strategies with greater fidelity. MR, by blending physical and digital objects, extends AR methods to capture behaviours across real-virtual interactions. For example, adaptive feedback validated in AR can be applied in MR classrooms, where students simultaneously interact with physical artifacts and virtual overlays. These intersections highlight synergies and broaden the relevance of AR enhanced analytics within the XR spectrum.

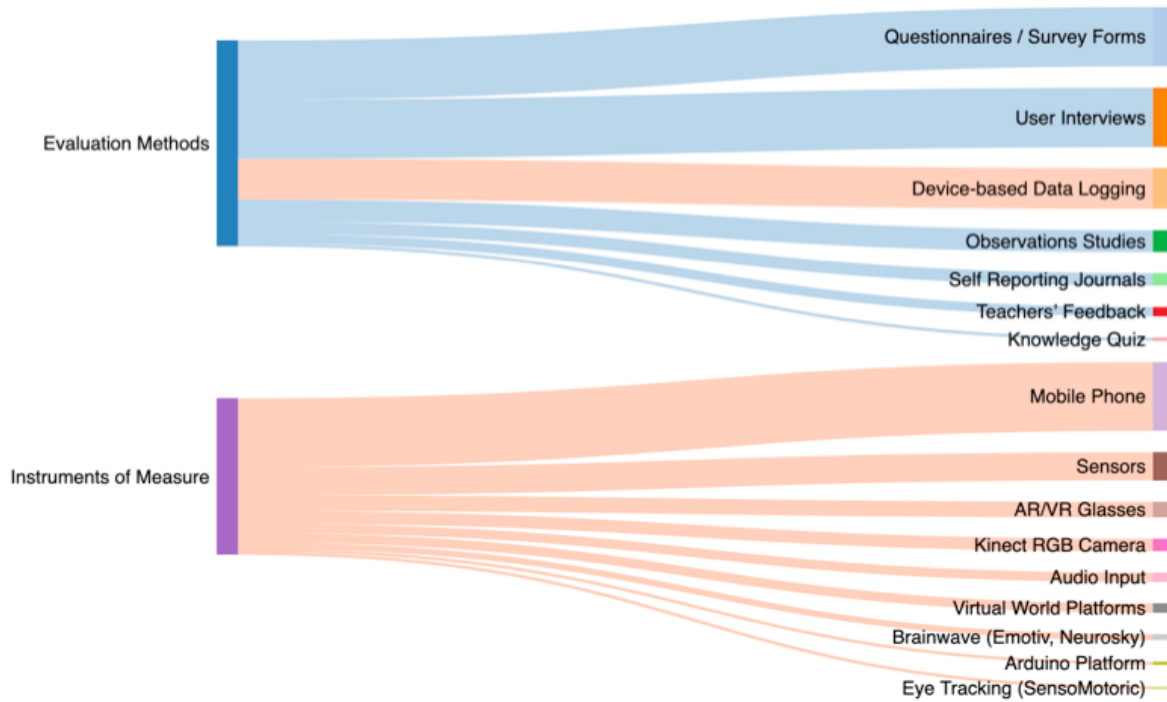


Figure 5. *Evaluation/instruments of measure of AR enhanced analytics used in education.*

5.3 RQ2: Evaluation Methods, Instruments, and Measurable Metrics of AR Enhanced Analytics in Learning

Evaluation methods and tools for AR enhanced analytics in learning vary, encompassing device-based biosensors, audio and video recordings, gesture sensing, eye-tracking technologies, and data-logging mechanisms (Figure 5). These are vital for comprehensive assessment, analysis, and feedback within AR enhanced learning environments. Garzón and Acevedo (2019) examined evaluation methods in educational AR environments, emphasizing biosensors and eye-tracking for assessing engagement and learning outcomes. Martin-Gutiérrez and colleagues (2017) discussed gesture sensing and data logging’s role in providing feedback and enhancing learning, suggesting that these tools offer valuable insights into AR’s effectiveness in education.

Methods for generating analytics through AR applications in education include quantitative approaches such as device-based data logging using mobile device sensors. These strategies record student classroom activities like task time, user sessions, object manipulations, user movement metrics, eye gaze tracking, and EEG brain data. Qualitative methods, including questionnaires, surveys, interviews with students and teachers, observations, and lesson feedback, are also used to gather analytics. Challenges include limited time for teacher observation during lessons, potential biases in observations and feedback, and the absence of a structured evaluation process leading to inconsistent results among teachers. Many studies supplement observational data collection with quantitative methods.

Various commercial and proprietary analytics platforms are used in studies to capture AR application analytics. Proprietary platforms, more commonly used, offer seamless integration during the design and development of AR applications, catering to specific research needs and complying with ethics and privacy requirements. Google Analytics is a widely used commercial platform, while Unity Analytics is favoured for AR applications built in Unity, allowing seamless code integration for analytics collection. However, using commercial platforms raises concerns regarding data ownership, privacy, and transparency in analytics collection methods, leading to debates on data accuracy and reliability. Proprietary platforms also pose limitations in data sharing and interoperability and customization of data presentation. Despite these challenges, commercial platforms offer ease of use, scalability, and flexibility in processing power based on data volumes. They also facilitate integration with other educational tools and systems, yet cost remains a primary challenge, typically incurred through a subscription model, which may be prohibitive for educational institutions with limited budgets.

Measurement instruments for AR enhanced analytics primarily rely on mobile devices and their embedded range of sensors, which are cost effective and readily available. Mobile devices like iPads, commonly used in classrooms, possess sensors enabling real-time data collection of various types, including audio, video, and images. The accelerometer in these devices measures movement, while screen touch tracking monitors student interaction and engagement levels. Additionally, portable devices such as VR glasses, Kinect RGB cameras, brainwave head-mounted devices, and eye-tracking equipment are used in studies. These instruments offer self-contained software for data collection without the need for additional equipment.

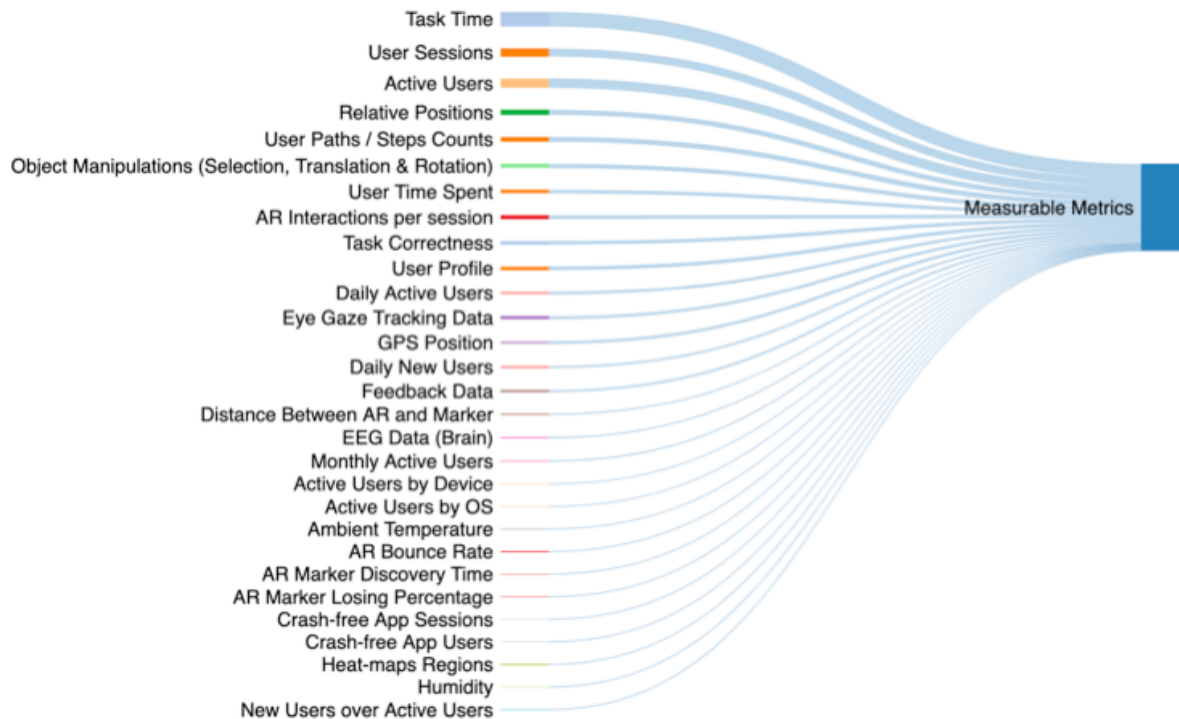


Figure 6. Measurable metrics in AR enhanced analytics used in education.

5.3.1 Growing Use of AR Enhanced Analytics

Use of AR in education settings makes it possible to enable learning in a relevant and engaging environment by creating engaging learning activities. Dunleavy and colleagues (2009) created an AR experience that allowed students to investigate the crash landing of an alien spacecraft, while learning a variety of math and science concepts. Although there were some limitations to the implementation of this AR experience, students who went through this experience were highly engaged and wanted to learn more to solve the mystery, but the study did not report on the measures associated with how engaged or disengaged students were during the AR experience. Klopfer and colleagues (2017) found that the types of roles that the students took on in the AR environment affected their level of disengagement. Specifically, they found that higher interdependence and interaction between distinct roles increased collaboration and engagement. The use of data analytics correlated with the level of engagement can, in fact, give better insights into the level of disengagement during lesson delivery. LA enables the identification of behaviour patterns and analysis of data on students and teachers that use the environment, assesses the learning process, improves the overall learning experience, and gives the opportunity to use this information to reflect on the learning activity of users (Einhardt et al., 2016). LA refers to the measurement, collection, analysis, and reporting of data about learners, teachers, and their contexts, for the purpose of understanding and optimizing learning and the environments in which it occurs (Sungkur et al., 2016). LA seeks to exploit educational data to provide feedback to learners and teachers in the system as well (McNely et al., 2012). Therefore, it becomes critical to capture student disengagement metrics that can be measured to gauge student performance or progress. These student disengagement analytics will give insight and reflections on the quantity and quality of a student’s participation in class from the perspective of user experience designs to identify interaction and cooperation with co-learners and teachers in their learning journeys. The use of AR enhanced analytics can contribute to solving some of the issues cited above.

5.3.2 Gathering AR Enhanced Analytics

The term “AR enhanced analytics” has not been used collectively as a phrase in any literature reviewed to date. Five key AR-based analytics have been identified from the review of the literature that focus on the key affective factors identified earlier. The reviewed studies have provided sufficient evidence that data analytics capture using AR applications is possible while using appropriate measurement tools together with measurement metrics used in various educational settings. The scope of the investigation will also identify novel metrics for measuring and reducing student disengagement, which will be discussed in the next section. Here, the five key AR-based analytics that contribute to the overall combination of metrics, measures, and settings for AR enhanced analytics are listed, as shown in Figure 6.

1. AR-based LA depend on student learning outcomes, which include affective factors defined earlier, such as motivation,

emotions, attention, control, enjoyment, and usability.

2. AR-based interaction analytics focus on users' touch actions on the mobile device, audio rendering, and eye gaze tracking.
3. AR-based spatial analytics are linked to physical locations of the users and devices, as well as physical body movements.
4. AR-based sensory analytics capture body language and pose recognition.
5. AR-based emotion analytics analyze facial expressions and voice semantics of the user.

5.3.3 Addressing Teachers' Need for AR Enhanced Analytics

Data collected by AR tools about students is shared with their teachers through the AR-based analytics platform developed. This data is used by teachers to support their students as part of the analytics process, but the data is not collected or used as part of the research process. This is information already used within the classroom environment but ideally more readily accessible through the platforms being evaluated.

Data (deidentified) is collected about the use of the AR tools, measured novel metrics, AR analytics engine, and the effectiveness of the tools to measure and mitigate disengagement learning and teaching. This data is reported in the results of this research.

The goal of investigating data collection opportunities with AR tools is achieved similarly, and the sessions will overlap with those described in the previous paragraphs. The points of distinction in this case are that the client applications are a series of AR tools specifically developed to support defined learning activities (for example, developing coordination skills by physically beating on some virtual drums). The data collected by the AR tools and transmitted to the server as part of the AR enhanced analytics consists of the following:

- (i) information sensed from the location: position and orientation of the AR devices; data feature values derived from the camera, microphone, and other sensors on the device;
- (ii) information sensed about the actions of the student(s) using the application: physical movements captured with the device's accelerometer, gyroscope, and magnetometer, and through feature points tracked visually; not personally identifiable, although identifiers will be assigned per session in order to match data recorded from different sources relating to the same individual;
- (iii) feedback captured using a short "emoji" (smilometer)-based approval rating for students integrated into the AR tools, using discussion in class, and through interviews with teachers in testing the various metrics for disengagement (in actual classroom settings/outdoors).

5.3.4 Recommendations for Educators and XR Developers

Guidelines for educators and XR developers implementing AR enhanced analytics in education contexts and educational technology ecosystems require clear alignment of AR tools with curricular objectives, explicit training for teachers, and robust technical support to manage analytics data. Educators should adopt mixed-methods analytics approaches combining interaction logs, self-reports, and physiological data to gain comprehensive learner insights. XR developers are encouraged to design intuitive dashboards presenting analytics clearly and efficiently. Recognizing these implementation challenges and adopting structured guidelines can maximize AR analytics' educational potential, ensuring meaningful, sustainable integration into classroom practice (Kazanidis et al., 2021; Papakostas et al., 2023).

5.3.5 Gaps Identified/Opportunities

From the studies reviewed, research has focused on no real-time measure of student disengagement, which gives immediate results to the teacher while the lesson is in progress. All results of the measure of student disengagement (or any other affective factor) have always been post-lessons or experiment. This is when students are given self-reporting questionnaires or surveys, which are collated and analyzed after class. On the contrary, student disengagement needs to be identified, measured, and mitigated immediately by the teacher during the lesson, if possible. It is fruitless if the teacher realizes that a student was disengaged after consolidating the feedback after class, carried out usually through knowledge quizzes or tests on the specific topic being taught. Observational studies and the gathering of teacher feedback are other means of gathering student disengagement data by an observer or researcher present during the experiment. Unfortunately, it is impractical for the observer to be present at all occasions of the lessons. Furthermore, post-interviews with teachers and students are also used by researchers to determine whether student disengagement is a problem when gathering feedback from teachers and students.

Prior research has identified the problems which teachers face when students are disengaged in class, first and foremost that there is constant distraction for the teacher to stop the lesson and manage the disengaged student. This inevitably disturbs other students, who can easily become disengaged because of the distractions. Also, teachers need to constantly look out for

students not paying attention in class and students who are not responsive to questions asked in class, and have to manage their communication effectively to ensure that no student is disengaged while delivering the lessons. This is a real problem in a typical classroom, especially with young children.

This review has provided substantial knowledge for ascertaining that the use of AR has advantages in addressing the problems highlighted. The planned research will identify novel AR-based metrics which will be included in AR tools when used in classroom learning. Recent technological advances in smartphones enable the collection of rich sensor data, which can be used to discover knowledge about the user’s activities and context. This enables new applications to provide tailored context-aware services to the user (Fazeen et al., 2012; Vaizman et al., 2017). Some of the promising AR-based (mobile device) novel metrics that we will investigate and validate in our research are included in Table 7.

Table 7. Metrics from sensors on mobile devices from smartphone sensor modalities (in the table are the various mobile devices and sensor-based measures that are AR-based capable metrics to be included in AR enhanced analytics for the measurement of body-related metrics such as disengagement.) Adapted from a research review by Gjoreski and colleagues (2018).

Sensor/Instrument of Measure	Metrics/Measure	Possible Application/Mitigation to Disengagement
Front-Facing Camera	Audio/Video Recording	Facial Non-verbal Semantics/Voice-Based/Eye Gaze/intangible
Accelerometer	Static/Dynamic Acceleration	Movement/Stationary/Not Responding/Too Fidgety
Gyroscope	Angular Velocity	Postural Stability/Motor Function/Concussions
Magnetometer	Magnetic Field Strength/Direction	Human Body Magnetic Fields/Electric Fields
Orientation in Quaternions	Spatial Rotation	Postural Stability/Motor Function/Concussions
Gravity	Force of Gravity	Postural Stability/Motor Function/Concussions
Linear Acceleration	Static/Dynamic Acceleration	Movement/Stationary/Not Responding/Too Fidgety
Ambient Pressure	Atmospheric Pressure	Environmental Factors
Google’s Activity Recognition API	Detect Users’ Activity	Activity Durations (Vehicle, Bicycle, Walking, Running, Still, Tilting, Standing)
Ambient Light	Screen Brightness Adjustment	Screen Readability/Environmental Factors
Temperature	Body Temperature	Human Body Temperature
Battery Level	Power Consumption	Length of Use
Signal/Wifi Reception	Signal Strength	Location
Cell Tower Reception	Signal Strength	Location
GPS Location	Longitude/Latitude	Location/Movement/Pathways
Audio	Audio Recording	Voice-Based Semantics

This review acknowledges technical gaps in current AR enhanced analytics research, notably regarding data collection methodologies and real-time processing challenges specific to AR environments. Accurate AR data collection requires reliable capturing of interaction logs, sensor data, and multimodal signals (eye-tracking, gesture recognition), demanding sophisticated real-time analytics processing capabilities. Additionally, integration of AR analytics with existing educational data sources and learning management systems (LMSs) remains underexplored. Addressing this integration would allow comprehensive learner profiles and support timely, data-driven interventions. Future research must prioritize seamless interoperability between AR platforms and educational infrastructures, enhancing both analytics accuracy and educational outcomes (Li et al., 2025; Kazanidis et al., 2021).

6. Conclusions

The evolution of AR enhanced analytics reveals significant advancements in analytics capabilities driven by developments in AR technology. Early AR studies relied primarily on basic interaction logs and self-report surveys, whereas recent research incorporates sophisticated multimodal analytics (eye-tracking, gesture analysis) and real-time adaptive feedback. Emerging trends suggest future analytics will increasingly use AI-driven personalization, real-time analytics dashboards, and deeper LMS integration. Continuous advancements will enhance predictive analytics capabilities, enabling proactive intervention strategies and improved educational outcomes through more nuanced, data-rich insights into learner interactions.

This review paper presents the state of the art in the use of AR enhanced analytics and has identified gaps and opportunities for further investigation in conjunction with the use of AR in education. Metrics are still being captured using traditional methods involving forms and surveys, and particularly not using the facilities of the AR application. Applications are still

treating smartphones as form-based collection devices and ignoring a range of affective factors, rather than using the sensing capabilities already being exploited by AR applications.

This systematic review provides a survey of the current state of the art in AR applications and how they enhance analytics during collection, analysis, and presentation to address learning outcomes and goals in classrooms. Qualitative analysis is used to extract and correlate subcategories related to the affordances, methods, measures, and forms of analytics used by students and teachers, and exhaustively addressing those subcategories.

The immersive and interactive learning experiences provided by AR applications are capable of collecting, analyzing, and presenting information that can engage students in the learning process and support teachers in their role as facilitators of learning. A range of affective factors, from attention through to usefulness, have been identified that are accessible through AR enhanced analytics.

6.1 RQ1: Uses, Advantages, and Limitations of AR Enhanced Analytics

AR enhanced analytics provide visualization that enables teachers to make informed decisions, improve lesson delivery, support student assessment, and effectively monitor student behaviour through interaction data. These analytics directly benefit learners by providing virtual lab instruments and simulated experiments, enriching exploration and active learning. The integration of responsive, context-aware feedback and game-theoretic elements further personalizes and motivates student engagement. Advantages include unobtrusive measurement of learning choices, physical interactions, emotional responses, and cognitive states on mobile devices, thus offering meaningful, personalized insights for teachers without additional hardware investments. However, limitations arise due to increased complexity in AR applications, particularly regarding data collection, presentation, and interpretation.

AR enhanced analytics also have some associated limitations, principally around additional complexity that was added to AR applications to support the collection and presentation of the analytics information and how the data is to be interpreted.

6.2 RQ2: Evaluation Methods, Instruments, and Metrics of AR Enhanced Analytics

Currently, AR enhanced analytics evaluation methods predominantly employ surveys and interviews conducted post-lesson, highlighting opportunities to develop real-time data collection and analytics presentation techniques. Emphasis should shift toward integrating objective and consistent measurements by combining data from multiple sources. Analytics implementations commonly use platforms such as Google Analytics and Unity Analytics, but critical challenges remain regarding data privacy, ownership, costs, and interoperability. Effective analytics platforms must also facilitate customized data presentations directly integrated within AR learning experiences. Measurement instruments primarily include low-cost, built-in mobile device sensors, complemented by additional specialized tools such as eye-tracking and motion-tracking depth cameras. These varied sensing devices offer promising avenues for developing robust, alternative assessment methods beyond traditional surveys.

6.3 Integration of AR Enhanced Analytics in Learning

The review shows the growing interest in using analytics to enhance AR application capabilities in educational contexts. Studies such as Akçayır and Akçayır (2017), Bacca Acosta and colleagues (2014), and Chen and colleagues (2017) have shown the potential of AR to enhance learning experiences by offering immersive, interactive, and personalized learning. This is particularly notable in specialized areas such as surgical training (Sheik-Ali et al., 2019) and special needs education (Baragash et al., 2020).

Despite the advantages, the integration of AR in education is not without challenges. One notable issue is the additional cognitive load it places on users, which could potentially hinder the learning process. Additionally, as indicated in the review, few studies have explored complex data management and analytics in educational AR contexts, highlighting a research gap.

The review highlights a relatively unexplored area: the use of enhanced analytics in AR for education. Although some studies, such as Hanid and colleagues (2020) and Garzón and Acevedo (2019), have begun to address this, there is significant room for growth. The ability to capture, analyze, and present data in real time could revolutionize educational feedback and assessment.

The review suggests strong potential for future research, especially in the convergence of AR and analytics. The educational sector could benefit significantly from more nuanced analytics that can provide real-time feedback and personalized learning experiences. However, this requires addressing existing gaps, such as the need for sophisticated data logging mechanisms and understanding the impact of cognitive load.

The use of analytics in AR for education raises underlying ethical considerations. The collection and analysis of detailed user data, especially in educational settings, raises questions about privacy, consent, and data security.

The review implies a technological challenge: ensuring that AR tools and analytics are accessible and user-friendly. This includes considerations for diverse learning needs and the varying levels of technological proficiency among educators and learners.

The review findings underscore the importance of interdisciplinary collaboration. Bridging the gap between technology developers, educators, and researchers is crucial for creating AR tools and analytics that are pedagogically sound and technologically advanced.

Although the review points out the potential benefits of using AR enhanced analytics in education, longitudinal studies are needed to assess their long-term impact on learning outcomes, retention, and skill acquisition. Through this systematic review, a comprehensive analysis of the current state of AR analytics usage in education has been highlighted with both potential and challenges. It opens doors for further research, particularly in the integration of sophisticated enhanced analytics to optimize AR applications in learning and educational contexts.

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Appendix

Table 8. Analysis topics of prior systematic reviews.

Review	Type of Review	Studies	Themes
Akçayır and Akçayır (2017)	Systematic	68	AR technologies, advantages, and challenges
Sheik-Ali et al. (2019)	Meta-analysis	11	VR/AR in surgical training
Bacca Acosta et al. (2014)	Systematic	32	AR in education: uses, advantages, limitations, effectiveness, challenges, and features; personalize learning
Bekele et al. (2018)	Scoping Review		MR in cultural heritage (CH) settings
Baragash et al. (2020)	Meta-analysis	16	AR use in special needs education and interventions; 4 skillsets: social, living, learning, and physical
Barsom et al. (2016)	Systematic	27	AR to support medical professional training
Berenguer et al. (2020)	Systematic	20	Impact of AR through social, cognitive, and behavioural domains in children and adolescents with autism
Chandra et al. (2019)	Scoping Review		AR data visualization
Chen et al. (2017)	Systematic	55	AR in education: uses, advantages, features, and effectiveness
Garzón and Acevedo (2019)	Meta-analysis	64	Student learning gains: with variables: control treatment, learning environment, learner type, domain subject
Gavilanes-Sagnay et al. (2018)	Scoping Review		Learning analytics (Virtual Worlds), personalized learning, adaptive learning, and educational intervention
Hanid et al. (2020)	Meta-analysis	17	AR learning strategies: interactive, game-based, collaborative, and experiential learnings
Hantono et al. (2018)	Meta-analysis	8	AR research in education
Ibáñez and Delgado-Kloos (2018)	Systematic	28	AR to support STEM learning
Laine (2018)	Systematic	31	Educational mobile AR games, guidelines
Lim et al. (2019)	Systematic	72	Mobile AR usability: identification, study, analyze metrics, methods, techniques in learning
Banihashem et al. (2018)	Systematic		Learning analytics in education
Parekh et al. (2020)	Systematic		AR improves and enhances user experience in entertainment, medicine, and retail.
Pellas et al. (2019)	Systematic	21	MR influence, insights, benefits, difficulties, and effectiveness across learning subjects; student engagement, participation, skill acquisition, and embodied learning experiences
Phon et al. (2014)	Scoping Review	10	Collaborative AR uses
Radu (2014)	Meta-review	26	AR in student learning
Raju and Joshith (2020)	Meta-review	20	AR in contemporary English language learning: motivation, positive attitudes, enjoyment; AR constraints and critical issues
Saidin et al. (2015)	Scoping Review		AR in subjects teaching: traditional technology vs. traditional teaching methods
Saltan and Arslan (2016)	Scoping Review		AR links to pedagogy and educational outcomes: student engagement, learning outcomes, motivation, satisfaction
Sırakaya and Alsancak Sırakaya (2020)	Systematic	42	AR in STEM: advantages and the contribution to learner, educational outcomes, and interactions

Table 9. *Uses of AR enhanced analytics over conventional AR use in learning.*

Subcategory	Studies
Visualize Information	Ball and Johnsen (2017), Casarin et al. (2019), Challenor and Ma (2019), ElSayed et al. (2016), Engelke et al. (2017), Santos et al. (2019), Savenije et al. (2020), Son and Cho (2017), Zheng and Campbell (2019), Altmeyer et al. (2020), Aoki et al. (2020), Arvanitis et al. (2007), Bos et al. (2019), Cai et al. (2016), Callaghan et al. (2014), Chang et al. (2014), Dilek and Erol (2018), Ens et al. (2021), Guarese et al. (2021), Harley et al. (2016), Holstein et al. (2018), Laine et al. (2016), Leue et al. (2014), Lytridis et al. (2018), Muthanna et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2018), Pombo and Marques (2020), Shao et al. (2020), Squires (2018, 2019), Trajkova and Cafaro (2018), Vergel et al. (2020), Vidal et al. (2018), Vidal-Balea et al. (2021), Whitlock et al. (2019), Yau et al. (2020), Zarraonandia et al. (2013, 2019), and Ohlei et al. (2020)
Knowledge Acquisition	Kickmeier-Rust and Albert (2013), Ogata (2013), Son and Cho (2017), Antoniou et al. (2017), Arvanitis et al. (2007), Callaghan et al. (2014), Chang et al. (2014), ElSayed et al. (2016), Harley et al. (2016), Leue et al. (2014), Lytridis et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2018), Pombo and Marques (2020), Roberto et al. (2019), Rodríguez et al. (2020), Squires (2018), Vidal et al. (2018), Vidal-Balea et al. (2021), Yau et al. (2020), Zarraonandia et al. (2013), and Secretan et al. (2019)
Manipulate Objects	Engelke et al. (2017), Manuel et al. (2017), Santos et al. (2019), Son and Cho (2017), Zheng and Campbell (2019), Antoniou et al. (2017), Aoki et al. (2020), Arvanitis et al. (2007), Chang et al. (2014), Ens et al. (2021), Harley et al. (2016), Laine et al. (2016), Pombo and Marques (2020), Roberto et al. (2019), Vergel et al. (2020), Vidal-Balea et al. (2021), Whitlock et al. (2019), and Ohlei et al. (2020)
Explore Locations	Challenor and Ma (2019), Savenije et al. (2020), Aoki et al. (2020), Arvanitis et al. (2007), Bos et al. (2019), Cai et al. (2016), Dilek and Erol (2018), Harley et al. (2016), Laine et al. (2016), Leue et al. (2014), Lytridis et al. (2018), Muthanna et al. (2018), Pombo and Marques (2018), Pombo and Marques (2020), Squires (2019), Trajkova and Cafaro (2018), Whitlock et al. (2019), and Ohlei et al. (2020)
Instructional Medium	Ogata (2013), Arvanitis et al. (2007), Callaghan et al. (2014), Dilek and Erol (2018), Guarese et al. (2021), Holstein et al. (2018), Leue et al. (2014), Lytridis et al. (2018), Nicola and Stoicu-Tivadar (2020), Roberto et al. (2019), Rodríguez et al. (2020), Squires (2019), Vergel et al. (2020), Whitlock et al. (2019), and Zarraonandia et al. (2019)
Gamified Learning	Manuel et al. (2017), Ogata (2013), Bos et al. (2019), Cai et al. (2016), Chang et al. (2014), Harley et al. (2016), Laine et al. (2016), Muthanna et al. (2018), Pombo and Marques (2018), Vidal et al. (2018), and Vidal-Balea et al. (2021)
Lab Equipment Use	Ball and Johnsen (2017), Altmeyer et al. (2020), Chang et al. (2014), ElSayed et al. (2016), and Yau et al. (2020)

Table 10. *Advantages of AR enhanced analytics over conventional AR use in learning.*

Subcategory	Studies
Measure Interactions	Ball and Johnsen (2017), ElSayed et al. (2016), Engelke et al. (2017), Gjoreski et al. (2018), Kickmeier-Rust and Albert (2013), Ogata (2013), Santos et al. (2019), Savenije et al. (2020), Son and Cho (2017), Altmeyer et al. (2020), Arvanitis et al. (2007), Bos et al. (2019), Cai et al. (2016), Callaghan et al. (2014), Chang et al. (2014), Ens et al. (2021), Guarese et al. (2021), Holstein et al. (2018), Laine et al. (2016), Lytridis et al. (2018), Muthanna et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2018), Pombo and Marques (2020), Roberto et al. (2019), Rodríguez et al. (2020), Shao et al. (2020), Squires (2018, 2019), Vergel et al. (2020), Whitlock et al. (2019), Yau et al. (2020), Zarraonandia et al. (2019), Secretan et al. (2019), and Ohlei et al. (2020)
Measure Learning Outcomes	Challenor and Ma (2019), Kickmeier-Rust and Albert (2013), Manuel et al. (2017), Ogata (2013), Santos et al. (2019), Savenije et al. (2020), Son and Cho (2017), Altmeyer et al. (2020), Antoniou et al. (2017), Cai et al. (2016), Callaghan et al. (2014), Chang et al. (2014), ElSayed et al. (2016), Harley et al. (2016), Holstein et al. (2018), Laine et al. (2016), Leue et al. (2014), Muthanna et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2018), Pombo and Marques (2020), Roberto et al. (2019), Shao et al. (2020), Squires (2018, 2019), Vidal-Balea et al. (2021), Yau et al. (2020), Ohlei et al. (2020), and Secretan et al. (2019)
Measure Cognitive Load	ElSayed et al. (2016), Altmeyer et al. (2020), Arvanitis et al. (2007), Bos et al. (2019), Cai et al. (2016), Callaghan et al. (2014), Guarese et al. (2021), Harley et al. (2016), Holstein et al. (2018), Leue et al. (2014), Lytridis et al. (2018), Nicola and Stoicu-Tivadar (2020), Roberto et al. (2019), Rodríguez et al. (2020), Squires (2018, 2019), Vergel et al. (2020), Vidal et al. (2018), and Vidal-Balea et al. (2021)
Effectiveness in Data Logging	Casarin et al. (2019), Engelke et al. (2017), Savenije et al. (2020), Son and Cho (2017), Zheng and Campbell (2019), Altmeyer et al. (2020), Arvanitis et al. (2007), Chang et al. (2014), Dilek and Erol (2018), ElSayed et al. (2016), Guarese et al. (2021), Holstein et al. (2018), Laine et al. (2016), Lytridis et al. (2018), Muthanna et al. (2018), Pombo and Marques (2018), Pombo and Marques (2020), Yau et al. (2020), and Zarraonandia et al. (2013, 2019)
Measure Movements	Challenor and Ma (2019), Kickmeier-Rust and Albert (2013), Manuel et al. (2017), Santos et al. (2019), Antoniou et al. (2017), Callaghan et al. (2014), Laine et al. (2016), Muthanna et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2018), Rodríguez et al. (2020), Shao et al. (2020), Trajkova and Cafaro (2018), Vergel et al. (2020), Vidal et al. (2018), Whitlock et al. (2019), Zarraonandia et al. (2013), Secretan et al. (2019), and Ohlei et al. (2020)
Locate Spatial Information	Ball and Johnsen (2017), Aoki et al. (2020), Ens et al. (2021), Guarese et al. (2021), Leue et al. (2014), Vidal et al. (2018), Vidal-Balea et al. (2021), and Savenije et al. (2020)
Easy Deployment	Chang et al. (2014), Dilek and Erol (2018), Guarese et al. (2021), Pombo and Marques (2018), Vidal et al. (2018), and Zarraonandia et al. (2019)
Low Cost	Callaghan et al. (2014), Chang et al. (2014), Dilek and Erol (2018), ElSayed et al. (2016), Yau et al. (2020), and Zarraonandia et al. (2019)
Numerical Accuracy	Zheng and Campbell (2019), Chang et al. (2014), Ens et al. (2021), Guarese et al. (2021), Pombo and Marques (2018), and Roberto et al. (2019)
Measure Safety	Altmeyer et al. (2020), Pombo and Marques (2020), Vidal-Balea et al. (2021), Whitlock et al. (2019), and Yau et al. (2020)
Measure Eye Gaze	Ens et al. (2021), Holstein et al. (2018), Vergel et al. (2020), and Zarraonandia et al. (2013)
Body Posture Recognition	Arvanitis et al. (2007), Holstein et al. (2018), and Trajkova and Cafaro (2018)
Facial Emotions	Holstein et al. (2018), Rodríguez et al. (2020), and Trajkova and Cafaro (2018)
Measure Accessibility for the Disabled	Arvanitis et al. (2007) and Lytridis et al. (2018)
Audio Input Analysis	Chang et al. (2014)

Table 11. *Limitations of AR enhanced analytics over conventional AR use in learning.*

Subcategory	Studies
Cognitive Overload	Ball and Johnsen (2017), Challenor and Ma (2019), Ogata (2013), Son and Cho (2017), Antoniou et al. (2017), Callaghan et al. (2014), ElSayed et al. (2016), Ens et al. (2021), Guarese et al. (2021), Holstein et al. (2018), Laine et al. (2016), Leue et al. (2014), Lytridis et al. (2018), Muthanna et al. (2018), Nicola and Stoicu-Tivadar (2020), Roberto et al. (2019), Rodríguez et al. (2020), Shao et al. (2020), Squires (2018, 2019), Vergel et al. (2020), Vidal et al. (2018), Vidal-Balea et al. (2021), and Zarraonandia et al. (2013)
Device Data Capture	Casarin et al. (2019), Engelke et al. (2017), Gjoreski et al. (2018), Kickmeier-Rust and Albert (2013), Manuel et al. (2017), Santos et al. (2019), Savenije et al. (2020), Zheng and Campbell (2019), Altmeyer et al. (2020), Arvanitis et al. (2007), Bos et al. (2019), Guarese et al. (2021), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2018), Pombo and Marques (2020), Roberto et al. (2019), Trajkova and Cafaro (2018), Vidal et al. (2018), Vidal-Balea et al. (2021), Whitlock et al. (2019), Ohlei et al. (2020), and Secretan et al. (2019)
Unfamiliarity	Antoniou et al. (2017), Arvanitis et al. (2007), Bos et al. (2019), Cai et al. (2016), Callaghan et al. (2014), Chang et al. (2014), ElSayed et al. (2016), Ens et al. (2021), Guarese et al. (2021), Harley et al. (2016), Holstein et al. (2018), Laine et al. (2016), Leue et al. (2014), Lytridis et al. (2018), Muthanna et al. (2018), Pombo and Marques (2018), Rodríguez et al. (2020), Vergel et al. (2020), Whitlock et al. (2019), and Zarraonandia et al. (2013, 2019)
Difficult to Use (Usability)	Challenor and Ma (2019), Kickmeier-Rust and Albert (2013), Ogata (2013), Zheng and Campbell (2019), Arvanitis et al. (2007), Chang et al. (2014), Dilek and Erol (2018), ElSayed et al. (2016), Ens et al. (2021), Holstein et al. (2018), Laine et al. (2016), Lytridis et al. (2018), Rodríguez et al. (2020), Squires (2018), and Vergel et al. (2020)
Content Creation	Ball and Johnsen (2017), Altmeyer et al. (2020), Cai et al. (2016), Callaghan et al. (2014), Ens et al. (2021), Harley et al. (2016), Lytridis et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2018), Vidal-Balea et al. (2021), and Yau et al. (2020)
Unstable	Aoki et al. (2020), Arvanitis et al. (2007), Cai et al. (2016), Chang et al. (2014), Dilek and Erol (2018), ElSayed et al. (2016), Holstein et al. (2018), Rodríguez et al. (2020), Trajkova and Cafaro (2018), and Zarraonandia et al. (2019)
Data Interpretation	ElSayed et al. (2016), Cai et al. (2016), Dilek and Erol (2018), Laine et al. (2016), Pombo and Marques (2020), Roberto et al. (2019), Shao et al. (2020), Whitlock et al. (2019), and Yau et al. (2020)
Acceptance	Savenije et al. (2020), Son and Cho (2017), Chang et al. (2014), Pombo and Marques (2020), Squires (2019), and Zarraonandia et al. (2013, 2019)
Persistence Location	Manuel et al. (2017), Aoki et al. (2020), Harley et al. (2016), Pombo and Marques (2020), Squires (2019), Vidal et al. (2018), and Ohlei et al. (2020)

Table 12. *Effectiveness of AR enhanced analytics over conventional AR use in learning.*

Subcategory	Studies
Tracking Interactions	Ball and Johnsen (2017), Casarin et al. (2019), Challenor and Ma (2019), ElSayed et al. (2016), Kickmeier-Rust and Albert (2013), Manuel et al. (2017), Ogata (2013), Santos et al. (2019), Son and Cho (2017), Zheng and Campbell (2019), Altmeyer et al. (2020), Aoki et al. (2020), Arvanitis et al. (2007), Bos et al. (2019), Chang et al. (2014), and Dilek and Erol (2018), ElSayed et al. (2016), Guarese et al. (2021), Harley et al. (2016), Holstein et al. (2018), Laine et al. (2016), Leue et al. (2014), Lytridis et al. (2018), Muthanna et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2018), Roberto et al. (2019), Rodríguez et al. (2020), Shao et al. (2020), Squires (2019), Trajkova and Cafaro (2018), Vergel et al. (2020), Vidal et al. (2018), Whitlock et al. (2019), Yau et al. (2020), Zarraonandia et al. (2013), Secretan et al. (2019), and Ohlei et al. (2020)
Context Awareness	Manuel et al. (2017), Altmeyer et al. (2020), Antoniou et al. (2017), Arvanitis et al. (2007), Cai et al. (2016), Callaghan et al. (2014), Chang et al. (2014), Dilek and Erol (2018), Ens et al. (2021), Laine et al. (2016), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2018), Pombo and Marques (2020), Roberto et al. (2019), Rodríguez et al. (2020), Squires (2018, 2019), Vidal et al. (2018), and Vidal-Balea et al. (2021)
Behaviour Monitor	Kickmeier-Rust and Albert (2013), Manuel et al. (2017), Ogata (2013), Santos et al. (2019), Son and Cho (2017), Bos et al. (2019), Cai et al. (2016), Callaghan et al. (2014), Harley et al. (2016), Holstein et al. (2018), Laine et al. (2016), Rodríguez et al. (2020), Vidal-Balea et al. (2021), Zarraonandia et al. (2013), and Secretan et al. (2019)
Multimodal	Casarin et al. (2019), Gjoreski et al. (2018), Arvanitis et al. (2007), Antoniou et al. (2017), Savenije et al. (2020), Callaghan et al. (2014), Chang et al. (2014), ElSayed et al. (2016), Ens et al. (2021), Guarese et al. (2021), Rodríguez et al. (2020), Squires (2018), Whitlock et al. (2019), and Secretan et al. (2019)
Better Learning Outcome Measures	Challenor and Ma (2019), Son and Cho (2017), Altmeyer et al. (2020), Chang et al. (2014), Holstein et al. (2018), Leue et al. (2014), Lytridis et al. (2018), Pombo and Marques (2018), Squires (2019), Vergel et al. (2020), Vidal et al. (2018), Secretan et al. (2019), and Ohlei et al. (2020)
Feedback Communication	Engelke et al. (2017), Savenije et al. (2020), Zheng and Campbell (2019), ElSayed et al. (2016), Holstein et al. (2018), Shao et al. (2020), Trajkova and Cafaro (2018), Yau et al. (2020), and Zarraonandia et al. (2013, 2019)
Clear Presentation	Ball and Johnsen (2017), Engelke et al. (2017), Ens et al. (2021), Muthanna et al. (2018), Pombo and Marques (2020), and Zarraonandia et al. (2019)
Variation of Use	Casarin et al. (2019), Ogata (2013), Zheng and Campbell (2019), Arvanitis et al. (2007), Cai et al. (2016), and Pombo and Marques (2018)
Communication Medium	Cai et al. (2016), Guarese et al. (2021), Pombo and Marques (2020), Roberto et al. (2019), and Vergel et al. (2020)

Table 13. *Affordance of AR enhanced analytics over conventional AR use in learning.*

Subcategory	Studies
Sensory (audio, visual, and tactile/capture of user inputs)	Bos et al. (2019), Cai et al. (2016), Chang et al. (2014), Couland et al. (2018), Gjoreski et al. (2018), Ogata (2013), Pombo and Marques (2020), Shao et al. (2020), Squires (2018), and Trajkova and Cafaro (2018)
Spatial Portability (explore surrounding environment; measure learners' interaction with the environment)	Arvanitis et al. (2007), Challenor and Ma (2019), Dilek and Erol (2018), Harley et al. (2016), Manuel et al. (2017), Ohlei et al. (2020), Pombo and Marques (2018), and Zheng and Campbell (2019)
3D Visual Overlay (visualize and explore abstract concepts; measure user goals, performance, and tasks)	Aoki et al. (2020), ElSayed et al. (2016), Guarese et al. (2021), Holstein et al. (2018), Lytridis et al. (2018), and Nicola and Stoicu-Tivadar (2020)
Projection of Contextual Information (learners' ability to project data onto physical environments)	Ball and Johnsen (2017), Holstein et al. (2018), Kolomeets et al. (2020), Laine et al. (2016), Muthanna et al. (2018), Roberto et al. (2019), Savenije et al. (2020), Squires (2018), Vergel et al. (2020), Yau et al. (2020), and Zheng and Campbell (2019)
Interaction (measure of interaction with projected data)	Casarin et al. (2019), Chang et al. (2014), ElSayed et al. (2016), Guarese et al. (2021), Holstein et al. (2018), Lytridis et al. (2018), Muthanna et al. (2018), Nicola and Stoicu-Tivadar (2020), Ohlei et al. (2020), Pombo and Marques (2018), Roberto et al. (2019), Santos et al. (2019), Savenije et al. (2020), and Squires (2019)

Table 14. *Evaluation methods of AR enhanced analytics used in learning.*

Subcategory	Studies
Device-Based Data Logging	Vidal et al. (2018), Whitlock et al. (2019), Zarraonandia et al. (2013), Aoki et al. (2020), Arvanitis et al. (2007), Ball and Johnsen (2017), Bos et al. (2019), Callaghan et al. (2014), Casarin et al. (2019), Chang et al. (2014), Dilek and Erol (2018), and ElSayed et al. (2016)
Questionnaires/Survey Forms	Vidal et al. (2018), Whitlock et al. (2019), Altmeyer et al. (2020), Arvanitis et al. (2007), Cai et al. (2016), Chang et al. (2014), ElSayed et al. (2016), Guarese et al. (2021), Harley et al. (2016), Laine et al. (2016), Lytridis et al. (2018), Manuel et al. (2017), Pombo and Marques (2018), Roberto et al. (2019), Squires (2018, 2019), Vergel et al. (2020), Vidal-Balea et al. (2021), and Ohlei et al. (2020)
User Interviews	Vidal et al. (2018), Whitlock et al. (2019), Zarraonandia et al. (2013), Antoniou et al. (2017), Arvanitis et al. (2007), Cai et al. (2016), Chang et al. (2014), ElSayed et al. (2016), Gjoreski et al. (2018), Harley et al. (2016), Laine et al. (2016), Manuel et al. (2017), Pombo and Marques (2018), Roberto et al. (2019), Squires (2018), Trajkova and Cafaro (2018), Vergel et al. (2020), Yau et al. (2020), and Ohlei et al. (2020)
Observational Studies	Zarraonandia et al. (2013), Dilek and Erol (2018), Gjoreski et al. (2018), Harley et al. (2016), Kickmeier-Rust and Albert (2013), Laine et al. (2016), and Lytridis et al. (2018)
Self-Reporting Journals	Altmeyer et al. (2020), Arvanitis et al. (2007), Gjoreski et al. (2018), and Harley et al. (2016)
Teachers' Feedback	Zarraonandia et al. (2013), Chang et al. (2014), and Yau et al. (2020)
Knowledge Quiz	Cai et al. (2016)

Table 15. *Instruments of measure of AR enhanced analytics used in learning.*

Subcategory	Studies
Mobile Phone	Vidal et al. (2018), Whitlock et al. (2019), Zarraonandia et al. (2013), Callaghan et al. (2014), Casarin et al. (2019), ElSayed et al. (2016), Gjoreski et al. (2018), Harley et al. (2016), Kickmeier-Rust and Albert (2013), Lytridis et al. (2018), Manuel et al. (2017), Muthanna et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2020), Roberto et al. (2019), Squires (2018, 2019), Vidal-Balea et al. (2021), Yau et al. (2020), Zheng and Campbell (2019), and Secretan et al. (2019)
Sensors	Aoki et al. (2020), Chang et al. (2014), Dilek and Erol (2018), Gjoreski et al. (2018), Guarese et al. (2021), Harley et al. (2016), Laine et al. (2016), Muthanna et al. (2018), and Zheng and Campbell (2019)
VR/AR Glasses (HoloLens, HTC, Google, Gear)	Kolomeets et al. (2020), Shao et al. (2020), Ball and Johnsen (2017), Zarraonandia et al. (2013), and Vergel et al. (2020)
Kinect RGB Camera	Cai et al. (2016), Savenije et al. (2020), Shao et al. (2020), and Trajkova and Cafaro (2018)
Audio Input	Harley et al. (2016), Kickmeier-Rust and Albert (2013), and Kolomeets et al. (2020)
Virtual World Platforms	Kickmeier-Rust and Albert (2013), Kolomeets et al. (2020), and Nicola and Stoicu-Tivadar (2020)
Brainwave (Emotiv, Neurosky)	Rodríguez et al. (2020) and Bos et al. (2019)
Arduino Platform	Chang et al. (2014)
SensoMotoric Eye-Tracking	Harley et al. (2016)

Table 16. *Analytics platforms used in AR enhanced analytics used in learning.*

Subcategory	Studies
Proprietary Analytics Software	Zarraonandia et al. (2013), Callaghan et al. (2014), Casarin et al. (2019), Kickmeier-Rust and Albert (2013), Kolomeets et al. (2020), Laine et al. (2016), Pombo and Marques (2020), Rodríguez et al. (2020), and Vidal-Balea et al. (2021)
Google Analytics	Nicola and Stoicu-Tivadar (2020) and Squires (2018, 2019)
Google Firebase	Roberto et al. (2019)
Unity Analytics	Vidal et al. (2018)

Table 17. *Measurable metrics in AR enhanced analytics used in learning.*

Subcategory	Studies
Task Time	Vidal et al. (2018), Zarraonandia et al. (2013), Ball and Johnsen (2017), Callaghan et al. (2014), Chang et al. (2014), ElSayed et al. (2016), Gjoreski et al. (2018), Harley et al. (2016), Kickmeier-Rust and Albert (2013), Kolomeets et al. (2020), Lytridis et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2020), Shao et al. (2020), Squires (2018, 2019), Trajkova and Cafaro (2018), Vergel et al. (2020), Yau et al. (2020), and Secretan et al. (2019)
Number of User Sessions	Zarraonandia et al. (2013), Callaghan et al. (2014), Casarin et al. (2019), Chang et al. (2014), Gjoreski et al. (2018), Kickmeier-Rust and Albert (2013), Kolomeets et al. (2020), Lytridis et al. (2018), Manuel et al. (2017), Pombo and Marques (2020), and Squires (2019)
Number of Active Users	Zarraonandia et al. (2013), Callaghan et al. (2014), Lytridis et al. (2018), Nicola and Stoicu-Tivadar (2020), Pombo and Marques (2020), Roberto et al. (2019), and Ohlei et al. (2020)
Relative Positions (AR Marker, Device, User)	Whitlock et al. (2019), Aoki et al. (2020), Casarin et al. (2019), Dilek and Erol (2018), Shao et al. (2020), Trajkova and Cafaro (2018), and Yau et al. (2020)
User Paths/Steps Counts	Whitlock et al. (2019), Zarraonandia et al. (2013), Pombo and Marques (2020), Savenije et al. (2020), Trajkova and Cafaro (2018), Vidal-Balea et al. (2021), and Ohlei et al. (2020)
Object Manipulations (Selection, Translation, and Rotation)	Casarin et al. (2019), ElSayed et al. (2016), Kolomeets et al. (2020), Lytridis et al. (2018), Nicola and Stoicu-Tivadar (2020), and Vergel et al. (2020)
Average User Time Spent	Callaghan et al. (2014), Pombo and Marques (2020), Roberto et al. (2019), Squires (2019), and Vidal-Balea et al. (2021)
Number of AR Interactions per Session	Manuel et al. (2017), Pombo and Marques (2020), Roberto et al. (2019), Squires (2019), and Ohlei et al. (2020)
Task Correctness	ElSayed et al. (2016), Kolomeets et al. (2020), Pombo and Marques (2020), Yau et al. (2020), and Secretan et al. (2019)
User Profile	Zarraonandia et al. (2013), Pombo and Marques (2020), Vergel et al. (2020), Vidal-Balea et al. (2021), and Yau et al. (2020)
Daily Active Users	Vidal et al. (2018), Muthanna et al. (2018), Roberto et al. (2019), and Squires (2019)
Eye Gaze Tracking Data	Ball and Johnsen (2017), Harley et al. (2016), Kickmeier-Rust and Albert (2013), and Vergel et al. (2020)
GPS Position	Whitlock et al. (2019), Manuel et al. (2017), Pombo and Marques (2020), and Zheng and Campbell (2019)
Daily New Users	Callaghan et al. (2014), Pombo and Marques (2020), and Roberto et al. (2019)
Feedback Data	Pombo and Marques (2020), Trajkova and Cafaro (2018), and Yau et al. (2020)
Distance between AR and Marker	Aoki et al. (2020) and Guarese et al. (2021)
EEG Data (Brain)	Bos et al. (2019) and Rodríguez et al. (2020)
Monthly Active Users	Callaghan et al. (2014) and Roberto et al. (2019)
Active Users by Device	Roberto et al. (2019)
Active Users by OS	Roberto et al. (2019)
Ambient Temperature	Muthanna et al. (2018)
AR Bounce Rate	Roberto et al. (2019)
AR Marker Discovery Time	Roberto et al. (2019)
AR Marker Losing Percentage	Roberto et al. (2019)
Crash-Free App Sessions	Roberto et al. (2019)
Crash-Free App Users	Roberto et al. (2019)
Heatmap Regions	Ohlei et al. (2020)
Humidity	Muthanna et al. (2018)
New Users over Active Users	Roberto et al. (2019)