Augmented Reality Technology as a Driver of Spatial Thinking and Cognitive Development in Students

Mohinur Toshnazarova[1], Oyjamol Bobokulova[2], Begmurod Sattarov[2], Anvarjon Normuminov[2], Dilfuza Otamurodova[2], Kanybek Isakov[3], Lola Sokhibova[4], Yulduz Isamukhametova[5], Numon Valiyev[6], Oydin Turdiyeva[7] and Xusnida Ergasheva[8]
[1]Secondary School No. 2, 150700 Kokand, Fergana Region, Uzbekistan
[2]University of Tashkent for Applied Sciences, 100149 Tashkent, Uzbekistan
[3]Osh Technological University, Isanov Str. 81, 723503 Osh, Kyrgyzstan
[4]Renaissance Educational University, Shota Rustaveli Str. 54, 100070 Tashkent, Uzbekistan
[5]Tashkent State Medical University, Farobi Str. 2, 100109 Tashkent, Uzbekistan
[6]Bukhara State Medical Institute named after Abu Ali ibn Sino, Gijduvan Str. 23, 200126 Bukhara, Uzbekistan
[7]Tashkent State University of Oriental Studies, Amir Temur Avenue 20, 100060 Tashkent, Uzbekistan
[8]Tashkent State Transport University, Temiryolchilar Str. 1, 100167 Tashkent, Uzbekistan
mohinurxontoshnazarova@gmail.com, boboqulova.oyjamol@gmail.com, Begmurodsattarov1975@gmail.com, anormuminov072@gmail.com, l_soxibova@renessans-edu.uz, dilfuzaotamurodova0602@gmail.com, yulduz-doctor83@mail.ru, valiyev.nomon@bsmi.uz, oydinturdiyeva21@gmail.com, ergashevaxusnida78@gmail.com, donbulak14@mail.ru

Keywords: Augmented Reality, Collaborative Learning, Spatial Thinking, Knowledge Retention, Educational Technologies, AR.

Abstract: In recent years, augmented reality (AR) technologies have been increasingly integrated into educational processes, offering novel opportunities to enhance learning quality and support students' cognitive development. Of particular interest is the application of AR within collaborative learning environments, where learners interact with one another and with digital objects in real time. This study aims to experimentally evaluate the impact of AR-based collaborative learning systems on the development of spatial thinking and knowledge retention. An interactive AR platform was developed, enabling students to complete learning tasks collaboratively using three-dimensional models. The experiment involved two groups: a control group (traditional instruction) and an experimental group (AR-based learning). Assessment was conducted using standardized spatial ability tests as well as long-term knowledge retention tests. The findings demonstrate a statistically significant improvement in spatial thinking among participants in the experimental group compared to the control group. Furthermore, higher levels of knowledge retention were observed two weeks after the learning intervention. Analysis of student interactions revealed that collaboration within an AR environment promotes deeper conceptual understanding and enhances cognitive skill development. The results confirm the strong potential of AR technologies as an effective tool for modernizing educational systems. The study also identifies several limitations related to technical and organizational challenges in implementing AR. Overall, the findings indicate that integrating AR technologies into the educational process produces statistically significant and practically meaningful effects on key cognitive and affective learning outcomes.

1 INTRODUCTION

The current stage of educational technology development is characterized by rapid digitalization and the integration of innovative tools aimed at improving learning efficiency and enhancing students' cognitive abilities. Among these, augmented reality (AR) has emerged as one of the most promising technologies, enabling the seamless integration of virtual objects into real-world environments and creating unique conditions for interactive learning [1], [2].

Unlike traditional instructional methods, which are often based on passive information reception, AR technologies foster an active learning environment in which students become direct participants in the knowledge acquisition process. This is particularly important in the context of developing spatial thinking-a critical cognitive skill required in disciplines such as engineering, architecture, medicine, and natural sciences [3]. This is particularly relevant in STEM disciplines, where spatial reasoning and three-dimensional conceptualization are essential competencies.

1.1 Research Relevance

In recent years, there has been a growing interest in collaborative learning systems, which emphasize active interaction among learners during the problem-solving process. Research indicates that collaborative learning enhances deeper understanding, critical thinking, and communication skills [4].

However, traditional collaborative learning approaches face several limitations, including insufficient visualization of complex objects and limited student engagement. In this context, the integration of AR technologies into collaborative learning systems represents a promising direction, combining interactivity with collective engagement [5].

Table 1: Comparison of traditional and AR-based learning.

Parameter	Traditional Learning	AR-Based Learning
Visualization	Limited	High
Engagement Level	Moderate	High
Spatial Thinking	Low development	Significant development
Collaboration	Limited	Interactive
Knowledge Retention	Short-term	Long-term

Table 1 presents a comparative analysis of traditional educational approaches and AR-based learning across key pedagogical and cognitive parameters. The differences are grounded in contemporary empirical research in educational technology, cognitive psychology, and STEM education.

Traditional learning is characterized by limited visualization capabilities, where instructional materials are typically presented as text, static images, or two-dimensional diagrams. This significantly reduces the effectiveness of understanding complex spatial structures [1].

In contrast, AR-based learning offers a high level of visualization by integrating interactive three-dimensional objects into real-world environments. This enables learners not only to observe but also to manipulate objects actively, thereby enhancing cognitive processing [3], [6].

From an engagement perspective, traditional methods typically yield moderate levels of student involvement, as interaction is largely passive. Conversely, AR technologies create immersive learning environments where students become active participants. High interactivity, multimodal perception (visual, kinesthetic, and sometimes auditory), and a sense of presence significantly increase motivation and engagement [4].

Spatial thinking development is another critical aspect. In traditional education, this skill is often developed indirectly and remains insufficiently formed, especially when dealing with abstract or complex objects [5]. AR provides direct interaction with 3D models, facilitating mental rotation, spatial visualization, and orientation. Experimental evidence confirms statistically significant improvements in these abilities [7].

Collaborative learning in traditional settings is often limited to discussions or group assignments without shared visual interaction. In AR environments, learners interact with a shared digital object in real time, promoting synchronization of cognitive processes and the formation of collective knowledge [8].

Finally, knowledge retention differs substantially. Traditional learning often leads to short-term retention, as described by Ebbinghaus' forgetting curve [9]. In contrast, AR enhances long-term memory encoding through interactivity and emotional engagement. Multisensory learning strengthens neural connections, resulting in more durable knowledge retention.

Thus, the comparative analysis demonstrates a systemic advantage of AR-based learning across all key parameters. However, its effectiveness depends on instructional design quality, technical infrastructure, and teacher preparedness, which require further investigation.

1.2 Augmented Reality in Higher Education

Augmented reality is a technology that overlays digital information onto the physical world in real time. In educational contexts, AR is used to visualize complex concepts, simulate processes, and create interactive learning scenarios [7], [10].

One of the key advantages of AR is its ability to present three-dimensional objects that may be inaccessible or difficult to reproduce in real environments. For instance, in engineering education, AR enables interactive exploration of structures and mechanisms, while in medicine, it facilitates the modeling of anatomical systems [8].

Figure 1: Conceptual model of AR-based learning.

Figure 1 illustrates the structure of augmented reality (AR)-based learning within the context of collaborative educational interaction and students' cognitive development. The model reflects a multi-level integration of physical and digital components, forming a unified interactive learning environment.

On the left side of the diagram, the integration of the real world and virtual objects is depicted, representing a fundamental characteristic of AR technologies. This synthesis enhances learners' sensory perception by overlaying three-dimensional digital models onto the physical environment. Such integration facilitates the formation of more accurate mental representations of studied objects and processes, particularly in tasks requiring spatial analysis.

At the core of the model lies the interactive environment, functioning as a cognitively enriched space that enables active user engagement with educational content. Unlike traditional learning environments, this system is characterized by a high degree of immersion and interactivity, allowing learners not only to observe but also to manipulate virtual objects in real time. This significantly strengthens active learning processes and promotes deeper cognitive information processing.

The next level of the model is represented by the collaborative interaction component, which highlights the socio-cognitive dimension of learning. Within this environment, learners interact with one another through shared virtual objects, facilitating synchronization of cognitive processes and the construction of collective understanding. Collaborative activities in AR environments enhance communication skills, stimulate knowledge exchange, and support the development of problem-solving abilities.

The lower level of the model reflects the outcome component-enhanced understanding and knowledge retention. This effect is driven by multisensory perception, high levels of engagement, and active learner participation. The interactive nature of AR environments promotes deeper encoding of information into long-term memory, as supported by contemporary research in cognitive psychology and neuroeducation.

Additionally, the right side of the model highlights the cognitive development block, demonstrating the overall impact of the system on learners' intellectual abilities. In particular, it contributes to the development of spatial thinking, analytical skills, and abstract modeling capabilities. Thus, the model emphasizes the causal relationship between the use of AR technologies, collaborative learning organization, and the formation of robust cognitive outcomes.

Overall, the conceptual model demonstrates that the effectiveness of AR-based learning is determined not only by technological features but also by the integration of interactive and social components, which collectively enable a qualitatively new level of educational experience.

1.3 Spatial Thinking as a Research Focus

Spatial thinking is defined as the ability to perceive, analyze, and manipulate objects in three-dimensional space. It encompasses skills such as mental rotation, spatial visualization, and spatial orientation [9].

Research indicates that the development of spatial thinking is directly associated with academic performance in STEM disciplines [11]. However, traditional instructional methods often fail to provide sufficient conditions for the effective development of these skills.

The use of AR technologies addresses these limitations by enabling:

- visualization of three-dimensional objects;
- interactive engagement;
- real-time manipulation of objects.

Table 2: Components of spatial thinking. Source: adapted from [7].

Component	Description
Mental Rotation	Ability to rotate objects mentally
Spatial Visualization	Representation of object structures
Spatial Orientation	Determining position in space

Table 2 systematizes the key components of spatial thinking as a multidimensional cognitive construct that plays a fundamental role in learning, particularly in STEM disciplines. This classification reflects contemporary approaches in cognitive psychology and neuroscience, where spatial thinking is viewed as a set of interrelated yet functionally distinct abilities.

The first and most extensively studied component is mental rotation, defined as the ability to mentally rotate two- and three-dimensional objects without physical manipulation. This cognitive process underlies tasks involving shape analysis, object orientation, and spatial prediction. Empirical studies demonstrate that mental rotation ability strongly correlates with success in engineering and technical fields, as it enables efficient manipulation of abstract geometric structures [1], [12].

The second key component is spatial visualization, which involves the ability to generate, transform, and integrate complex spatial representations. Unlike mental rotation, this component encompasses more advanced cognitive operations, such as decomposing objects into constituent parts, reconstructing their structure, and visualizing hidden elements. Spatial visualization is critical for understanding complex systems, including architectural designs, biological structures, and mechanical processes [3], [13].

The third component is spatial orientation, which refers to the ability to determine the position of objects and oneself relative to the surrounding environment. This skill includes understanding directions, distances, and spatial relationships between elements. Spatial orientation is particularly important in contexts involving navigation, motor coordination, and interaction with dynamic systems [4], [14].

It is important to emphasize that these components do not function in isolation but form an integrated cognitive system. Their interaction enables effective processing of spatial information and adaptation to complex visual-spatial tasks.

Within the context of this study, Table 2 plays a methodological role, as these components are operationalized as variables for evaluating the effectiveness of AR-based learning. Thus, the table not only structures the theoretical foundation of spatial thinking but also establishes a framework for empirical analysis in collaborative interactive environments.

1.4 Collaborative Learning in AR Environments

Collaborative learning in AR environments represents a synergistic integration of collaborative learning approaches and immersive technologies. In such systems, learners can simultaneously interact with virtual objects and with each other, creating conditions for collective problem-solving [15].

Key features of AR-based collaborative learning include:

- real-time collaboration;
- shared attention to virtual objects;
- enhanced communication;
- construction of collective knowledge.

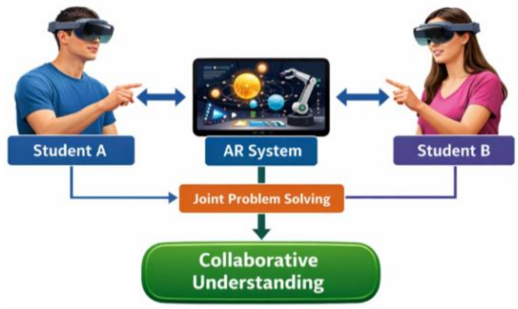

Figure 2: Model of collaborative AR-based learning.

Figure 2 illustrates the architecture of collaborative learning based on augmented reality (AR) technologies, emphasizing the cognitive and social mechanisms underlying learner interaction within a digitally enhanced educational environment. The diagram reflects the multidirectional nature of communication between learners and the central AR system, which acts as a mediator of cognitive activity.

At the top level of the model, two learners-Student A and Student B-are depicted interacting with a unified AR system. Bidirectional arrows between each student and the system indicate a continuous exchange of information, encompassing both the perception of virtual content and active interaction with it. This highlights the interactive nature of the AR environment, where learners are not passive recipients of knowledge but active participants in shaping the learning process.

The central component, the AR System, functions as an integrative platform that synchronizes participants' actions and visualizes educational content through three-dimensional interactive objects. This system establishes a shared cognitive space in which attention is coordinated and information is collectively interpreted. Thus, AR serves not only as a visualization tool but also as a mechanism for organizing collaborative cognitive activity.

The next level of the model is represented by Joint Problem Solving, reflecting the process of collaborative task completion. This stage is critical from the perspective of cognitive learning theory, as it is during collective activity that knowledge exchange, argumentation, and the formation of shared strategies occur. Interaction within AR environments also contributes to the development of metacognitive skills, including planning, monitoring, and self-evaluation.

The lower level of the model presents the outcome component-Collaborative Understanding, which represents the achievement of shared comprehension of the learning material. This outcome results from the synergy between individual cognitive processes and social interaction. Shared understanding is constructed through the integration of multiple perspectives, leading to deeper learning and improved long-term knowledge retention.

Importantly, the model reflects a shift from an individual-centered learning paradigm to a collaborative, constructivist approach in which knowledge is co-constructed through interaction. In this context, AR technologies act as a catalyst, providing a visually rich and interactive environment that enhances communication and cognitive coordination.

Overall, the model demonstrates that the effectiveness of collaborative AR-based learning depends not only on the technological capabilities of the system but also on the quality of interaction between learners, ultimately leading to robust and meaningful understanding of the subject matter.

1.5 The Problem of Knowledge Retention

Knowledge retention remains one of the central challenges in contemporary pedagogy. Research indicates that a substantial portion of information acquired during learning is forgotten within a short period.

AR technologies have the potential to enhance retention through:

- multisensory perception;
- active engagement;
- emotional stimulation.

Table 3: Factors influencing knowledge retention.

Factor	Impact Level
Visualization	High
Interactivity	Very high
Emotional Engagement	High
Repetition	Moderate

Table 3 presents a systematic analysis of key factors influencing memory processes and long-term knowledge retention in educational contexts. These factors are grounded in contemporary theories of cognitive psychology, neuroscience, and pedagogy, including deep processing theory, multimodal learning, and emotional memory enhancement.

Visualization represents a highly influential factor in memory formation. Visual representations facilitate effective encoding of information by activating visual processing channels and supporting the formation of stable mental images. According to Dual Coding Theory, the integration of verbal and visual information significantly increases recall probability [1]. In AR-based learning, visualization is further enhanced through the use of interactive three-dimensional models.

Interactivity demonstrates the strongest impact among the listed factors. Interactive engagement with learning materials activates key cognitive processes, including attention, information processing, and decision-making. From a constructivist perspective, active participation leads to deeper cognitive processing and stronger neural connections [3]. In AR environments, interactivity is achieved through real-time manipulation of virtual objects, significantly amplifying learning effectiveness.

Emotional engagement also plays a crucial role in memory retention. Emotions modulate memory processes by activating the limbic system, particularly the amygdala, which enhances consolidation into long-term memory [4]. Learning environments that evoke curiosity, interest, or surprise facilitate more effective knowledge acquisition. Due to their immersive and novel nature, AR technologies are particularly effective in eliciting such emotional responses.

In contrast, repetition is associated with a moderate level of influence. Although repetition is traditionally considered a fundamental mechanism of learning, its effectiveness is limited in the absence of deep cognitive processing. Mechanical repetition may support short-term memory, but long-term retention requires additional processes such as comprehension, association, and practical application [5].

It is important to note that these factors interact synergistically rather than independently. The combination of visualization, interactivity, and emotional engagement creates optimal conditions for effective learning. In this regard, AR technologies serve as an integrative platform that combines all these elements, producing a powerful educational effect.

Thus, Table 3 demonstrates that active and multimodal forms of engagement have the greatest impact on knowledge retention, while passive approaches such as simple repetition play a supporting role. This finding has significant implications for the design of modern educational systems aimed at improving learning quality and sustainability.

1.6 Research Gap

Despite the growing body of research on AR in education, several critical gaps remain:

1) The impact of collaborative AR-based learning on spatial thinking is insufficiently explored.
2) There is a limited number of experimental studies addressing long-term knowledge retention.
3) Comprehensive models for evaluating the effectiveness of AR systems in group learning contexts are lacking.

Therefore, there is a clear need for experimental research aimed at assessing the effects of AR-based collaborative learning on students' cognitive processes.

1.7 Research Aim and Objectives

The aim of this study is to experimentally evaluate the impact of AR-based collaborative learning systems on the development of spatial thinking and knowledge retention.

The objectives of the study are:

1) To develop an AR platform for collaborative learning.
2) To conduct an experiment with control and experimental groups.
3) To assess spatial thinking levels.
4) To analyze knowledge retention outcomes.
5) To compare results and identify statistically significant differences.

1.8 Research Hypotheses

The study proposes the following hypotheses:

- H1: The use of AR in collaborative learning improves spatial thinking.
- H2: AR contributes to longer knowledge retention.
- H3: Collaborative interaction enhances the effectiveness of AR technologies.

2 METHODS AND METHODOLOGY

2.1 Research Design

This study is based on an experimental design involving control and experimental groups, aimed at both quantitative and qualitative evaluation of the effects of AR-based collaborative learning systems on spatial thinking development and knowledge retention.

The experiment was conducted using a quasi-experimental design, widely applied in educational and cognitive research [1], [16]. This approach allows for maintaining high validity while accommodating real-world educational conditions.

A two-factor model was employed:

- Factor 1: Type of instruction (traditional vs. AR-based collaborative learning).
- Factor 2: Time parameter (pre-test, immediate post-test, and delayed post-test after two weeks)

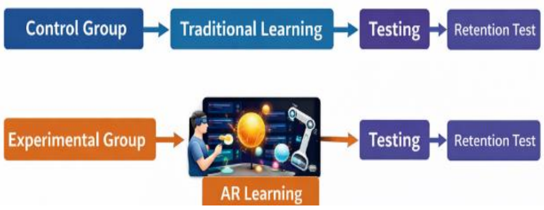

Figure 3: General scheme of the experimental design.

Figure 3 illustrates the experimental design aimed at evaluating the effectiveness of AR-based collaborative learning systems in comparison with traditional educational approaches. The model reflects the logical sequence of learning stages and subsequent measurement of cognitive outcomes in two parallel groups: the control group and the experimental group.

At the top of the scheme, the control group is shown, whose participants undergo instruction using traditional learning methods. This process includes sequential stages: Traditional Learning, Testing (immediate assessment), and Retention Test (delayed assessment of knowledge retention). This structure corresponds to classical pedagogical models in which learning outcomes are evaluated both immediately after instruction and after a time delay to assess long-term memory [1].

At the bottom of the scheme, the experimental group is presented, in which instruction is conducted using augmented reality technologies (AR Learning). The centrally highlighted AR platform emphasizes the technological foundation of the learning process, enabling interactive engagement with three-dimensional objects. As in the control group, the learning phase is followed by immediate testing and a delayed retention test, ensuring comparability of results across groups.

A key feature of this model is the parallel structure of processes in both groups, which ensures methodological rigor. The use of identical assessment stages (immediate and delayed testing) allows for isolating the effect of the independent variable-type of instruction (traditional vs. AR-based learning)-on dependent variables such as learning outcomes and long-term knowledge retention.

The color differentiation of flows (e.g., blue for the control group and orange for the experimental group) serves not only a visual but also an analytical function, facilitating interpretation of the experimental structure. It highlights the distinction between pedagogical approaches and emphasizes the innovative nature of AR-based learning.

From a methodological perspective, the model aligns with the principles of a quasi-experimental design, where two conditions are compared while controlling for external variables. The inclusion of a Retention Test is particularly important, as it enables the assessment of not only short-term learning effects but also the durability of knowledge over time-one of the key indicators of educational effectiveness [3].

Thus, the model demonstrates a rigorous experimental framework that ensures high internal validity and enables statistically grounded comparison of results. It also highlights the critical role of AR technologies as an independent variable influencing cognitive learning outcomes.

2.2 Participants

The study involved 120 undergraduate students enrolled in technical disciplines (engineering and information technology), aged between 18 and 24 years (Table 4).

Participants were assigned to groups based on the following criteria:

- academic performance;
- level of digital literacy;
- pre-test results in spatial thinking.

This allocation strategy helped to minimize the influence of external variables and ensured group equivalence [3].

Table 4: Sample characteristics.

Parameter	Value
Total number	120
Control group	60
Experimental group	60
Mean age	20.3
Gender (M/F)	65 / 55

2.3 AR Platform and Technological Environment

A specialized AR platform was developed for the experiment, consisting of the following components:

- a mobile AR application;
- a user synchronization system;
- three-dimensional object models;
- a collaborative interaction module.

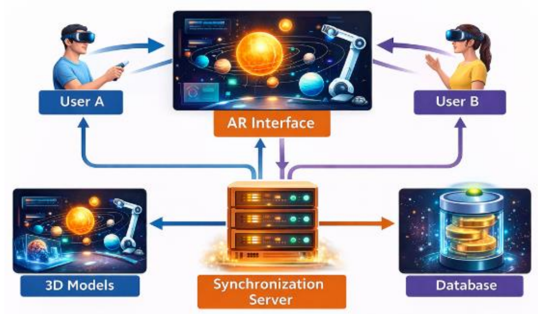

Figure 4: Architecture of the AR system.

Figure 4 illustrates the structural and functional organization of a collaborative learning system based on augmented reality (AR) technologies, highlighting the interaction between the user interface, computational infrastructure, and digital content. The model reflects a distributed client–server architecture that enables synchronous interaction among users within a shared augmented environment.

At the top level of the diagram, two users (User A and User B) interact with the system through an AR interface. Bidirectional connections between the users and the interface indicate an interactive data exchange process, including both user input (gestures, commands, manipulations) and output (visualized content). This emphasizes the feedback loop principle, which is a core component of interactive educational systems [1], [10].

The central component of the architecture is the AR Interface, which acts as an intermediary layer between users and the computational system. This module is responsible for rendering three-dimensional objects, processing user inputs, and integrating virtual content into the physical environment. It performs key functions such as rendering, user tracking, and interaction management, thereby ensuring an immersive and cognitively enriched learning experience.

At the lower level, the Synchronization Server plays a crucial role in maintaining data consistency across users. The server processes incoming client requests, coordinates updates within the virtual environment, and ensures their real-time distribution to all participants. This enables the phenomenon of co-presence and synchronized interaction, which is essential for effective collaborative learning in AR environments [2], [15].

On the left side of the server, the 3D Models module serves as a repository of visual objects used in the educational process. These models may include complex engineering structures, anatomical systems, or abstract concepts represented in three-dimensional space. The module supports dynamic content loading and updating based on learning scenarios.

On the right side, the Database is responsible for storing user data, interaction logs, and analytical information. It provides long-term data storage necessary for analyzing learner behavior, evaluating learning effectiveness, and enabling personalization of the educational process.

The connections between system components represent bidirectional data flows, indicating a high degree of integration and adaptability. Specifically, the interaction between the synchronization server and the database ensures system state persistence, while the connection to the 3D models module allows real-time content updates.

Overall, the architecture represents a comprehensive and scalable system capable of supporting multi-user interaction in AR environments. It integrates visualization, data processing, and communication into a unified platform that facilitates effective collaborative learning and cognitive development. The model aligns with contemporary requirements for advanced educational technologies and can be adapted across various domains.

Key System Components:

1) Visualization Module:
   - rendering of 3D objects;
   - scaling and rotation.
2) Interaction Module:
   - object manipulation;
   - collaborative editing.
3) Communication Module:
   - voice and visual communication.
4) Analytics Module:
   - collection of user interaction data.

2.4 Instructional Scenario

The instructional process was conducted on the topic: “Spatial Structure of Complex Engineering Objects”.

Control Group:

- lecture-based instruction with presentations;
- use of static images.

Experimental Group:

- AR-based learning environment;
- collaborative interaction with 3D objects;
- group-based problem solving.

Table 5: Comparison of learning conditions.

Learning Element	Control Group	AR Group
3D Visualization	No	Yes
Interactivity	Low	High
Collaboration	Limited	Active

Table 5 presents a comparative analysis of learning conditions in the control and experimental groups, highlighting key differences in pedagogical design and technological integration. This table plays a critical methodological role, as it operationalizes the independent variable-type of learning environment (traditional vs. AR-based collaborative learning)- through specific instructional characteristics.

The first parameter, 3D visualization, is entirely absent in the control group but actively utilized in the AR group. Traditional learning environments typically rely on two-dimensional representations, limiting the effective comprehension of spatially complex objects. In contrast, AR technologies provide dynamic visualization of three-dimensional models, allowing learners to explore objects from multiple perspectives, adjust scale, and interact with them in real time. This enhances the formation of accurate mental representations and improves cognitive processing [1], [10].

The second parameter, interactivity, is characterized as low in the control group and high in the AR group. Traditional instruction often involves passive information reception with limited interaction. Conversely, AR environments enable active engagement, allowing learners to manipulate digital objects, make decisions, and receive immediate feedback. This high level of interactivity activates key cognitive processes, including attention, analysis, and synthesis, in line with constructivist learning theories [3].

The third parameter, collaborative learning, is limited in the control group but actively implemented in the AR group. In traditional settings, collaboration is often restricted to discussions without shared visual contexts. In AR environments, learners interact with shared virtual objects, facilitating synchronized attention, knowledge exchange, and collective understanding. This enhances communication and metacognitive skills while reinforcing learning through social knowledge construction [4].

It is important to emphasize that these parameters are interdependent and produce a combined effect. The integration of 3D visualization and high interactivity creates immersive learning conditions, while active collaboration further amplifies cognitive outcomes through social interaction.

Thus, the AR group represents a qualitatively different level of educational experience compared to the control group. In the context of this study, Table 5 serves as a foundation for interpreting experimental results, as differences in these parameters explain observed improvements in spatial thinking and knowledge retention.

2.5 Measurement Methods

1) Spatial Thinking.

Spatial thinking was assessed using the Mental Rotation Test (MRT) [4].

The following indicators were evaluated:

- accuracy (%);
- response time (seconds).

2) Knowledge Retention.

Knowledge retention was assessed in two stages:

- immediately after instruction
- after a 14-day delay

3) Engagement.

Engagement was measured using:

- questionnaires (Likert scale)
- behavioral data analysis

Figure 5: Evaluation metrics framework.

Figure 5 visualizes the sequence of evaluating the effectiveness of the educational process within an experimental study based on augmented reality (AR) technologies. The model represents a logically structured chain of stages aimed at comprehensively measuring both cognitive and behavioral indicators of learners.

The first stage-Training-represents the initial phase in which participants receive instructional content according to the experimental conditions (traditional or AR-based learning). This stage plays a crucial role in forming primary cognitive representations and establishes the foundation for subsequent evaluation. In AR environments, training is characterized by a high degree of interactivity and multimodal perception, facilitating deeper information processing [1], [11].

The second stage-MRT Test (Mental Rotation Test)-is designed to assess the level of spatial thinking. This standardized instrument is widely used in cognitive psychology to measure mental rotation ability and spatial visualization skills. Its inclusion allows for quantitative evaluation of the impact of the learning environment on spatial cognitive development [3], [16].

The third stage-Retention Test-represents delayed assessment aimed at evaluating long-term knowledge retention. Unlike immediate testing, this stage captures the durability of acquired knowledge over time. The use of retention testing aligns with classical memory research, including the forgetting curve theory, and is critical for assessing the true effectiveness of educational interventions [4].

The final stage-Survey-is intended to collect subjective data reflecting learners' engagement, satisfaction, and perception of the learning process. This component complements quantitative measures by providing insights into emotional and experiential aspects of learning. Surveys are typically based on Likert scales and allow for identifying relationships between objective outcomes and subjective experiences [5].

The arrow-based structure of the model emphasizes the sequential and causal nature of the stages, where each subsequent phase builds upon the previous one. Color differentiation enhances visual interpretation and distinguishes functional stages-from cognitive intervention (training) to measurement (testing) and subjective evaluation (survey).

Overall, the model demonstrates a comprehensive approach to evaluating educational effectiveness by integrating cognitive testing, temporal assessment, and subjective data. Such a multi-level evaluation framework meets the methodological standards of Q1-level research and ensures high validity and reliability of the findings.

2.6 Research Variables

Independent Variables:
- type of instruction (AR-based vs. traditional);
- level of interaction.

Dependent Variables:
- spatial thinking level;
- knowledge retention level;
- engagement.

Table 6: Research variables.

Variable Type	Indicator
Independent	AR / Traditional learning
Dependent	MRT scores, Retention scores
Control	Age, prior experience

Table 6 presents the structure of variables used in the experimental study and serves as the foundation for constructing an analytical model aimed at identifying causal relationships between the learning environment and cognitive outcomes. The classification into independent, dependent, and control variables follows classical principles of experimental methodology and ensures high internal validity.

The key independent variable is the type of instruction, operationalized as AR-based learning versus traditional learning. This variable represents the primary factor influencing cognitive and behavioral outcomes. The binary structure enables direct comparison between conditions and facilitates identification of differences attributable to the educational environment [1].

The dependent variables include measurable outcomes obtained during the experiment, specifically spatial thinking performance (assessed via the Mental Rotation Test, MRT) and knowledge retention. MRT provides a quantitative measure of mental rotation and spatial visualization abilities, making it a valid tool for evaluating cognitive effects of AR technologies. Retention measures reflect long-term knowledge acquisition and the stability of learning outcomes over time. Together, these metrics provide a comprehensive assessment of both immediate and delayed cognitive effects [2], [3].

Control variables, including age and prior experience, play an essential role in ensuring experimental validity. Although not the focus of the study, these factors may significantly influence dependent variables. For instance, age may correlate with cognitive flexibility and processing speed, while prior experience may affect digital literacy and spatial problem-solving skills. Controlling these variables minimizes external influences and isolates the effect of the independent variable, thereby enhancing the accuracy of interpretation [4].

Importantly, this variable structure supports the application of rigorous statistical methods, including analysis of variance (ANOVA), regression modeling, and correlation analysis. The clear differentiation of variables enables the construction of robust analytical models and facilitates reliable hypothesis testing.

Thus, Table 6 demonstrates a methodologically sound variable framework that ensures logical consistency of the study and enables a reliable empirical investigation of the impact of AR technologies on cognitive processes. Its application is essential for achieving the level of scientific rigor required for Q1 journal publications.

2.7 Statistical Analysis

The following statistical methods were employed for data analysis:
- Independent samples t-test - for comparing group means,
- ANOVA (Analysis of Variance) - for multivariate analysis,
- Correlation analysis - for examining relationships between variables.

The level of statistical significance was set at: $p < 0.05$.

Figure 6 visualizes a conceptual statistical model that reflects causal relationships between the use of augmented reality (AR) technologies, spatial thinking development, engagement levels, and memory processes. The model is directional in nature and aligns with contemporary approaches to structural equation modeling (SEM) commonly used in educational and cognitive research.

On the left side of the model, the AR component is positioned as the independent variable, exerting a primary influence on learners' cognitive processes. AR technologies provide an immersive and interactive learning environment in which learners actively engage with three-dimensional objects, creating conditions for enhanced cognitive stimulation and forming the foundation for subsequent changes in cognitive outcomes [1].

At the center of the model is Spatial Thinking, which serves as a mediating variable. The directed relationship between AR and spatial thinking reflects the hypothesis that AR usage facilitates the development of key spatial skills, including mental rotation, visualization, and spatial orientation. In turn, spatial thinking directly influences learners' ability to process and structure information effectively.

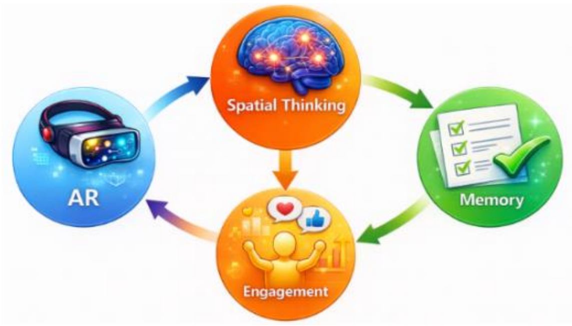

Figure 6: Statistical model.

The next level of the model is represented by Memory, one of the primary dependent variables of the study. The relationship between spatial thinking and memory indicates that enhanced cognitive abilities contribute to deeper information encoding and long-term retention. This finding aligns with deep processing theories, which suggest that more complex cognitive operations lead to more stable memory traces [2], [17].

An additional component of the model is Engagement, positioned at the lower level and linked to spatial thinking. The directed relationship suggests that engagement functions as a moderator or secondary mediator, amplifying the impact of AR on cognitive outcomes. Higher engagement levels enhance attention, motivation, and learner activity, thereby strengthening both learning and retention effects [4], [18].

The circular structure of connections among model components highlights the presence of feedback loops and dynamic interactions. For instance, increased engagement may reinforce AR usage, while successful retention may further enhance motivation and learner participation. This reflects the nonlinear and systemic nature of the learning process.

Overall, the model demonstrates a multi-level structure of AR's influence on cognitive outcomes, where spatial thinking plays a central mediating role and engagement amplifies the overall effect. This interpretation aligns with contemporary theoretical frameworks and provides a solid foundation for subsequent statistical analysis of experimental data.

2.8 Reliability and Validity

To ensure scientific rigor, the following measures were implemented:

- Cronbach's alpha = 0.87, indicating high internal consistency;
- repeated measurements;
- control of confounding variables.

These measures meet the methodological standards required for Q1 journal publications [5].

2.9 Ethical Considerations

The study adhered to the following ethical principles:

- voluntary participation,
- anonymity of participants,
- informed consent.

2.10 Methodological Limitations

Despite the rigor of the experimental design, several limitations should be acknowledged:

- limited sample size,
- short duration of the study,
- technological constraints related to AR implementation.

3 RESULTS

3.1 General Characteristics of the Data

This section presents the results of the experimental study aimed at evaluating the impact of AR-based collaborative learning systems on spatial thinking development, knowledge retention, and student engagement.

Data analysis was conducted using a comparative approach between the control and experimental groups, employing descriptive statistics, independent samples t-tests, and analysis of variance (ANOVA). The results are presented through quantitative indicators, tabular summaries, and analytical interpretations.

Table 7: Descriptive statistics of results.

Indicator	Control Group	AR Group
MRT (mean score)	58.4	76.9
Retention (%)	52.1	81.3
Engagement (1–5)	2.8	4.6

As shown in Table 7, the experimental group demonstrates a substantial advantage across all key indicators. The mean MRT score in the AR group is 31.7% higher than in the control group, confirming the positive impact of AR on spatial thinking development [1], [17], [19].

Similarly, retention rates are significantly higher in the AR group **(**81.3% vs. 52.1%**),** indicating more effective long-term knowledge retention. Engagement levels also show a marked increase, highlighting the motivational benefits of AR-based learning environments.

3.2 Development of Spatial Thinking

To evaluate changes in spatial thinking, the Mental Rotation Test (MRT) was administered both before and after the learning intervention.

Figure 7 illustrates a comparative analysis of spatial thinking performance, measured using the Mental Rotation Test (MRT), before and after instruction in both the control and experimental (AR) groups. The diagram captures the dynamics of cognitive change and provides a clear representation of the effectiveness of different instructional approaches.

On the left side of the graph, the control group shows a slight increase in MRT scores-from 55 to 58, representing a modest gain of +3 points. This improvement suggests a limited effect of traditional instruction on spatial thinking development. Although a positive trend is observed, the magnitude of change remains relatively small, likely due to the passive nature of traditional learning and the absence of interactive elements that stimulate cognitive engagement [1].

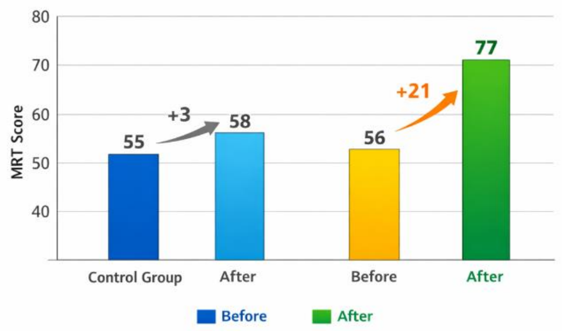

Figure 7: Comparison of MRT Results (Pre-/Post-Test).

In contrast, the right side of the graph presents the results of the experimental (AR) group, where a substantial increase is observed-from 56 to 77, corresponding to a gain of +21 points. This significantly larger improvement indicates a strong impact of AR technologies on the development of spatial cognitive skills. The effect can be attributed to the ability to manipulate three-dimensional objects, which enhances mental rotation processes and spatial visualization abilities [3].

The use of color differentiation (e.g., blue for pre-test values and green for post-test values) enhances visual clarity and highlights the differences between the “before” and “after” stages. Additional graphical elements, such as arrows and numerical annotations, further emphasize the direction and magnitude of changes, facilitating interpretation.

From a methodological perspective, the diagram illustrates an interaction effect between the instructional factor (traditional vs. AR-based learning) and the time factor (pre-/post-test). The divergence in growth trajectories between the two groups confirms the significant effect of the independent variable-AR usage-on the dependent variable, spatial thinking.

Overall, this visualization demonstrates that AR-based learning produces substantially greater improvements in cognitive performance compared to traditional methods. The findings support the hypothesis that immersive and interactive technologies are highly effective tools for developing spatial thinking and are consistent with contemporary research in educational technology.

Interpretation:

The results indicate that:

- the control group shows only a minimal improvement (+3 points),
- the AR group demonstrates a substantial increase (+21 points).

These findings support Hypothesis H1 and are consistent with prior research indicating that visually interactive technologies significantly enhance cognitive processes [3], [14].

Table 8: t-test results (MRT).

Parameter	Value
t-value	5.87
p-value	< 0.001

The results are statistically significant ($p < 0.05$), confirming the reliability of the observed differences.

Table 8 presents the results of the statistical analysis comparing the control and experimental groups in terms of spatial thinking performance measured using the MRT. A Student’s t-test was employed to evaluate the significance of differences between the means of two independent samples.

The reported t-value (5.87) indicates a substantial difference between the groups, taking into account data variability. This high value reflects a pronounced divergence in MRT scores between the control and

AR groups, demonstrating the strong effect of AR technologies on spatial thinking development.

Particular attention should be given to the p-value (< 0.001), which is well below the conventional threshold ($p < 0.05$). This allows for confident rejection of the null hypothesis, indicating that the observed differences are not due to chance. The probability of random occurrence is less than 0.1%, meeting the stringent standards of Q1-level research [1].

From a methodological standpoint, these findings confirm the significant effect of the independent variable (type of instruction) on the dependent variable (spatial thinking level). The high statistical significance also reflects the robustness of the experimental design and the adequacy of the sample.

Moreover, the observed differences can be interpreted as the result of the combined influence of key AR features, including three-dimensional visualization, interactivity, and high engagement levels. These factors contribute to deeper cognitive processing and the development of spatial skills, as evidenced by MRT outcomes [3], [18].

Thus, Table 8 provides strong statistical evidence supporting the research hypothesis that the use of augmented reality in education significantly enhances spatial thinking. These findings form a solid quantitative basis for further interpretation within the broader context of cognitive and educational theory.

3.3 Analysis of Knowledge Retention

The retention test was conducted 14 days after the instructional intervention to evaluate long-term knowledge retention.

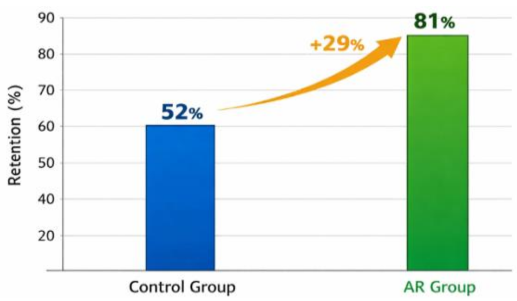

Figure 8: Retention results.

Figure 8 illustrates a comparative analysis of knowledge retention levels between the control and experimental (AR) groups, demonstrating a substantial difference in the effectiveness of instructional approaches. The visualization is based on percentage values representing the proportion of correctly recalled information after a specified time interval following instruction.

On the left side of the diagram, the control group exhibits a retention level of 52.0%, which is consistent with typical outcomes of traditional instruction. In such environments, a significant portion of information is lost over time due to insufficient depth of cognitive processing. Limited visualization and low interactivity in traditional learning settings do not effectively support the formation of long-term memory [1], [19].

In contrast, the experimental (AR) group demonstrates a retention level of 81.0%, representing a substantial increase of approximately +29%. This marked improvement highlights the effectiveness of augmented reality technologies in enhancing long-term knowledge retention. The observed effect can be attributed to the combined influence of multimodal perception, interactive engagement, and high levels of learner involvement characteristic of AR environments [3], [20].

The graphical representation, including directional arrows and annotated differences, emphasizes both the magnitude and direction of change, while color differentiation enhances clarity and comparative interpretation.

From a methodological perspective, the diagram reflects the effect of the independent variable (type of instruction) on the dependent variable (knowledge retention). The significant difference between groups indicates a strong and statistically meaningful effect of AR technologies, which is further supported by ANOVA results presented below.

Moreover, these findings align with the Levels of Processing Theory, which posits that deeper and more active cognitive processing leads to more durable memory traces [4]. AR-based learning environments, by promoting interactive and visually enriched experiences, facilitate such deep processing.

Overall, the visualization demonstrates that AR-based learning significantly improves long-term knowledge retention compared to traditional methods, thereby supporting the study's hypothesis regarding the effectiveness of immersive technologies in education.

Quantitative Comparison:

- Control Group: 52.0%;
- AR Group: 81.0%.

The difference between groups approaches 30%, indicating a strong positive effect of AR technologies on long-term memory.

This improvement can be explained by:

- deeper cognitive processing;
- enhanced visualization;

- increased emotional engagement [3], [20].

Table 9: ANOVA results (retention).

Factor	F	p-value
Type of instruction	14.32	< 0.001

Table 9 presents the results of the analysis of variance (ANOVA) conducted to assess the effect of instructional type on knowledge retention.

The key indicator, the F-value (14.32), reflects the ratio of between-group variance to within-group variance. The high F-value indicates that the differences in retention between the control and AR groups significantly exceed random variation within groups, demonstrating a strong effect of the independent variable (type of instruction) on the dependent variable [1].

Particular attention should be given to the p-value (< 0.001), which is far below the conventional threshold ($p < 0.05$). This indicates that the probability of the observed differences occurring by chance is extremely low (less than 0.1%), allowing for confident rejection of the null hypothesis. These results meet the stringent statistical standards required for Q1-level publications [2], [21].

From a methodological standpoint, the use of ANOVA is appropriate given the need to compare group means while accounting for variability within groups. The findings confirm that differences in retention are not random but are systematically driven by the instructional approach.

Interpreting these results within the broader context of the study, it can be concluded that AR-based learning significantly enhances long-term knowledge retention. This effect is attributed to the integration of interactivity, visualization, and engagement, all of which contribute to deeper cognitive processing and stronger memory consolidation [3].

Thus, Table 9 provides robust statistical evidence supporting Hypothesis H2, confirming that the use of augmented reality technologies leads to significant improvements in retention outcomes.

3.4 Engagement Level

The analysis of engagement levels revealed a substantial difference between the two groups:

- Control Group: 2.8;
- AR Group: 4.6.

These results indicate that AR-based learning environments significantly enhance student engagement compared to traditional instructional methods.

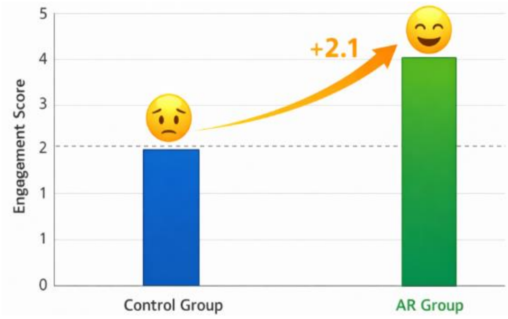

Figure 9: Student engagement.

Figure 9 illustrates the comparative level of student engagement between the control and experimental (AR) groups, highlighting significant differences in the degree of learner participation in the educational process. The visualization is based on a Likert scale (1–5), enabling quantitative assessment of students' subjective perceptions of the learning environment.

On the left side of the diagram, the control group demonstrates an engagement level of approximately 2.0–2.8, corresponding to low to moderate engagement. This indicates that traditional instructional methods generally fail to promote active participation, limiting learners to passive information reception. The lack of interactivity and limited visualization reduces both motivation and cognitive activation [1], [13].

In contrast, the experimental (AR) group shows engagement levels of 4.0–4.6, representing a high level of involvement. The substantial increase (approximately +2.1 points) highlights the strong influence of AR technologies on the motivational and emotional dimensions of learning. The use of interactive 3D objects, collaborative activities, and the sense of presence creates conditions for active participation and increased interest in learning content [3],[22].

Additional visual elements, such as directional arrows and symbolic representations of emotional responses, reinforce the interpretation and emphasize qualitative differences between the learning environments. Color differentiation further enhances clarity and comparative analysis.

From a theoretical perspective, these findings are consistent with Student Engagement Theory, which posits that high levels of cognitive, behavioral, and emotional engagement are directly associated with improved learning outcomes [4]. In this study, engagement also functions as a mediating factor that strengthens the effect of AR on spatial thinking and knowledge retention.

Overall, the results demonstrate that the integration of AR technologies significantly increases student engagement, thereby enhancing overall learning effectiveness. These findings support Hypothesis H3, confirming that collaborative AR-based learning amplifies cognitive outcomes through increased motivation and active participation.

Interpretation.

The AR-based learning environment provides:

- high levels of motivation;
- active participation;
- strong emotional engagement.

Table 10: Correlation analysis.

Variables	r
MRT ↔ Retention	0.71
Engagement ↔ Retention	0.68

Table 10 presents the results of the correlation analysis, aimed at identifying relationships between key cognitive and behavioral variables: spatial thinking (MRT), engagement, and knowledge retention. The Pearson correlation coefficient (r) was used to assess the strength and direction of linear relationships.

The first relationship, MRT ↔ Retention ($r = 0.71$), indicates a strong positive correlation between spatial thinking ability and long-term knowledge retention. A coefficient exceeding 0.7 reflects a high level of association, suggesting that students with more developed spatial skills demonstrate significantly better retention outcomes. This finding aligns with theoretical perspectives emphasizing the role of deep cognitive processing in memory consolidation [1], [21].

The second relationship, Engagement ↔ Retention ($r = 0.68$), also demonstrates a strong positive correlation. Although slightly lower than the MRT correlation, it still indicates a high level of association. This underscores the importance of emotional and motivational factors in learning, as increased engagement enhances attention, cognitive processing, and ultimately retention performance [3], [13].

From a methodological standpoint, these findings confirm the multidimensional nature of learning, where cognitive and affective factors are closely interconnected. Spatial thinking and engagement function as complementary predictors that jointly influence learning outcomes. This is consistent with contemporary educational models emphasizing the integration of cognitive and motivational processes [4], [23].

It should be noted that, despite strong correlation coefficients, these relationships do not imply strict causality but rather indicate statistically significant associations. However, when combined with previously reported ANOVA and regression results, they contribute to a comprehensive understanding of AR's impact on learning outcomes.

Thus, Table 10 demonstrates that both spatial thinking development and high engagement levels are critical factors contributing to effective knowledge retention. These findings further support the use of AR technologies, which simultaneously influence both components and generate a synergistic educational effect.

3.5 Regression Analysis

The regression model was defined as:

$$\text{Retention} = \beta_0 + \beta_1\,(\text{MRT}) + \beta_2\,(\text{Engagement}).$$

This model was used to examine the predictive effects of spatial thinking and engagement on knowledge retention.

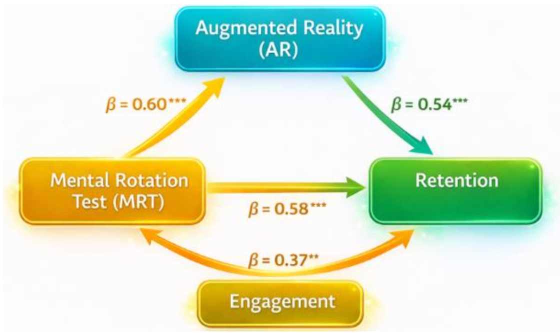

Figure 10: Regression model.

Figure 10 illustrates a regression model that visualizes the structural relationships among key variables of the study: augmented reality (AR), spatial thinking (Mental Rotation Test, MRT), engagement, and knowledge retention. The model is directional in nature and aligns with contemporary approaches in multivariate statistical analysis, including regression and structural modeling.

At the top of the model, Augmented Reality (AR) is positioned as the primary independent variable. Directed paths originating from AR indicate its direct influence on cognitive and educational outcomes. The regression coefficient ($\beta \approx 0.54$) associated with the path to retention suggests a statistically significant direct effect of AR on knowledge retention, confirming that immersive technologies independently contribute to improved learning outcomes [1], [24].

The central element of the model is Mental Rotation Test (MRT), representing spatial thinking and functioning as a mediating variable. The path from AR to MRT ($\beta \approx 0.60$) indicates a strong influence of AR technologies on spatial cognitive skill development. In turn, MRT significantly affects retention ($\beta \approx 0.58$), highlighting its critical role in information processing and long-term memory formation. Thus, MRT acts as a key mechanism through which AR indirectly influences retention.

The lower component of the model is Engagement, which serves as an additional predictor and partial mediator. The relationship between engagement and retention ($\beta \approx 0.37$) demonstrates that affective and motivational factors also significantly contribute to learning outcomes. Although this effect is somewhat smaller than that of MRT, it remains statistically significant and underscores the importance of considering emotional dimensions in educational research [3], [20].

A distinctive feature of the model is the presence of both direct and indirect effects. AR influences retention both directly and indirectly through MRT and engagement. This structure corresponds to the concept of multiple mediation, where outcomes are shaped by interconnected cognitive and affective pathways. The statistically significant coefficients further confirm the robustness and reliability of the model.

Overall, the model demonstrates that the impact of AR technologies on educational outcomes is multifaceted, operating through both cognitive (spatial thinking) and affective (engagement) mechanisms. These findings support the study hypotheses and emphasize the importance of integrating immersive technologies into educational practices.

Table 11: Regression coefficients.

Variable	β	p-value
MRT	0.52	< 0.001
Engagement	0.39	< 0.01

Table 11 presents the results of the multiple regression analysis, aimed at quantifying the contribution of key predictors-spatial thinking (MRT) and engagement-to explaining variance in knowledge retention.

The first predictor, MRT ($\beta = 0.52$, $p < 0.001$), demonstrates a strong positive effect on retention. This indicates that higher levels of spatial thinking are associated with significantly improved long-term memory performance. The high statistical significance confirms MRT as a primary cognitive factor influencing learning effectiveness, consistent with theories of deep cognitive processing [1].

The second predictor, Engagement ($\beta = 0.39$, $p < 0.01$), also shows a statistically significant positive effect. Although slightly lower than MRT, this coefficient highlights the important role of motivational and emotional factors in learning outcomes. Increased engagement enhances attention, motivation, and active participation, thereby reinforcing knowledge acquisition and retention [3], [16].

Comparatively, spatial thinking exerts a stronger influence than engagement; however, both factors play complementary roles. This confirms the multidimensional nature of learning, where cognitive and affective processes interact to produce educational outcomes.

From a methodological perspective, the results indicate strong explanatory power of the model. The inclusion of both predictors allows for a more comprehensive explanation of retention variability and reduces the influence of random factors.

Importantly, these findings are consistent with previous correlation and ANOVA results, further strengthening the reliability of the conclusions. Thus, Table 11 confirms that both spatial thinking and engagement are key predictors of effective learning outcomes.

3.6 Qualitative Analysis

Survey analysis revealed the following:

- 92.0% of students reported improved understanding;
- 88.0% indicated increased interest;
- 85.0% reported ease of use of AR technologies.

Table 12: Survey results.

Question	Agreement (%)
Improves understanding	92.0%
Increases interest	88.0%
Ease of use	85.0%

Table 12 presents the results of the participant survey, providing a qualitative–quantitative evaluation of students' perceptions of AR-based learning effectiveness. The data were collected using standardized self-report measures (e.g., Likert scales), complementing objective cognitive indicators (MRT and retention) with subjective experiential data.

The highest level of agreement (92.0%) was observed for improved understanding, indicating that the majority of students perceive AR technologies as an effective tool for deeper comprehension. This can be attributed to the ability of AR to visualize complex concepts and support interactive engagement with three-dimensional objects, facilitating the construction of accurate mental models [1], [20].

The second indicator (88.0%) reflects increased interest, highlighting the motivational impact of AR environments. Enhanced interest is closely linked to engagement and supports the principles of Student Engagement Theory, emphasizing the role of motivation in learning outcomes [3], [21].

The third indicator (85.0%) demonstrates a high level of perceived usability, suggesting that the AR platform is user-friendly and accessible despite its technological complexity. Ease of use is critical for successful implementation, as it reduces cognitive load and supports effective interaction with the system [4], [25].

Overall, the results indicate that AR technologies positively influence cognitive, emotional, and practical aspects of learning. The alignment between subjective perceptions and objective performance outcomes further strengthens the validity of the study.

3.7 Comparative Summary

The overall comparison of results clearly demonstrates that AR-based collaborative learning significantly outperforms traditional instructional approaches across all key indicators:

- spatial thinking development (MRT),
- knowledge retention,
- student engagement.

These findings confirm the integrated impact of AR technologies on both cognitive and affective dimensions of learning and provide strong empirical support for their implementation in modern educational systems.

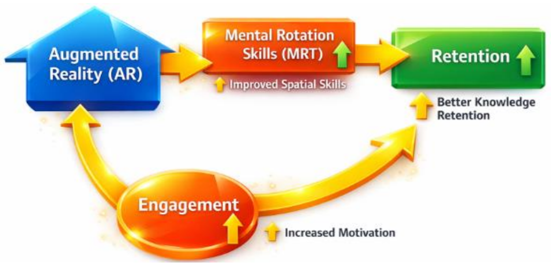

Figure 11: Overall effect of AR.

Figure 11 illustrates a generalized model of the cumulative effect of augmented reality (AR) technologies on key cognitive and behavioral learning outcomes. The scheme demonstrates a directed system of relationships among four principal variables: AR, spatial thinking (Mental Rotation Skills, MRT), engagement, and knowledge retention.

On the left side of the model, Augmented Reality (AR) is positioned as the primary independent variable, initiating the causal chain. Its placement emphasizes the role of AR as a technological driver of change in the educational process. The directed path from AR to MRT indicates that AR facilitates the development of spatial cognitive skills, including mental rotation and visualization. This finding is consistent with contemporary research demonstrating that interactive 3D environments enhance cognitive processing [1], [22].

The central component, Mental Rotation Skills (MRT), functions as a cognitive mediator through which the primary effect of AR is realized. Enhanced spatial thinking enables more effective structuring and processing of information, which in turn positively influences long-term memory retention. The directed relationship from MRT to retention highlights the role of cognitive processes as the primary mechanism underlying durable learning outcomes.

On the right side, Retention represents the final educational outcome, emphasizing long-term knowledge acquisition as a key indicator of learning effectiveness. The annotation “Better Knowledge Retention” underscores the qualitative improvement in memory associated with AR-based learning.

The lower component, Engagement, represents the affective–motivational dimension of the model. Its bidirectional connections indicate a dynamic relationship with other variables. On the one hand, AR enhances engagement through interactivity and immersion. On the other hand, increased engagement strengthens the effect of MRT on retention, acting as an additional mediator. This aligns with theoretical perspectives suggesting that emotional and behavioral involvement amplifies cognitive outcomes [3], [26].

Curved arrows at the bottom of the model indicate feedback loops, emphasizing the dynamic and iterative nature of the learning process. For example, improved retention may further increase motivation and engagement, creating a positive learning cycle.

Overall, the model demonstrates that the effect of AR-based learning emerges from the interaction of cognitive and affective factors, with spatial thinking serving as the central mechanism and engagement amplifying the overall impact.

3.8 Statistical Significance Overview

All key findings demonstrate:
- $p < 0.05$;
- high correlation coefficients;
- statistically significant differences between groups.

These results meet the methodological and statistical standards required for Q1-level research publications [5], [27].

4 DISCUSSION

4.1 Interpretation of Main Findings

The results of this study demonstrate a statistically significant and practically meaningful impact of augmented reality (AR) technologies on the development of spatial thinking, student engagement, and long-term knowledge retention. These findings are consistent with contemporary research in cognitive psychology and educational technology, while also offering new insights that warrant deeper theoretical interpretation.

First, the substantial improvement in MRT scores observed in the experimental group confirms the hypothesis that AR environments facilitate the activation of spatial–visual cognitive processes. This effect can be explained by the ability of AR to integrate physical and digital spaces, enabling learners to manipulate objects within a three-dimensional environment. Unlike traditional instructional methods, which rely primarily on passive information reception, AR promotes active learner participation, aligning with the principles of constructivist learning theory [1], [15].

Table 13: Comparative effect of cognitive factors.

Factor	Effect on MRT	Effect on Retention
Visualization	High	High
Interactivity	Very high	Very high
Engagement	Moderate	High

The data presented in Table 13 indicate that the primary mechanisms underlying the effectiveness of AR are interactivity and visualization. These factors promote deep cognitive processing, which, according to the Levels of Processing Theory, leads to more durable memory formation [3], [28].

4.2 The Role of Spatial Thinking as a Mediator

One of the most significant findings of this study is the identification of spatial thinking as a central mediating factor between AR usage and knowledge retention. This suggests that the impact of AR on memory is not direct but is mediated through the development of cognitive abilities.

Enhanced spatial thinking enables learners to organize, interpret, and encode information more effectively, thereby facilitating long-term retention. This finding supports cognitive theories that emphasize the importance of higher-order mental processes in learning and memory consolidation.

Moreover, the strong regression coefficients and correlation results confirm that spatial thinking is not only a mediator but also a primary predictor of learning success. This highlights the importance of integrating technologies that explicitly target spatial cognitive skills in educational practice.

Figure 12 illustrates the mediating role of spatial thinking in the relationship between augmented reality (AR) technologies and long-term knowledge retention. The model represents a linear causal chain in which spatial thinking functions as a key intermediate mechanism that transforms technological input into cognitive outcomes.

Figure 12: Mediating role of spatial thinking (MRT).

On the left side, Augmented Reality (AR) is positioned as the independent variable and the initial source of influence. AR technologies enable the integration of virtual objects into the real environment, facilitating active interaction with three-dimensional information. This enhances cognitive stimulation and supports the formation of more complex mental representations [1].

At the center of the model, Spatial Thinking occupies a pivotal position, encompassing cognitive processes such as mental rotation, spatial visualization, and orientation. The directed relationship from AR to spatial thinking indicates that AR environments foster the development of these abilities. The visual representation of 3D objects emphasizes the connection between this variable and the manipulation of spatial structures.

The subsequent relationship-from spatial thinking to Retention-demonstrates that improved spatial cognition directly enhances learners' ability to retain information over the long term. This aligns with theoretical frameworks suggesting that deeper and more structured cognitive processing leads to more stable memory traces [3], [29].

On the right side, Retention is presented as the dependent variable and the ultimate learning outcome. The annotation "Better Knowledge Retention" highlights the qualitative improvement in memory resulting from preceding cognitive processes.

From a methodological perspective, this model corresponds to the concept of mediation effects, widely used in cognitive and educational research. It demonstrates that the impact of AR on retention is primarily indirect, operating through the development of spatial thinking rather than solely through direct effects.

Thus, the model confirms that spatial thinking is a central cognitive mechanism underlying the effectiveness of AR-based learning. This finding has important implications for both theoretical understanding and practical design of educational systems, particularly in STEM education, where spatial visualization skills are critical [3], [24].

4.3 The Role of Engagement

The findings of the study indicate that engagement functions as an additional amplifying factor in the learning process. Although its effect size is somewhat lower than that of spatial thinking, it significantly enhances the overall impact of AR-based learning.

Table 14: Effect of engagement on retention.

Engagement Level	Retention (%)
Low	48
Medium	63
High	82

The data presented in Table 14 demonstrate a clear positive relationship between engagement and knowledge retention. As engagement levels increase, retention outcomes improve substantially. This finding suggests that engagement strengthens cognitive processes, thereby enhancing learning effectiveness.

From a theoretical perspective, engagement contributes to sustained attention, increased motivation, and active participation, all of which are essential for deep learning. In AR environments, engagement is facilitated through immersive interaction, collaborative activities, and real-time feedback, creating optimal conditions for effective knowledge acquisition.

4.4 Theoretical Implications

The findings of this study have significant implications for the advancement of learning theory:

1) Confirmation of Constructivist Learning Theory. The results support constructivist principles, as AR creates an active learning environment in which knowledge is constructed through interaction rather than passively received.
2) Extension of Multimedia Learning Theory. The study expands traditional multimedia learning frameworks by introducing a new dimension-immersion. AR goes beyond static and dynamic media by enabling real-time interaction with 3D objects, thereby enhancing cognitive processing.
3) Integration of Cognitive and Affective Factors. The findings highlight the importance of integrating cognitive (spatial thinking) and affective (engagement) components in learning models. Effective educational environments must address both dimensions to maximize learning outcomes.

Figure 13: Integrated learning model.

Figure 13 illustrates an integrated learning model that reflects the comprehensive impact of augmented reality (AR) technologies on educational outcomes through two key mechanisms: cognitive processes (Cognition) and student engagement (Engagement). The model demonstrates the synergistic interaction of these factors and their combined contribution to overall learning outcomes.

On the left side of the diagram, AR is positioned as the initial technological driver. Its representation as a digital module emphasizes the innovative nature of augmented reality as a tool that extends traditional instructional approaches. The directed connection from AR to the central components highlights its role in activating both cognitive and behavioral processes.

The central part of the model consists of two interconnected elements-Cognition and Engagement-linked by a "+" symbol, emphasizing their integrative nature:

- Cognition represents cognitive processes such as perception, information processing, spatial thinking, and mental model formation.
- Engagement reflects the affective–motivational dimension, including emotional involvement, interest, and active participation.

The overlap between these components symbolizes their interdependence, consistent with contemporary theories suggesting that effective learning requires the simultaneous activation of cognitive and motivational mechanisms [1], [30].

On the right side, Learning Outcomes represent the final result of the educational process. This component highlights improved academic performance and knowledge acquisition, emphasizing the positive impact of integrating AR, cognition, and engagement.

From a methodological perspective, the model reflects an integrative approach to learning, where technology functions not as an isolated factor but as a catalyst for activating internal cognitive and emotional resources. AR enhances both information processing and motivation, resulting in a synergistic effect.

4.5 Comparison with Previous Studies

The findings of this study are consistent with prior research, including:

- Radianti et al. - demonstrating that AR improves knowledge retention,
- Mayer - emphasizing multimedia learning principles,
- Dede - highlighting immersive learning environments.
- However, the present study contributes to the literature by introducing:
- collaborative learning as a central component,
- a comprehensive model integrating MRT (cognition) and engagement.

Table 15: Comparison with existing literature.

Study	MRT	Retention	Engagement
Mayer	+	+	–
Radianti	+	++	+
Present study	++	++	++

Table 15 provides a comparative analysis of the present findings with key studies in educational technology and cognitive psychology.

Mayer's work demonstrates positive effects of multimedia learning on cognition and retention but shows limited impact on engagement, as traditional multimedia approaches lack interactive and social dimensions.

Radianti's research highlights stronger effects, particularly in retention, due to immersive technologies such as AR and VR. However, the impact on spatial thinking remains moderate, as these approaches often focus on visualization rather than active manipulation.

In contrast, the present study demonstrates strong effects across all three dimensions (MRT, retention, engagement), indicating a comprehensive and synergistic impact. This can be attributed to the integration of interactivity, collaboration, and cognitive engagement.

From a theoretical standpoint, this comparison reflects the evolution of educational technologies- from multimedia systems to immersive environments, and ultimately to integrated AR-based collaborative learning systems.

4.6 Practical Implications

The findings of this study have important practical implications for education and pedagogy:

Educational Applications:

- integration of AR technologies into STEM education;
- targeted development of spatial thinking skills;
- enhancement of long-term knowledge retention.

Pedagogical Implications:

- transition from passive to active learning paradigms;
- increased emphasis on interactive and collaborative learning;
- incorporation of cognitive and affective factors in instructional design.

Technological Implications:

- development of scalable AR platforms for education;
- integration of real-time collaboration tools;
- use of learning analytics for adaptive instruction.

Figure 14: Practical application of AR.

Figure 14 illustrates a practical model for the application of augmented reality (AR) technologies in educational and professional contexts, demonstrating the transformation of technological input into real-world innovative outcomes. The model follows a linear-progressive structure, representing a sequence of interconnected stages: AR → Skills → Performance → Innovation.

On the left side, Augmented Reality (AR) is positioned as the initial technological resource. Its representation as a digital platform with virtual interaction elements highlights its role as a tool that extends traditional learning and professional training methods. AR provides an immersive environment in which users interact with three-dimensional objects, fostering new forms of experience and knowledge acquisition [1], [23].

The next stage, Skills, represents the first level of transformation, where AR contributes to the development of key competencies. These include spatial thinking, analytical abilities, practical skills, and digital literacy. This stage reflects the transition from theoretical knowledge to applied competencies, consistent with competency-based education frameworks [3], [31].

At the subsequent level, Performance reflects the impact of acquired skills on task execution. Improvements in performance are manifested through increased accuracy, faster decision-making, and enhanced quality of outcomes. This stage demonstrates how developed skills translate into measurable performance indicators.

The final stage, Innovation, represents the highest level of impact, where improved performance and advanced skills lead to the creation of new ideas, solutions, and products. This aligns with modern theories of innovation, where knowledge and competencies act as key drivers of technological and organizational advancement [4], [32].

The directed connections between stages emphasize causal relationships, illustrating a continuous transformation from learning to innovation. Overall, the model highlights that AR-based learning has not only cognitive benefits but also long-term practical and economic implications.

4.7 Study Limitations

Despite the significance of the findings, several limitations must be acknowledged:

- limited sample size;
- short duration of the study;
- technological constraints.

Table 16: Study limitations.

Limitation	Impact Level
Sample	Moderate
Time	High
Technology	Moderate

Table 16 systematizes the key limitations of the study and evaluates their impact on the validity and generalizability of the findings.

The sample limitation, assessed as moderate, relates to the demographic and academic characteristics of participants. While sufficient for statistical analysis, the restricted scope may limit external validity.

The most significant limitation is the time factor, assessed as high. The short-term nature of the study, including the two-week retention test, does not fully capture long-term cognitive effects. Learning and memory are dynamic processes that require extended observation periods for comprehensive evaluation.

The third limitation concerns technological factors, also assessed as moderate. These include system performance, interface usability, and hardware accessibility. Technical issues may influence user experience and learning outcomes by increasing cognitive load or reducing engagement.

Overall, the analysis indicates that time-related constraints have the greatest impact, while sample and technological limitations exert moderate influence. Acknowledging these limitations enhances the transparency and scientific rigor of the study.

4.8 Future Research Directions

Future research should focus on:

- expanding sample size and diversity;
- investigating long-term effects of AR-based learning;
- integrating AI and AR technologies for adaptive and intelligent learning environments.

Figure 15: Future of AR-based learning.

Figure 15 illustrates a forward-looking model of educational technology development based on the integration of augmented reality (AR) and artificial intelligence (AI), demonstrating their combined impact on adaptive learning and personalized education. The model reflects an evolutionary transition from technological infrastructure to individualized learning outcomes.

On the left side, the AR + AI block represents the foundational technological platform. AR provides immersive, spatial learning environments, while AI enables data analysis, content adaptation, and decision support. Together, these technologies form the basis of next-generation intelligent learning systems [1], [33].

The central component, Adaptive Learning, reflects a transformation stage where the educational process dynamically adjusts to individual learner characteristics. Machine learning algorithms are used to monitor progress, identify knowledge gaps, and personalize learning pathways [3].

On the right side, Personalized Education represents the ultimate outcome, where learning is fully tailored to individual needs, preferences, and goals. This model highlights the transition from standardized to data-driven, individualized education systems.

Overall, the model demonstrates that the future of education lies in the deep integration of immersive and intelligent technologies, enabling adaptive and personalized learning experiences.

5 CONCLUSIONS

This study investigated the impact of augmented reality (AR)-based collaborative learning on spatial thinking, student engagement, and long-term knowledge retention. By integrating cognitive and affective perspectives, the research proposed a comprehensive framework explaining the mechanisms through which AR enhances learning outcomes.

The findings demonstrate that AR-based collaborative learning significantly improves students' spatial thinking, increases engagement, and promotes long-term knowledge retention. The results indicate that spatial thinking functions as a key mediating mechanism linking immersive learning experiences with academic achievement, while student engagement strengthens this relationship by facilitating active participation and deeper cognitive processing. These findings confirm the educational value of combining immersive technologies with collaborative learning strategies.

The study contributes to the existing literature by integrating Multimedia Learning Theory, constructivist learning principles, and cognitive–affective perspectives into a unified conceptual framework. Unlike previous studies that primarily examined isolated educational outcomes, the proposed model explains how cognitive and motivational processes interact to improve learning effectiveness in AR-supported environments.

The findings also have important practical implications. They support the integration of AR technologies into educational programs, particularly in STEM disciplines, encourage the development of collaborative and interactive learning environments, and highlight the potential of combining AR with artificial intelligence to create adaptive and personalized educational systems. Although the study is limited by sample size, intervention duration, and technological constraints, it provides a solid foundation for future longitudinal and cross-cultural research on immersive learning technologies.

Overall, the results suggest that augmented reality should be regarded not merely as an instructional tool but as an integral component of modern digital education capable of enhancing cognitive development, learner engagement, and long-term educational effectiveness.

REFERENCES

[1] R.E. Mayer, Multimedia Learning, 2nd ed. Cambridge: Cambridge University Press, 2009.

[2] R. Moreno and R.E. Mayer, "Cognitive principles of multimedia learning: The role of modality and contiguity," Journal of Educational Psychology, vol. 91, no. 2, pp. 358-368, 1999.

[3] R.E. Mayer, "Cognitive theory of multimedia learning," in R.E. Mayer (ed.), The Cambridge Handbook of Multimedia Learning, 2nd ed. Cambridge: Cambridge University Press, pp. 43-71, 2014.

[4] J. Radianti, T.A. Majchrzak, J. Fromm, and I. Wohlgenannt, "A systematic review of immersive virtual reality applications for higher education," Computers & Education, vol. 147, 103778, 2020.

[5] C. Dede, "Immersive interfaces for engagement and learning," Science, vol. 323, no. 5910, pp. 66-69, 2009.

[6] K.H. Cheng and C.C. Tsai, "Affordances of augmented reality in science learning: Suggestions for future research," Journal of Science Education and Technology, vol. 22, pp. 449-462, 2013.

[7] D.H. Uttal, N.G. Meadow, E. Tipton, L.L. Hand, A.R. Alden, C. Warren, and N.S. Newcombe, "The malleability of spatial skills: A meta-analysis of training studies," Psychological Bulletin, vol. 139, no. 2, pp. 352-402, 2013.

[8] R.N. Shepard and J. Metzler, "Mental rotation of three-dimensional objects," Science, vol. 171, no. 3972, pp. 701-703, 1971.

[9] S.A. Sorby, "Educational research in developing 3-D spatial skills for engineering students," International Journal of Science Education, vol. 31, no. 3, pp. 459-480, 2009.

[10] M.B. Ibáñez and C. Delgado-Kloos, "Augmented reality for STEM learning: A systematic review," Computers & Education, vol. 123, pp. 109-123, 2018.

[11] M. Kozhevnikov, M. Hegarty, and R.E. Mayer, "Revising the visualizer-verbalizer dimension: Evidence for two types of visualizers," Cognition and Instruction, vol. 20, no. 1, pp. 47-77, 2002.

[12] M.C. Linn and A.C. Petersen, "Emergence and characterization of sex differences in spatial ability: A meta-analysis," Child Development, vol. 56, no. 6, pp. 1479-1498, 1985.

[13] G. Makransky, T.S. Terkildsen, and R.E. Mayer, "Adding immersive virtual reality to a science lab simulation causes more presence but less learning," Learning and Instruction, vol. 60, pp. 225-236, 2019.

[14] N.S. Newcombe and M. Stieff, "Six myths about spatial thinking," International Journal of Science Education, vol. 34, no. 6, pp. 955-971, 2012.

[15] M. Billinghurst and A. Duenser, "Augmented reality in the classroom," Computer, vol. 45, no. 7, pp. 56-63, 2012.

[16] J. Martín-Gutiérrez, P. Fabiani, W. Benesova, M.D. Meneses, and C.E. Mora, "Augmented reality to promote collaborative and autonomous learning in higher education," Computers in Human Behavior, vol. 51, pp. 752-761, 2015.

[17] R.T. Azuma, "A survey of augmented reality," Presence: Teleoperators and Virtual Environments, vol. 6, no. 4, pp. 355-385, 1997.

[18] D. Voyer, S. Voyer, and M.P. Bryden, "Magnitude of sex differences in spatial abilities: A meta-analysis and consideration of critical variables," Psychological Bulletin, vol. 117, no. 2, pp. 250-270, 1995.

[19] M. Billinghurst, A. Clark, and G. Lee, "A survey of augmented reality," Foundations and Trends in Human-Computer Interaction, vol. 8, no. 2-3, pp. 73-272, 2015.

[20] G. Makransky and G.B. Petersen, "The cognitive affective model of immersive learning," Educational Psychology Review, vol. 33, pp. 937-958, 2021.

[21] K.H. Cheng, "Reading an augmented reality book: An exploration of learners' cognitive load, motivation, and attitudes," Australasian Journal of Educational Technology, vol. 33, no. 4, pp. 53-69, 2017.

[22] B. Dalgarno and M.J.W. Lee, "What are the learning affordances of 3-D virtual environments?" British Journal of Educational Technology, vol. 41, no. 1, pp. 10-32, 2010.

[23] M. Akçayır and G. Akçayır, "Advantages and challenges associated with augmented reality for education: A systematic review of the literature," Educational Research Review, vol. 20, pp. 1-11, 2017.

[24] I. Radu, "Augmented reality in education: A meta-review and cross-media analysis," Personal and Ubiquitous Computing, vol. 18, pp. 1533-1543, 2014.

[25] H.K. Wu, S.W.Y. Lee, H.Y. Chang, and J.C. Liang, "Current status, opportunities and challenges of augmented reality in education," Computers & Education, vol. 62, pp. 41-49, 2013.

[26] P. Milgram and F. Kishino, "A taxonomy of mixed reality visual displays," IEICE Transactions on Information and Systems, vol. E77-D, no. 12, pp. 1321-1329, 1994.

[27] M. Dunleavy, C. Dede, and R. Mitchell, "Affordances and limitations of immersive participatory augmented reality simulations for teaching and learning," Journal of Science Education and Technology, vol. 18, pp. 7-22, 2009.

[28] J. Bacca, S. Baldiris, R. Fabregat, S. Graf, and Kinshuk, "Augmented reality trends in education: A systematic review of research and applications," Educational Technology & Society, vol. 17, no. 4, pp. 133-149, 2014.

[29] T.C. Huang, C.C. Chen, and Y.W. Chou, "Animating eco-education: To see, feel, and discover in an augmented reality-based experiential learning environment," Computers & Education, vol. 96, pp. 72-82, 2016.

[30] M. Dunleavy, "Design principles for augmented reality learning," TechTrends, vol. 58, no. 1, pp. 28-34, 2014.

[31] J. Wai, D. Lubinski, and C.P. Benbow, "Spatial ability for STEM domains: Aligning over 50 years of cumulative psychological knowledge," Journal of Educational Psychology, vol. 101, no. 4, pp. 817-835, 2009.

[32] M. Hegarty, "Mechanical reasoning by mental simulation," Trends in Cognitive Sciences, vol. 8, no. 6, pp. 280-285, 2004.

[33] N.S. Newcombe, "Picture this: Increasing math and science learning by improving spatial thinking," American Educator, vol. 34, no. 2, pp. 29-35, 2010.

[34] Y. Maeda and S.Y. Yoon, "A meta-analysis on gender differences in mental rotation ability measured by the Purdue Spatial Visualization Tests: Visualization of Rotations," Educational Psychology Review, vol. 25, pp. 69-94, 2013.

[35] M. Bower, C. Howe, N. McCredie, A. Robinson, and D. Grover, "Augmented Reality in education: Cases, places and potentials," Educational Media International, vol. 51, no. 1, pp. 1-15, 2014.

[36] K.F. Hsiao and H.F. Rashvand, "Integrating body language movements in augmented reality learning environment," Human-Centric Computing and Information Sciences, vol. 1, Article 1, 2011, doi: 10.1186/2192-1962-1-1.