



MOBILE AUGMENTED REALITY AS A REMEDIATION TOOL FOR ASSEMBLY DRAWING DECODING: A MIXED-METHODS STUDY

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ABSTRACT

Aim/Purpose	Many learners struggle to decode complex mechanical assembly drawings because decoding requires coordinating 2D interpretation, inferred 3D structure, and kinematic reasoning. This study examines whether a single-session mobile augmented reality (AR) intervention may support below-proficiency learners in reaching a curriculum-relevant competence threshold, how they perceive the AR tool, and what experiential themes characterize AR-supported decoding practice.
Background	Most AR studies in engineering graphics address introductory visualization rather than the higher-order task of interpreting complete assembly diagrams, and few offer theory-grounded explanations of mechanism. This study frames assembly decoding as a representational integration task. It draws on Cognitive Load Theory, the Cognitive Theory of Multimedia Learning, and scaffolding

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	theory to explain which specific AR affordances may reduce extraneous reconstruction demands and support schema formation for struggling learners.
Methodology	A quasi-experimental design with an embedded mixed-methods component was used with 60 second-year baccalaureate students (Sciences et Technologies Mécaniques track, Moroccan technical high school). Students scoring below a diagnostic cutoff ($n = 25$) received a single-session AR remediation using the eDrawings app; the remaining 35 followed the standard pathway without AR. Data sources included pretest and posttest scores, a Technology Acceptance Model questionnaire, and open-ended comments and classroom observation notes.
Contribution	This study contributes theoretically by advancing an integrated framework of cognitive load, multimedia learning, and scaffolding theory to assembly decoding; empirically by providing mixed-method evidence from a classroom remediation context; and practically by translating findings into actionable guidance for implementing AR as a remediation tool.
Findings	All AR remediation learners reached or exceeded the curriculum proficiency threshold on the full-decoding posttest (minimum score = 66/100). On a parallel identification measure, the AR group showed a large pre-to-post improvement ($\Delta M = 49.75$ percentage points, Cohen's $d_z = 3.62$). Technology acceptance was high across all four TAM constructs, with perceived ease of use significantly predicting both perceived usefulness and attitude toward use. Four qualitative themes were identified, spanning representational understanding, engagement, peer collaboration, and technical implementation constraints.
Recommendations for Practitioners	Instructors should structure AR use around explicit 2D-to-3D mapping prompts, sequenced to rubric indicators; assign collaborative roles to formalize peer reasoning; and proactively plan for technical readiness through device specifications and backup provisions.
Recommendations for Researchers	Research should examine which specific AR affordances benefit different learner profiles and clarify the underlying cognitive mechanisms using process-level measures.
Impact on Society	Mobile AR, embedded in well-designed instructional sequences, may help struggling learners reach competency thresholds in technical drawing, with potential implications for workforce readiness in the engineering and manufacturing sectors.
Future Research	Future studies should employ randomized or matched, multi-session designs with delayed posttests and transfer tasks, compare AR with alternative approaches such as CAD or VR, and validate the framework in neighboring domains such as geometric dimensioning and hydraulic schematic interpretation.
Keywords	augmented reality, assembly drawing decoding, cognitive load theory, technology acceptance model, scaffolding; spatial reasoning

INTRODUCTION

Technical drawing is a foundational language in engineering and technical education. In the Moroccan Sciences et Technologies Mécaniques (STM) track, a specialized upper-secondary pathway

broadly comparable to engineering-focused technical programs in other national systems, a core outcome is the ability to understand and use technical documents, especially assembly drawings, which support communication across design, manufacturing, maintenance, and quality assurance.

This paper focuses on decoding complex assembly drawings. Decoding is defined here as an integrative competence comprising three abilities: (a) correctly identifying components using standardized drawing conventions and appropriate technical terminology, (b) inferring coherent 3D structure from 2D representations, and (c) explaining functional links and basic kinematic relations within the assembled system. This definition frames decoding as a representational integration and reasoning task in engineering graphics rather than a purely perceptual or symbol-recognition activity. These three components directly structure RQ1, which examines changes in performance across component identification, functional analysis, and kinematic representation following AR-supported instruction.

Despite its importance, decoding complex assemblies remains difficult for many learners, particularly those who begin with weaker spatial visualization skills. Spatial ability is a strong predictor of performance in engineering graphics learning trajectories (Sorby, 2007) and can be improved through training (Uttal et al., 2013). However, the educational challenge is not simply to develop spatial ability in isolation; it is to help learners apply spatial processing to authentic, information-dense representations in which hidden structures, interfaces, and functional dependencies must be coordinated.

A persistent instructional difficulty is that conventional teaching often relies on static 2D drawings and teacher explanations. For learners below proficiency, this approach imposes substantial cognitive demands: complex assembly decoding requires coordinating multiple information sources simultaneously, and without structured support, mental reconstruction of 3D structures from 2D cues consumes working-memory resources that could otherwise support functional and kinematic reasoning (Sweller et al., 2019). The theoretical foundations underlying this challenge, including cognitive load theory, the cognitive theory of multimedia learning, and scaffolding theory, are developed in the literature review.

These constraints motivate a shift toward learning environments that support representational integration during authentic decoding tasks. Augmented reality (AR) is increasingly considered a pedagogical support because it can provide interactive 3D representations linked to traditional learning artifacts, potentially reducing unnecessary demands for mental reconstruction and supporting multimedia integration processes (Makransky & Petersen, 2021). Evidence syntheses suggest that AR can improve learning and motivation under appropriate design conditions while also documenting constraints such as device issues and usability barriers, and a need for stronger methodological rigor and better alignment between AR features and learning objectives (Akçayır & Akçayır, 2017; Garzón et al., 2019; Mystakidis et al., 2022; Sırakaya & Alsancak Sırakaya, 2022).

However, a clear gap remains. Most AR studies in engineering graphics focus on introductory visualization skills rather than the higher-order task of interpreting complete assembly diagrams that involve hidden interfaces, kinematic constraints, and multi-component reasoning. Studies focusing specifically on AR as targeted remediation for below-proficiency learners are underrepresented, and few provide theory-driven explanations linking specific AR affordances to the cognitive subtasks of assembly decoding. A purely media-comparison framing further risks obscuring mechanisms by conflating the medium with instructional design choices (Buchner & Kerres, 2023). This study addresses this gap by evaluating a mobile AR intervention explicitly designed for struggling learners and grounding its rationale in an integrated theoretical framework.

PURPOSE AND RESEARCH QUESTIONS

The purpose of this study is to evaluate whether a mobile AR-supported instructional workflow can support learners' decoding of complex assembly drawings and to examine learners' acceptance of the AR tool. The study addresses the following research questions:

- RQ1:** What performance changes are observed in decoding complex assembly drawings (component identification, functional analysis, and kinematic representation) following an AR-supported instructional workflow, particularly for initially struggling learners?
- RQ2:** How do learners perceive the AR tool in terms of perceived usefulness, perceived ease of use, attitude toward use, and intention to use?
- RQ3:** What qualitative themes characterize learners' experiences when using AR to decode complex assemblies?

The remainder of the paper is organized as follows. The literature review synthesizes the theoretical rationale, drawing on cognitive load theory, the cognitive theory of multimedia learning, and scaffolding theory, and reviews the empirical evidence on AR in engineering graphics and assembly learning. The Methodology section describes the quasi-experimental mixed-methods design, participants, AR intervention, instruments, and analysis procedures. The Results section presents findings organized by research questions, covering decoding performance, technology acceptance, and qualitative themes. The discussion interprets these findings through the integrated theoretical lens, addresses implications for practice, and acknowledges limitations. The paper concludes with directions for future research.

LITERATURE REVIEW

DECODING AS REPRESENTATIONAL INTEGRATION

Assembly drawing decoding requires learners to coordinate two-dimensional (2D) representations with inferred three-dimensional (3D) structures while reasoning about functional and kinematic relationships among components. This process extends beyond recognizing isolated symbols or applying projection rules. Learners must integrate multiple representational cues, including section views, hidden lines, dimensions, assembly constraints, and component interactions, into a coherent mental model of the mechanical system.

Spatial visualization plays an important role in this process and has long been associated with success in engineering graphics education (Sorby, 2007). Spatial ability is also malleable, with evidence indicating that training can improve performance across diverse learner populations (Uttal et al., 2013). However, authentic assembly decoding involves more than spatial visualization alone. Learners must coordinate structural, functional, and kinematic information simultaneously, making decoding a representational integration task rather than a purely spatial one.

AN INTEGRATED THEORETICAL FRAMEWORK FOR AR-SUPPORTED ASSEMBLY DECODING

This study draws on Cognitive Load Theory (CLT), the Cognitive Theory of Multimedia Learning (CTML), and scaffolding theory. Rather than treating these theories as separate perspectives, they are integrated into a common explanatory framework for understanding how AR may support assembly drawing decoding.

From a CLT perspective, assembly decoding is cognitively demanding because learners must process multiple interacting elements simultaneously. Complex assemblies require attention to component geometry, hidden structures, interfaces, and functional relationships. Additional cognitive demands arise when learners must mentally reconstruct 3D structures from static 2D representations, increasing extraneous cognitive load and reducing the resources available for higher-order reasoning (Sweller et al., 2019).

CTML complements this explanation by focusing on how learners integrate information from multiple representations. Learning is enhanced when instructional materials support meaningful connections between related representations and minimize unnecessary processing demands such as split

attention (Mayer, 2021). In assembly drawing interpretation, learners must continuously coordinate 2D views with inferred 3D structures and functional relationships. Difficulties often arise when these representations remain disconnected or when learners must establish correspondences through extensive mental effort.

Scaffolding theory explains how instructional support can assist learners during such demanding tasks. Scaffolds are temporary forms of assistance that enable learners to perform tasks beyond their unaided capabilities and are progressively reduced as competence develops (Wood et al., 1976). In engineering graphics education, scaffolding may support learners in identifying relevant structural features, interpreting hidden components, and understanding component interactions. Recent work further suggests that tailored cognitive support is particularly beneficial for learners with lower initial competence levels (Vanneste et al., 2024).

Taken together, these theories suggest a common mechanism. CLT identifies excessive reconstruction demands as a source of cognitive difficulty. CTML explains how learning can be improved by supporting integration across representations. Scaffolding theory explains how such support can be delivered during learning activities. Within this framework, AR is not viewed as a scaffold in itself. Rather, AR provides affordances that enable scaffolding through features such as interactive 3D manipulation, visualization of hidden structures, and explicit 2D-to-3D mapping. These affordances are expected to reduce unnecessary reconstruction demands while supporting representational integration and higher-order reasoning.

AR EVIDENCE BASE: BENEFITS AND CONSTRAINTS

A substantial body of research has examined AR in educational settings. Reviews and meta-analyses generally report positive effects on learning achievement, engagement, and motivation (Akçayır & Akçayır, 2017; Garzón et al., 2019; Mystakidis et al., 2022; Sırakaya & Alsancak Sırakaya, 2022). However, these studies consistently emphasize that AR effectiveness depends heavily on instructional design quality and alignment with learning objectives.

Research also identifies recurring implementation challenges, including technical instability, usability barriers, device limitations, and inconsistent methodological practices. Broader syntheses highlight instructional integration as a key moderator of learning outcomes in STEM education (Hidayat & Wardat, 2024), while recent mapping studies document continued growth in applications of engineering and technology education alongside persistent research gaps (Ozyurt & Ozyurt, 2025). These findings suggest that AR should be evaluated not as a technology alone but as part of a broader instructional design strategy.

AR, VR, PHYSICAL MODELS, AND OTHER APPROACHES TO ENGINEERING VISUALIZATION

Several instructional approaches have been used to support engineering visualization and assembly learning, each presenting specific affordances and constraints for the present study's focus on struggling learners and classroom scalability.

Physical models have traditionally been employed to help learners understand component relationships and assembly structures. Recent evidence suggests that AR can provide similar visualization support while offering additional opportunities for interactive exploration and inspection of internal structures that are not easily accessible with physical artifacts (Younes, Younes, Salah, & Khalifa, 2025). Moreover, physical models are limited in their ability to support dynamic annotation, such as highlighting hidden components or illustrating assembly sequences sequentially.

Virtual reality (VR) provides highly immersive learning experiences that can support spatial understanding. However, VR often requires dedicated equipment and greater implementation resources, potentially limiting classroom scalability (Makransky & Petersen, 2021). For tasks that require simul-

taneous coordination between a 2D technical drawing and a 3D model, fully immersive VR environments may isolate learners from the drawing artifact, increasing split-attention demands rather than reducing them.

Computer-aided design (CAD) software offers powerful tools for 3D modeling and visualization in professional engineering contexts. However, operating CAD tools requires substantial procedural and strategic knowledge that extends beyond the visualization task itself (Chester, 2007). For learners who already struggle with assembly decoding, this additional procedural demand may divert cognitive resources away from the core learning objective. The learning curve associated with CAD interfaces can thus represent a barrier to rapid, focused remediation.

Simulation-based learning environments, while effective for understanding dynamic system behavior (De Jong et al., 2013), are typically designed to illustrate operational processes rather than to support the static representational integration required in assembly drawing decoding. The primary challenge for struggling learners in the present context is not understanding how an assembly functions, but rather constructing an accurate mental model from 2D projections before functional reasoning can begin.

Compared with these approaches, mobile AR offers a distinctive combination of advantages for the specific problem addressed in this study. It can connect interactive 3D visualizations directly to existing 2D drawings while relying on relatively accessible and scalable devices (Criollo-C et al., 2021). This capacity to overlay virtual models onto physical drawings makes AR particularly suited to supporting transitions between 2D technical representations and 3D understanding, while minimizing the procedural and cognitive barriers introduced by alternative technologies.

AR IN ENGINEERING DRAWING AND ASSEMBLY LEARNING

AR has been increasingly applied in engineering graphics and broader engineering education contexts (Criollo-C et al., 2021). Recent studies have explored its use in technical drawing activities such as orthographic projection, assembly interpretation, and engineering graphics instruction, reporting improvements in visualization and learner engagement (Tiwari & Bhagat, 2024; Tiwari et al., 2024; Younes et al., 2025a).

A recent meta-analysis reported an overall positive effect of AR in engineering education, with instructional design quality and interactivity emerging as important moderators (Lin & Yu, 2023). Methodological critiques nevertheless caution against attributing learning gains solely to technological features. Media-comparison studies may confound technology effects with instructional design decisions, highlighting the importance of theory-driven evaluations that focus on learning mechanisms rather than technology comparisons alone (Buchner & Kerres, 2023). In guided assembly contexts, Leins et al. (2024) compared head-mounted and handheld AR and reported trade-offs in attention, distraction, and support, underscoring the importance of justifying handheld mobile AR designs for classroom use, where feasibility constraints are central.

REMEDIATION AND SUPPORT FOR STRUGGLING LEARNERS

Although spatial skills training has received considerable attention in engineering education (Sorby, 2007; Uttal et al., 2013), less research has examined instructional approaches specifically designed for learners who struggle to interpret complex assemblies. Traditional remediation strategies frequently focus on isolated spatial exercises, mental rotation tasks, sketching activities, or projection practice. While these approaches can improve foundational spatial abilities, their transfer to authentic assembly decoding tasks remains less certain.

Assembly decoding requires learners to integrate structural, functional, and kinematic information within realistic engineering representations. Consequently, learners who begin below proficiency levels may benefit from interventions that embed support directly within authentic decoding activities.

Recent work on adaptive support and cognitive assistance suggests that scaffolded interventions may be particularly valuable for learners with lower initial competence levels (Vanneste et al., 2024).

CLASSROOM IMPLEMENTATION AND TECHNOLOGY ACCEPTANCE

Educational effectiveness alone does not guarantee sustainable classroom adoption. Factors such as teacher readiness, curriculum alignment, technological infrastructure, usability, and scalability influence whether AR interventions can be successfully implemented in authentic educational settings. These considerations are especially important in technical and vocational education, where instructional innovations must fit existing curricula and available resources.

The Technology Acceptance Model (TAM) provides a useful framework for examining these issues. TAM proposes that perceived usefulness and perceived ease of use influence attitudes toward technology and subsequent intentions to use it (Davis, 1989). Extensions such as TAM2 and UTAUT further highlight the importance of social influence and facilitating conditions (Venkatesh & Davis, 2000; Venkatesh et al., 2003). Recent educational studies continue to support these relationships in explaining adoption intentions for emerging technologies (Saif et al., 2024; Zhang & Zhou, 2024).

GAP AND SYNTHESIS GUIDING THE PRESENT STUDY

Taken together, the literature suggests that assembly drawing decoding is a cognitively demanding representational integration task and that AR can support learning when its affordances are aligned with instructional objectives. However, most AR studies in engineering graphics focus on introductory visualization tasks rather than the higher-order decoding of authentic assembly drawings, which involve component identification, functional reasoning, and kinematic interpretation. Research specifically targeting learners who begin at below-proficiency levels remains limited, and relatively few studies provide theory-driven explanations linking AR affordances to the cognitive subtasks involved in assembly decoding. Preliminary classroom studies have reported encouraging results for AR-supported technical drawing and assembly learning, including orthographic projection, assembly interpretation, and comparisons with physical models (Younes et al., 2025a, 2025b, 2025). Nevertheless, these studies remain exploratory and highlight the need for more rigorous evaluations focused on advanced assembly decoding and struggling learners.

The present study addresses these gaps through an integrated framework combining CLT, CTML, and scaffolding theory. Within this framework, AR affordances, particularly interactive 3D manipulation, visualization of hidden structures, and explicit 2D-to-3D mapping, are conceptualized as scaffold-enabled supports that may reduce unnecessary reconstruction demands and facilitate representational integration during assembly decoding. The study further examines learner acceptance through TAM-based constructs to evaluate conditions for sustainable classroom adoption.

METHODOLOGY

RESEARCH DESIGN AND OVERVIEW

This study employed a quasi-experimental quantitative design with a concurrent embedded mixed-methods component to examine learning outcomes (RQ1), technology acceptance (RQ2), and learners' experiences (RQ3) during a technical drawing practical activity supported by mobile augmented reality (AR). Following Creswell and Plano Clark's (2018) embedded mixed-methods typology, the qualitative strand was nested within the dominant quantitative design to provide explanatory depth and triangulation. Specifically, qualitative data were collected to help interpret quantitative findings, contextualize learners' experiences with the AR intervention, and identify perceived affordances and constraints associated with AR-supported assembly decoding (Fetters et al., 2013).

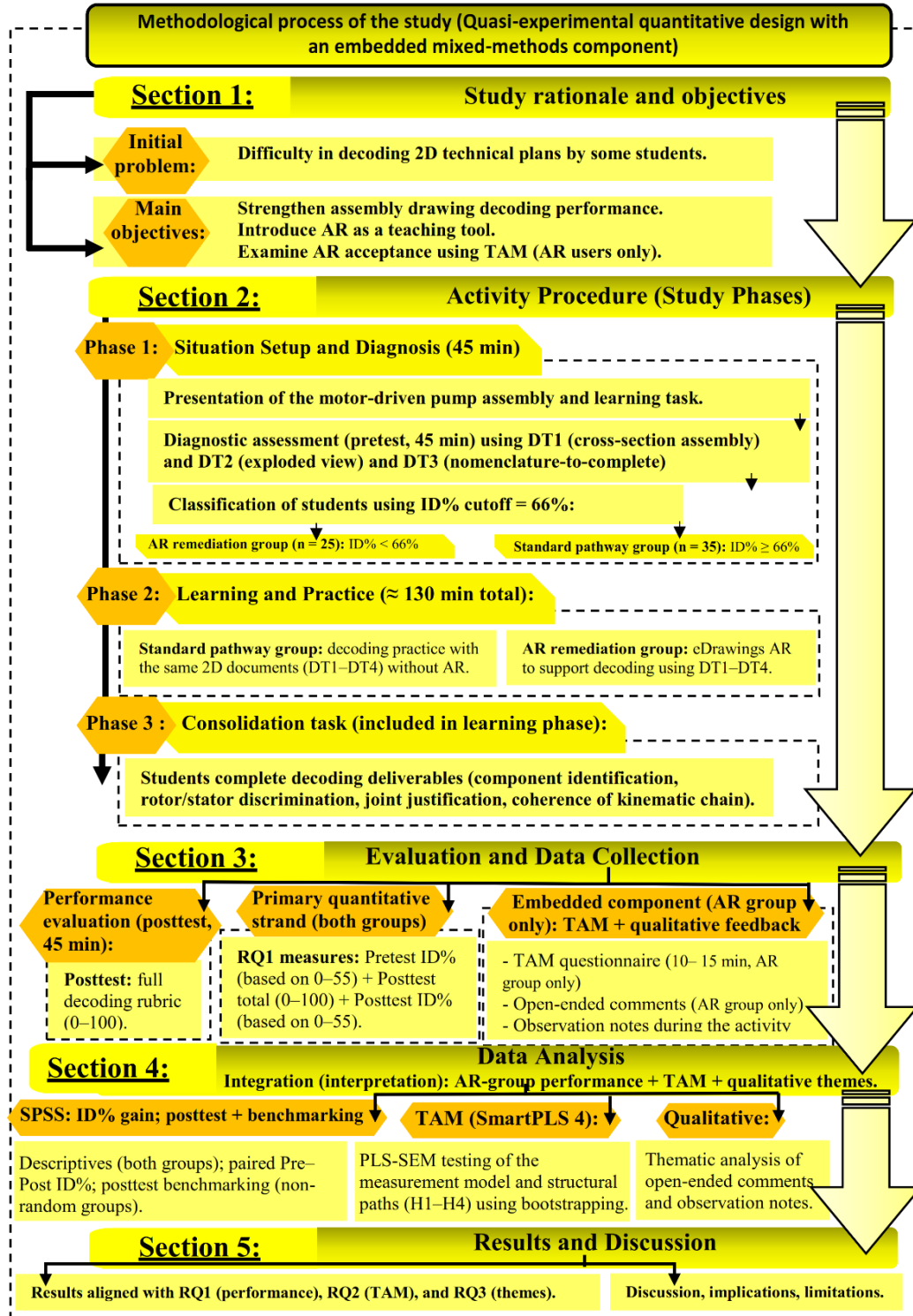


Figure 1. Methodological process of the study (quasi-experimental quantitative design with an embedded mixed-methods component)

Note: N = 60 STM students. Cutoff = 66% (AR remediation: n = 25; standard: n = 35). Both groups used DT1–DT4; only AR group used eDrawings. Outcomes: Pretest ID%, Posttest ID%, full posttest (0–100; threshold=66/100). Embedded (AR only): TAM + qualitative feedback. Analyses: SPSS (paired t-tests, benchmarking) and SmartPLS 4 (PLS-SEM). DT1–DT4 detailed in text.

The primary strand was quantitative, with performance outcomes collected for both groups. Technology acceptance and qualitative evidence were embedded within the AR remediation group only to explain acceptance patterns and provide complementary insight into how learners experienced the intervention. This design was considered appropriate because the study sought to evaluate performance outcomes while also understanding the conditions and learner perceptions associated with AR-supported remediation. The overall study procedure is summarized in Figure 1.

CURRICULUM CONTEXT AND PREREQUISITES

The learning activity was designed to align with the Sciences et Technologies Mécaniques (STM) curriculum issued by the Ministry of National Education, Higher Education, Staff Training and Scientific Research (2006). Although this curriculum document is not currently accessible on the ministry's official web portal, it was retrieved from an academic repository and verified against the study's institutional context.

The assessment targets are consistent with curriculum expectations related to (a) understanding technical objects by identifying parts and mechanical joints and producing schematic representations (Competence C2, especially C22) and (b) communicating using standardized scientific and technological languages and conventions, including technical drawings (Competence C3) (Ministry of National Education, Higher Education, Staff Training and Scientific Research, 2006, p. 12).

Before this activity, students had studied orthographic projection and mechanical joints during the first semester. These competencies were treated as prerequisites. The present study, therefore, focused on the more complex task of decoding a full assembly drawing, including component identification, rotor/stator discrimination, and justification of key joints in the kinematic chain.

CONTEXT, PARTICIPANTS, AND GROUPING PROCEDURE

The study was conducted in a technical drawing module within the STM track at a Moroccan technical high school. Participants were second-year baccalaureate (STM) students enrolled in the same course during the same academic term. A total of $N = 60$ students completed the diagnostic assessment and the posttest.

Sampling rationale

A convenience sample was used because the study was conducted in an intact classroom setting, consistent with authentic classroom-based educational research (Fraenkel et al., 2019). Group classification followed a diagnostic-remediation logic aligned with normal instructional practice.

Several design limitations should be acknowledged explicitly. First, selection bias is inherent because learners were assigned to groups based on a diagnostic cutoff rather than through random assignment. Consequently, the two groups were intentionally nonequivalent at baseline. Second, regression toward the mean is a plausible partial explanation for some gains among learners selected based on low pretest performance (Campbell & Stanley, 1963). Third, the absence of random assignment and the lack of an equivalent control group limit causal inference. Observed differences between groups, therefore, cannot be interpreted as treatment effects. Throughout this study, between-group results are reported only as benchmarking comparisons intended to contextualize posttest performance rather than estimate instructional effects.

Instructional design and learning sequence

The practical session followed an inductive, problem-based approach aligned with the STM curriculum. Students began with a realistic decoding problem (the pump assembly). They progressively mobilized prior knowledge, tested interpretations using the provided technical documents (DT1–DT4), and refined their explanations of how the system operates. Both groups worked with the same learning objectives, technical documents, and time on task. The only difference was the availability of the AR tool for the remediation group.

Figure 2 summarizes the instructional logic of the activity and the intended learning outcomes, illustrating how technical drawing analysis was combined with guided exploration of the assembly.

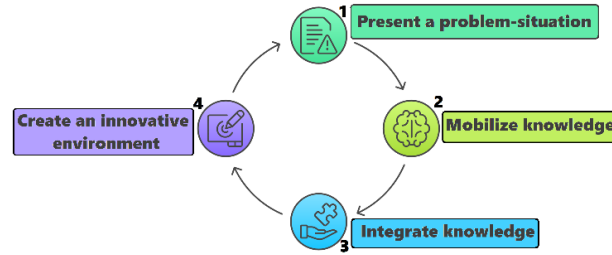


Figure 2. Enhanced student learning through diversified teaching strategies

Figure 3 presents the inductive learning cycle that structured the activity, showing the progression from problem situation to knowledge assimilation.

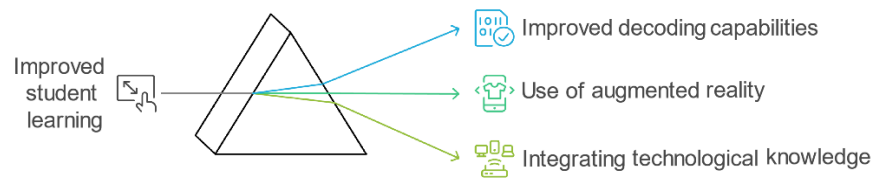


Figure 3. Inductive learning cycle based on problem-solving

Diagnostic assessment and grouping cutoff (Pretest ID%)

All students completed a 45-minute diagnostic pretest based on three technical documents: a cross-section assembly drawing (DT1), an exploded view (DT2), and a nomenclature-to-complete sheet (DT3). The diagnostic pretest assessed component identification only (0--55 points). Pretest identification was converted to a percentage using $\text{Pretest ID}\% = (\text{score}/55) \times 100$ (see Appendix A).

A diagnostic cutoff of $\text{Pretest ID}\% = 66\%$ was used to classify students:

- (i) AR remediation group ($n = 25$): $\text{Pretest ID}\% < 66\%$
- (ii) Standard-pathway group ($n = 35$): $\text{Pretest ID}\% \geq 66\%$

Only the AR remediation group used the AR tool and completed the TAM questionnaire (see Appendix B).

LEARNING TASK AND INSTRUCTIONAL MATERIALS

The learning task required students to decode a complex mechanical assembly and explain key functional and kinematic relationships. The reference system was a motor-driven pump assembly.

The learning materials included four technical documents: DT1 = cross-section assembly drawing; DT2 = exploded view; DT3 = nomenclature-to-complete sheet; and DT4 = kinematic analysis and justification task sheet.

The instructional materials used in the activity are illustrated in the following figures:

- (i) Figure 4 (SCHEMASOFT flash application for mastery exercises): mastery exercise supporting equivalence-class reasoning and functional linkage understanding.
- (ii) Figure 5 (General drawing of a motor-driven pump): shows the main assembly drawing used for decoding.

- (iii) Figure 6 (DT2 General drawing of a motor-driven pump): shows the exploded view used for part identification and assembly reasoning.

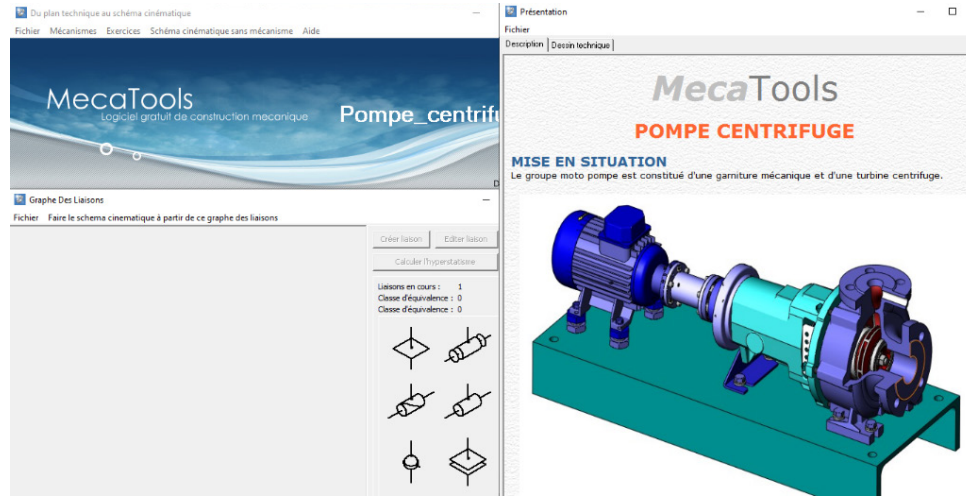


Figure 4. SCHEMASOFT flash application for mastery exercises

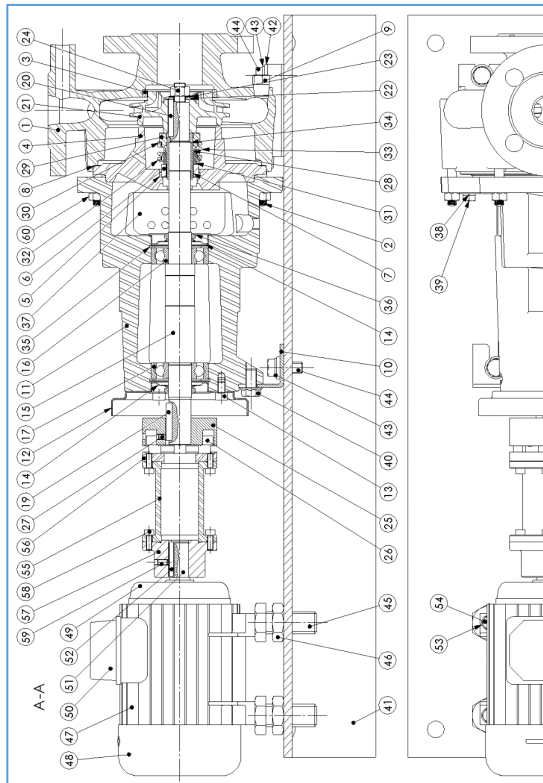


Figure 5. General drawing of a motor-driven pump

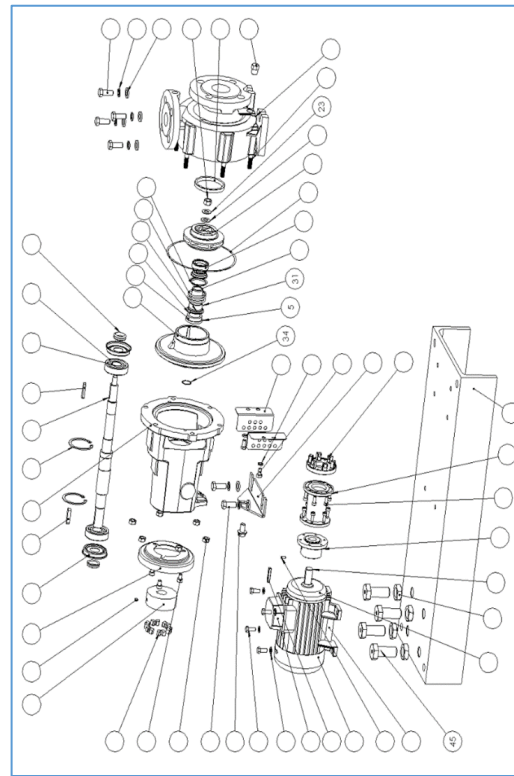


Figure 6. DT2 General drawing of a motor-driven pump

The diagnostic pretest used DT1–DT3, whereas the learning and practice phase used DT1–DT4. The posttest used DT1–DT4 and the full decoding rubric (/100), on the same assembly-decoding task context.

As noted in the instructional design section above, both groups shared the same learning objectives, technical documents, and time allocation; the sole difference was the availability of the eDrawings AR tool for the remediation group.

AR INTERVENTION

AR tool

Students in the remediation group used the **eDrawings** application in a smartphone-based AR mode. The tool allowed visualization and manipulation of a 3D model of the pump assembly. Figure 7 illustrates the interface and the type of AR interactions used during the sessions.

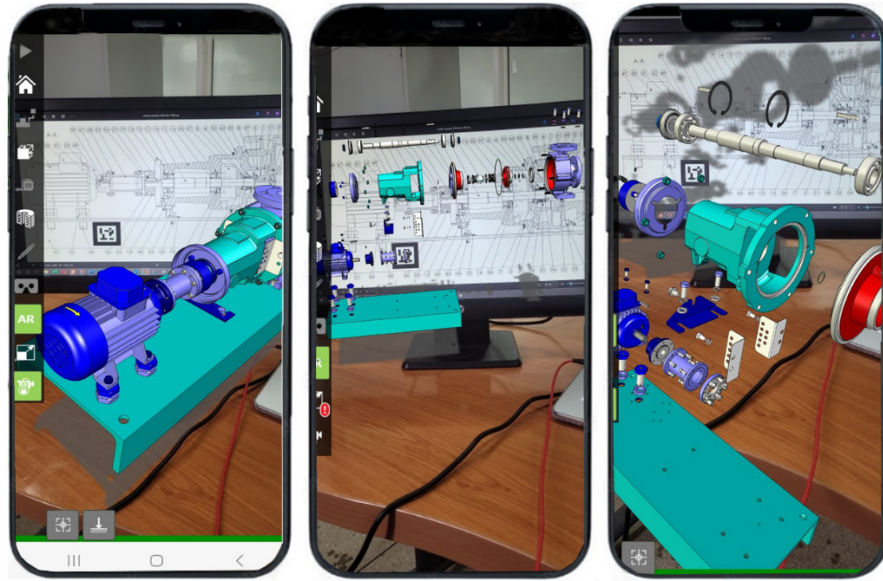


Figure 7. Snapshots of eDrawings application: Moto-pump

AR learning supports

The remediation emphasized AR functions directly linked to assembly decoding:

- (i) viewpoint control through rotation and zoom,
- (ii) internal inspection through transparency and cut views,
- (iii) mapping between 2D drawings and the 3D model to support 2D to 3D interpretation.

These supports were selected to reduce unnecessary demands on mental reconstruction and to support representational integration, consistent with Cognitive Load Theory and multimedia learning principles (Mayer, 2021; Sweller et al., 2019).

Duration and session structure

The full experience was implemented as a single 4-hour practical activity session. The timeline was:

- (i) Diagnostic assessment (pretest): 45 minutes
- (ii) Learning phase (instruction and practice): approximately 2 hours to 2 hours 10 minutes
 - AR remediation group: decoding tasks supported by eDrawings AR
 - Standard-pathway group: decoding tasks using the same documents without AR
- (iii) Posttest: 45 minutes
- (iv) TAM questionnaire (AR group only): 10 to 15 minutes

A short familiarization period of approximately 10 to 15 minutes was included at the start of the learning phase for the AR group. Classroom implementation photos are provided in Appendix C (Figure C1).

Instructional guidance and instructor role

The same instructor facilitated both the AR remediation group and the standard-pathway group throughout the intervention. The practical session followed an inductive, problem-based instructional sequence consistent with the STM curriculum. At the beginning of the session, the instructor introduced the problem situation using the pump assembly as the reference system and clarified the decoding objectives (component identification, rotor/stator discrimination, joint justification, and coherence of the kinematic chain). During the learning phase, guidance was process-focused rather than answer-giving. Specifically, the instructor guided learners' observation and manipulation by prompting them to justify their interpretations with evidence from DT1–DT4 (e.g., section cues, reference numbers, interfaces, and motion constraints), while avoiding the direct provision of solutions or final answers. A whole-class debrief ("mise en commun") was conducted to consolidate shared decoding rules and to align reasoning with standardized technical drawing conventions.

To reduce instructor-related bias, both groups worked under the same learning objectives, technical documents, time on task, and classroom conditions, and received the same pedagogical guidance (questioning, prompting, and justification requests). As established above, the only instructional difference between groups was access to the eDrawings AR tool. AR learners received an additional brief technical familiarization (approximately 10–15 minutes) focused on installing, launching, and manipulating the eDrawings AR model (e.g., rotation, zoom, transparency/cut views). This support was limited to tool operation and troubleshooting and was not intended to provide additional conceptual instruction beyond the shared pedagogical prompts used with both groups. When device limitations prevented some learners from running the application, access was maintained through temporary device sharing/loaning to enable participation in the AR-supported activities.

MEASURES AND INSTRUMENTS

Performance assessments (RQ1)

To interpret end-of-session decoding competence, the curriculum proficiency threshold for the full posttest score was set at 66/100. To address RQ1, performance was measured using the diagnostic pretest and the posttest. Both assessments were designed to capture the decoding competency expected in the STM curriculum. Observable evidence of competency included: correct identification of components using standardized technical terminology, correct interpretation of fixed and moving subassemblies (stator vs rotor), and correct identification and justification of key joints with coherent kinematic reasoning. The targeted competency dimensions are summarized in Figure 8.

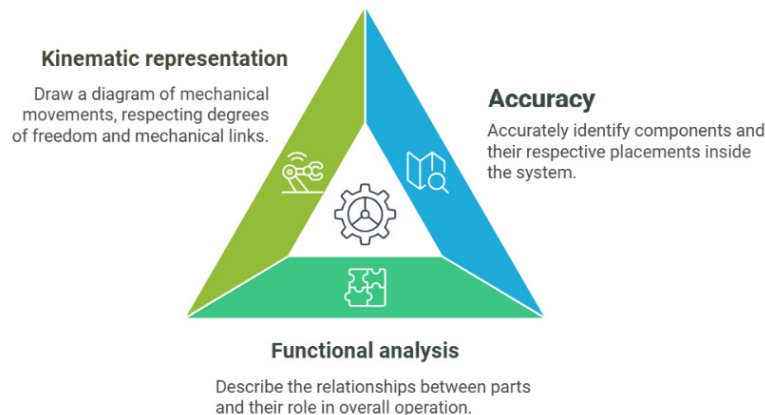


Figure 8. Advanced mechanical engineering skills assessment

Assessment structure and parallel identification measure

The diagnostic pretest (45 minutes) assessed component identification only (0–55 points) using DT1 (cross-section assembly drawing), DT2 (exploded view), and DT3 (nomenclature-to-complete sheet). Pretest identification was converted to a percentage using $\text{Pretest ID\%} = (\text{score}/55) \times 100$. The posttest (45 minutes) used the full decoding rubric (0–100 points), comprising (a) component identification (55 points) based on DT1–DT3 (DT1 cross-section assembly drawing, DT2 exploded view, and DT3 nomenclature-to-complete sheet) and (b) kinematic analysis and justification (45 points) based on DT4 (kinematic analysis and justification task sheet). To enable a strictly comparable pre–post analysis on the identification dimension, the posttest identification subscore (0–55) was extracted and converted using $\text{Posttest ID\%} = (\text{score}/55) \times 100$. This parallel identification measure was used for within-group pre–post testing, whereas the full posttest score (/100) and kinematic subscores (/45) were treated as end-of-session decoding outcomes. It is important to note that the pretest and posttest are not fully parallel instruments. The pretest assessed only identification, while the posttest additionally assessed kinematic reasoning. Therefore, gains on the parallel identification measure support inferences only about progress on the identification dimension. Development in kinematic reasoning must be interpreted through posttest outcomes and subcomponent profiles rather than as a direct pre–post gain estimate.

Rubric structure and scoring rules

The performance rubric produced a total score out of 100 points. It included (a) component identification (55 points) and (b) kinematic analysis and justification (45 points). For transparency and reproducibility, the rubric structure and scoring rules are summarized in Table 1, and the full scoring sheet is provided in Appendix A. The component identification dimension (55 points) was also used to derive a posttest identification subscore for the parallel pre–post analysis described above.

Content validity and scoring reliability: Rubric criteria were reviewed by technical drawing instructors to confirm alignment with STM curriculum expectations and with the decoding tasks used in the module. Scoring followed explicit rules specified in the scoring guide (Appendix A). Calibration examples were used prior to scoring to improve scoring consistency across scripts and across the pretest and posttest administrations.

Table 1. Curriculum-aligned diagnostic and posttest performance rubric for assembly drawing decoding (total = 100 points)

Assessment dimension	Criterion and task	Observable indicator (how evidence is judged)	Scoring rule	Max. pts.
Component identification	Identify components using DT1–DT3	Correct use of standardized technical names for each referenced part. (DT1 cross-section assembly, DT2 exploded view, DT3 nomenclature-to-complete)	1 point = correct terminology; 0.5 = approximate terminology; 0 = missing or incorrect	55
Kinematic analysis and colorization (fixed parts)	Classify stator sub-assembly (fixed parts) using DT4	Completeness and accuracy of fixed-part classification (e.g., casing, bearings, fixed seals, frame, covers) with clear color coding	Score based on completeness, accuracy, and clarity	15
Kinematic analysis and colorization (moving parts)	Classify rotor sub-assembly (moving parts) using DT4	Completeness and accuracy of moving-part classification (e.g., shaft, impeller, keys, inner rings) with clear color coding	Score based on completeness, accuracy, and clarity	15

Assessment dimension	Criterion and task	Observable indicator (how evidence is judged)	Scoring rule	Max. pts.
Mechanical joint justification (primary)	Identify and justify primary rotor-stator joint using DT4	Correct identification of the main joint and a technically coherent justification (e.g., pivot joint with DOF)	Score based on correctness and clarity of justification	5
Mechanical joint justification (secondary)	Identify and justify a critical secondary joint using DT4	Correct identification of a key secondary joint and justification of its mechanical function (e.g., shaft/impeller interference fit)	Score based on correctness and clarity of justification	5
Overall analysis coherence	Provide coherent interpretation of the assembly using DT4	Coherent and consistent explanation of the kinematic chain and functional grouping	Score based on systemic coherence and logical consistency	5
Total				100

Note. DT1 = cross-section assembly drawing; DT2 = exploded view; DT3 = nomenclature-to-complete sheet (identification subscore, 55 points); DT4 = kinematic analysis and justification task sheet (45 points). The post-test used DT1–DT4 and the full decoding rubric (0–100); the identification subscore (0–55) was extracted to compute Posttest ID%. The diagnostic pretest assessed identification only (0–55) using DT1–DT3.

Technology acceptance measures (RQ2)

To address RQ2, technology acceptance was measured only for the AR remediation group using a questionnaire grounded in the original Technology Acceptance Model (TAM) (Davis, 1989). The questionnaire measured four constructs: perceived ease of use (PEOU), perceived usefulness (PU), attitude toward using (ATU), and intention to use (ITU).

A conventional TAM diagram was used to present the constructs and hypotheses tested (Figure 9):

- H1: PEOU positively influences PU
- H2: PEOU positively influences ATU
- H3: PU positively influences ATU
- H4: ATU positively influences ITU

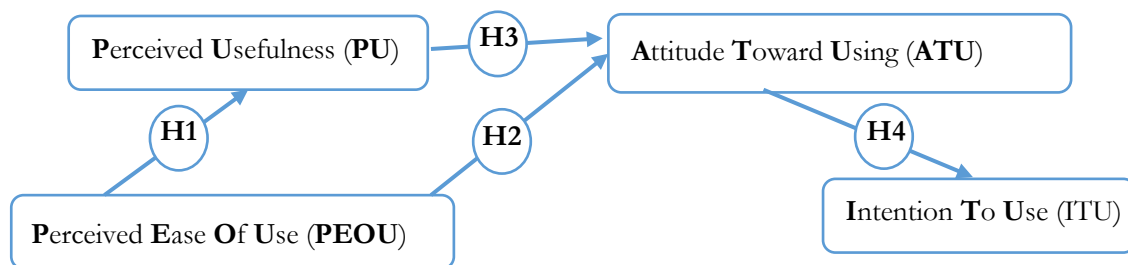


Figure 9. Technology Acceptance Model (TAM) used in this study and hypothesized relationships (H1–H4)

The structure of the questionnaire is summarized in Table 2, and the full questionnaire form is provided in Appendix B. The basic TAM (Davis, 1989) was preferred over extended models such as TAM2 (Venkatesh & Davis, 2000) or UTAUT (Venkatesh et al., 2003) because this study represents an initial exploratory investigation of AR acceptance in this instructional context. The parsimony of the core TAM relationships (PEOU, PU, ATU, and ITU) was considered appropriate before intro-

ducing additional predictors whose relevance would require separate theoretical justification. Moreover, the relatively small AR remediation sample ($n = 25$) constrained the number of latent constructs that could be estimated without increasing model complexity. The potential contribution of constructs such as social influence and facilitating conditions is therefore discussed as a direction for future research.

Table 2. TAM constructs and questionnaire structure (AR remediation group only)

Construct	Abbrev.	Number of items	Item codes (Appendix B)	Scale	Notes for analysis
Perceived Ease of Use	PEOU	4	PEOU1–PEOU4	1–5 Likert	Direct-coded
Perceived Usefulness	PU	4	PU1–PU4	1–5 Likert	Direct-coded
Attitude Toward Using	ATU	3	ATU1–ATU3	1–5 Likert	Direct-coded
Intention to Use	ITU	3	ITU1–ITU3	1–5 Likert	Direct-coded
Implementation constraint (not TAM)	TECH	1	TECH1	1–5 Likert	Reported descriptively; not included in TAM structural model
Open-ended feedback	NA	1	Comment	Open text	Thematic analysis

Qualitative data (RQ3)

Qualitative evidence consisted of (a) open-ended learner comments collected through the post-intervention questionnaire and (b) structured classroom observation notes recorded during the activity. These data were collected to complement the quantitative findings by providing explanatory insight into learners' experiences with AR-supported assembly decoding.

DATA ANALYSIS AND SOFTWARE

Performance analysis (RQ1)

Performance data were analyzed using IBM SPSS Statistics (v26). Descriptive statistics and 95% confidence intervals were computed for (a) Pretest ID% and Posttest ID% (component identification measured on the same 0–55 scale and converted to percent), (b) the posttest total decoding score (/100), and (c) posttest kinematic outcomes (/45) and their subcomponents (Table 1; Appendix A). Inferential procedures and assumption checking followed Field (2018) and Tabachnick and Fidell (2019). Within-group change on the parallel identification measure (Pretest ID% vs. Posttest ID%) was evaluated using paired-samples *t* tests, and effect sizes and confidence intervals were reported to support interpretation. Distributional diagnostics (including Q–Q plots) were inspected, and Wilcoxon signed-rank tests were conducted as a robustness check. Because group membership was defined by a diagnostic cutoff, between-group comparisons were reported as benchmarking rather than causal estimates.

TAM model analysis (RQ2)

TAM hypotheses were tested using PLS-SEM in SmartPLS 4. PLS-SEM was selected because the TAM component was exploratory in nature and involved a relatively small sample ($n = 25$), conditions under which variance-based structural equation modeling is commonly employed (Hair et al., 2021). The measurement model was evaluated using internal consistency and validity indices (Cronbach's alpha, composite reliability, AVE, and HTMT), while the structural model was assessed using bootstrapped path coefficients, confidence intervals, and R^2 values.

Nevertheless, the sample size limits the statistical power to detect small-to-medium effects. Consequently, non-significant paths should be interpreted cautiously, and acceptance-related findings should be considered exploratory and context-specific rather than definitive.

Qualitative analysis (RQ3)

Qualitative data consisted of 25 open-ended learner responses and structured classroom observation notes recorded during the practical activity. Analysis followed Braun and Clarke's (2006) six-phase thematic analysis procedure: (1) familiarization with the dataset through repeated reading, (2) generation of initial codes, (3) searching for themes, (4) reviewing candidate themes, (5) defining and naming themes, and (6) selecting illustrative excerpts.

Coding was primarily inductive, allowing themes to emerge from the data rather than being imposed a priori from the theoretical framework. Initial codes included 2D-to-3D mapping, understanding of component relationships, rotation and inspection behaviors, motivation, peer explanation, shared visual reference, device limitations, and application instability.

To enhance trustworthiness, two researchers independently coded a subset of ten learner responses and compared coding decisions. Initial inter-coder agreement reached 87%. Discrepancies were discussed and resolved through refinement of code definitions before the coding framework was applied to the remaining dataset. The final responses did not yield substantively new codes, indicating thematic sufficiency for this classroom-based dataset (Guest et al., 2006).

Researcher positionality was also considered. Because the first author was involved in the instructional implementation, coding decisions and theme interpretations were reviewed collaboratively with a second researcher to reduce the influence of prior expectations and strengthen analytic credibility (Lincoln & Guba, 1985). Qualitative findings are therefore intended to provide explanatory and contextual insight into learners' experiences rather than independent causal evidence.

All student comments were collected in written French during the session. Excerpts presented in the Results section are direct translations into English; the translation aimed to preserve learner voice and meaning as closely as possible while ensuring grammatical clarity in the target language. Translations were produced by the first author and independently reviewed by the remaining co-authors, all fluent in both languages, to verify accuracy and fidelity to the original responses. Original French responses are retained in the authors' data archive. Each excerpt reported in the Results section is accompanied by an anonymous participant identifier (AR01–AR25) to support traceability while preserving participant anonymity.

ETHICAL CONSIDERATIONS

Participation was voluntary. Students were informed that participation would not affect course grades. Data were anonymized prior to analysis.

RESULTS

In response to RQ1, the following analyses examine decoding performance.

RQ1. DECODING PERFORMANCE (DT1–DT4)

Performance measures and curriculum link

Consistent with STM curriculum expectations related to understanding technical objects (Competence C2, especially C22) and communicating through standardized technical representations (Competence C3) (Ministry of National Education, Higher Education, Staff Training and Scientific Research, 2006, p. 12), decoding performance was evaluated through observable evidence of (a) accurate component identification using standardized terminology and (b) kinematic interpretation of the assembly (stator/rotor discrimination, joint justification, and overall coherence). Scoring followed the rubric described in Table 1 and Appendix A.

The diagnostic pretest (45 minutes) assessed component identification only (0–55) using DT1–DT3, and the score was converted to a percentage as $\text{Pretest ID}\% = (\text{score}/55) \times 100$. The posttest (45 minutes) used the full decoding rubric (0–100), including component identification (55) and kinematic analysis and justification (45). To ensure comparability between time points, the posttest component identification subscore (0–55) was also extracted and converted to $\text{Posttest ID}\% = (\text{score}/55) \times 100$, enabling a strictly parallel pre–post analysis on the identification dimension.

Descriptive results

Table 3 summarizes baseline identification performance and posttest outcomes by group. As expected from cutoff-based grouping, baseline identification differed substantially by design. In practical terms, all learners in the AR remediation group met the curriculum proficiency threshold by the end of the activity (minimum score = 66/100), indicating that learners who initially performed below the diagnostic benchmark achieved an acceptable level of decoding competence during the session. Although the standard-pathway group remained higher on posttest outcomes, the AR remediation group demonstrated meaningful end-of-session performance on the full decoding rubric.

Table 3. Baseline identification and posttest outcomes by group

Group	n	Pretest ID% M (SD)	95% CI	Posttest ID% M (SD)	95% CI	Posttest total (/100) M (SD)	95% CI
Standard pathway	35	75.95 (3.87)	[74.62, 77.28]	84.00 (5.70)	[82.04, 85.96]	85.26 (4.07)	[83.86, 86.65]
AR remediation	25	26.91 (3.89)	[25.30, 28.52]	76.65 (11.74)	[71.81, 81.50]	74.56 (7.65)	[71.40, 77.72]

Note. Pretest ID% and Posttest ID% are based on the same identification scale (0–55) converted to percent.

Parallel within-group improvement on a strictly comparable measure (identification)

Because the pretest assessed identification only, within-group improvement was evaluated on the parallel identification measure (Pretest ID% vs. Posttest ID%). Distributional diagnostics were inspected (including Q–Q plots). Kolmogorov–Smirnov tests on identification change were non-significant in both groups (Standard: $p = .078$; AR: $p = .082$), supporting the use of paired-samples t -tests. Because gain distributions in remediation contexts may still depart from normality, Wilcoxon signed-rank tests were also conducted as a robustness check. As shown in Table 4, both tests converged on the same conclusion.

From a practical perspective, the magnitude of improvement was particularly notable for the AR remediation group. AR remediation learners who initially struggled with component identification were able to identify substantially more components correctly following the AR-supported session, suggesting meaningful progress on the decoding tasks addressed during the intervention.

Table 4. Improvement on the parallel identification measure (0–55 converted to %)

Group	n	Mean change (post–pre)	95% CI of change	t(df)	p	Cohen's dz	Wil- coxon Z	Wil- coxon p
Standard pathway	35	8.05	[6.18, 9.92]	8.75 (34)	< .001	1.48	–5.17	< .001
AR remediation	25	49.75	[44.07, 55.42]	18.10 (24)	< .001	3.62	–4.38	< .001

Note. Identification change is computed on a strictly comparable measure (0–55 converted to percent). Cohen's dz is reported for paired change.

Posttest breakdown (kinematic interpretation subcomponents, /45)

To clarify which higher-order decoding behaviors were demonstrated at the end of the activity, Table 5 reports posttest kinematic subcomponent scores aligned with Appendix A (Part 2 of the rubric). The AR remediation group achieved mid-to-high-performance levels across stator/rotor discrimination, joint justification, and coherence. This pattern suggests that learners not only improved at naming components but also demonstrated competence in interpreting the functional and kinematic aspects of the assembly. Although the standard-pathway group remained higher across these outcomes, the remediation group's performance indicates that learners were able to engage successfully with higher-order decoding tasks by the end of the session.

Table 5. Posttest kinematic interpretation and justification subcomponents (max = 45 pts)

Subcomponent	Max	Standard pathway (n = 35) M (SD)	AR remediation (n = 25) M (SD)
Stator classification	15	13.51 (1.10)	11.88 (1.97)
Rotor classification	15	13.34 (0.97)	10.88 (1.05)
Primary joint justification	5	4.46 (0.51)	3.44 (0.77)
Secondary joint justification	5	3.77 (0.65)	2.96 (0.79)
Overall analysis coherence	5	3.97 (0.71)	3.24 (0.52)
Total kinematics	45	39.06 (1.41)	32.40 (1.96)

Benchmark comparisons between groups (reported descriptively)

Because group membership was determined by a diagnostic cutoff rather than random assignment, between-group comparisons are presented descriptively and should not be interpreted as estimates of instructional effects. Table 6 provides posttest benchmarking outcomes that contextualize the performance of the AR remediation group relative to learners who entered the activity above the diagnostic threshold. The observed differences reflect baseline proficiency differences by design and are reported solely for benchmarking purposes.

Table 6. Descriptive benchmarking outcomes at posttest

Outcome	Standard M (SD), n	AR M (SD), n	Mean difference
Posttest ID%	84.00 (5.70), 35	76.65 (11.74), 25	7.35
Posttest total (/100)	85.26 (4.07), 35	74.56 (7.65), 25	10.70
Posttest kinematics (/45)	39.06 (1.41), 35	32.40 (1.96), 25	6.66

In response to RQ2, technology acceptance was assessed exclusively for the AR remediation group.

RQ2. HOW DO AR USERS PERCEIVE THE AR TOOL (TAM)?

Technology acceptance was assessed exclusively for the AR remediation group, as only these students used the eDrawings AR tool during the remediation phase (Appendix B). This analysis addresses RQ2 by examining learners' perceptions of AR through the Technology Acceptance Model (Davis, 1989).

Descriptive acceptance results

Table 7 reports descriptive statistics for the four TAM constructs (5-point Likert scale). Overall, mean ratings were high across all constructs (all means ≥ 4.5), indicating that learners perceived the AR tool as easy to use and useful for learning and reported positive attitudes and intentions to reuse AR in future learning contexts. In practical terms, learners viewed the AR tool positively across all

dimensions of acceptance. High ratings for perceived usefulness and perceived ease of use suggest that participants considered the AR tool both accessible and beneficial for learning assembly drawing, while positive attitude and intention scores indicate openness to future use in similar educational contexts.

Table 7. Descriptive TAM results
(AR remediation group only; 5-point Likert scale)

Construct	Mean	SD	Interpretation
Perceived Ease of Use (PEOU)	4.6	0.49	High perceived simplicity and intuitiveness
Perceived Usefulness (PU)	4.7	0.45	Strong recognition of AR's learning benefits
Attitude Toward Using (ATU)	4.5	0.50	Favorable disposition toward AR technology
Intention to Use (ITU)	4.6	0.48	Strong willingness to reuse AR in future contexts

Note. Descriptive scores were computed from the raw item responses for each construct (PEOU1–PEOU4, PU1–PU4, ATU1–ATU3, ITU1–ITU3). Higher scores indicate more favorable perceptions.

Measurement model evaluation (SmartPLS 4)

Before testing the structural relationships, the measurement model was evaluated following established PLS-SEM guidelines (Hair et al., 2021). Detailed outputs are provided in Appendix D (Tables D1–D6).

Reliability and convergent validity: Indicator loadings were above the recommended threshold of .70 (Table D1). Internal consistency was satisfactory, with Cronbach's alpha values ranging from .837 to .895 and composite reliability values ranging from .891 to .935 (Table D6). Convergent validity was supported because all AVE values exceeded .50 (range: .672 to .826) (Table D6).

Discriminant validity: Discriminant validity was supported by HTMT ratios below .85 for all construct pairs (range: .113 to .819) (Table D3). Cross-loadings showed that each indicator loaded highest on its intended construct (Table D2).

These results indicate that the TAM constructs were measured reliably and distinctly in this sample, providing an adequate basis for structural model testing.

Structural model results (H1–H4)

The structural model was estimated using the PLS-SEM algorithm, and path significance was assessed using bootstrapping with 5,000 subsamples. Figure 10 presents the TAM structural model with standardized path coefficients and R^2 values for endogenous constructs. Table 8 reports the corresponding bootstrapping results, including confidence intervals, significance tests, and effect sizes (f^2).

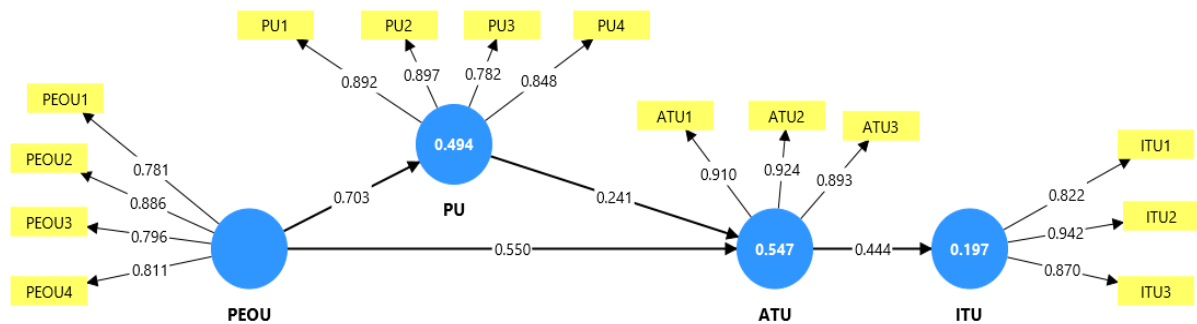


Figure 10. TAM structural model results
(SmartPLS 4 - PLS-SEM algorithm)
with standardized path coefficients and R^2 values

Path coefficients and R^2 values are from the PLS-SEM algorithm. Bootstrapped significance tests, BCa confidence intervals, and effect sizes (f^2) are reported in Table 8. Standardized outer loadings are reported in Table D1.

Table 8. TAM structural model results
(SmartPLS 4; bootstrapping with 5,000 subsamples)

Hypothesis (path)	β	SD	t	p	95% CI	Supported	Effect size (f^2)
H1 (PEOU $\rightarrow$ PU)	0.703	0.062	11.338	< .001	[0.542, 0.781]	Yes	0.975 (Large)
H2 (PEOU $\rightarrow$ ATU)	0.550	0.237	2.321	.020	[0.078, 0.962]	Yes	0.339 (Medium)
H3 (PU $\rightarrow$ ATU)	0.241	0.231	1.043	.297	[-0.151, 0.708]	No	0.065 (Small)
H4 (ATU $\rightarrow$ ITU)	0.444	0.143	3.100	.002	[0.077, 0.654]	Yes	0.246 (Medium)

Note. Confidence intervals were calculated using the bias-corrected and accelerated (BCa) bootstrap method. Effect size interpretation follows Cohen (1988): 0.02 = small, 0.15 = medium, 0.35 = large.

As shown in Table 8, perceived ease of use emerged as the central predictor within the model. Learners who found the AR tool easier to use were more likely to perceive it as useful and to develop positive attitudes toward its use. Positive attitudes, in turn, were associated with stronger intentions to use AR in future learning contexts. The perceived usefulness-to-attitude relationship was not statistically significant in this exploratory sample and should therefore be interpreted cautiously, given the limited statistical power associated with the small sample size.

Explained variance and predictive relevance

The model explained a moderate proportion of variance in perceived usefulness (PU: $R^2 = .494$) and attitude toward using (ATU: $R^2 = .547$), and a smaller proportion of variance in intention to use (ITU: $R^2 = .197$) (Table D4). Predictive assessment using PLSpredict yielded positive $Q^2_{predict}$ values for all endogenous constructs (PU = .413; ATU = .482; ITU = .211), supporting predictive relevance (Table D5) (Shmueli et al., 2019). These results suggest that learners' acceptance of AR in this classroom context was influenced primarily by usability and attitude-related factors, while additional influences beyond the basic TAM framework may also contribute to future adoption intentions.

In response to RQ3, qualitative evidence was collected from two sources within the AR remediation group.

RQ3. WHAT QUALITATIVE THEMES CHARACTERIZE LEARNERS' EXPERIENCES WHEN USING AR?

Qualitative data sources. Qualitative evidence was collected from two sources within the AR remediation group ($n = 25$): (a) open-ended comments written at the end of the questionnaire (Appendix B) and (b) structured observation notes recorded during the 4-hour practical session. These two sources were used to triangulate learners' self-reported experiences with classroom behaviors observed during AR-supported decoding.

Thematic analysis procedure and trustworthiness. Data were analyzed using thematic analysis following Braun and Clarke (2006) six-phase framework: (1) familiarization through repeated reading of comments and observation notes; (2) generation of initial codes (e.g., 2D $\rightarrow$ 3D mapping, clarity of relationships, rotation/inspection, motivation, peer explanation, shared pointing, device limitations, app freezing); (3) searching for themes by clustering related codes; (4) reviewing candidate themes to ensure internal coherence and distinctiveness across the dataset; (5) defining and naming themes; and (6) selecting illustrative excerpts. To enhance trustworthiness, two researchers independently coded a subset of 10 written responses, achieving 87% inter-coder agreement; disagreements were resolved through discussion and refinement of theme definitions. After coding all 25 responses, the

final responses did not yield additional meaningful codes, indicating thematic sufficiency for this classroom-based dataset (Guest et al., 2006).

Qualitative themes

Four themes emerged that characterize AR remediation learners' experiences with the eDrawings AR tool during assembly drawing decoding. Each theme is accompanied by a brief interpretation and an illustrative excerpt drawn from student comments, identified by an anonymous participant code (Table 9). These themes provide explanatory context for RQ1 (performance change) and RQ2 (technology acceptance) without implying causal mechanisms beyond what the design allows.

**Table 9. Qualitative themes with representative excerpts
(AR remediation group only)**

Theme	Short interpretation	Representative excerpt
Improved 2D→3D mapping and understanding	AR helped learners integrate 2D drawings with a manipulable 3D representation, clarifying spatial relations and functional connections during decoding.	<i>"Seeing the parts move in 3D helped me understand how the pump actually works. Before, I could see the lines on paper but didn't know what they meant for the real object."</i> (AR09)
Engagement and sustained attention	AR supported active exploration (rotation/inspection) and persistence on a difficult decoding task.	<i>"It was more like exploring than studying; I lost track of time. I kept wanting to rotate the model to see more details."</i> (AR03)
Collaboration via a shared visual reference	AR facilitated peer explanation and reduced ambiguity in technical communication by providing a common referent.	<i>"We could discuss what we were seeing together – I'd say 'look at this joint' and my partner could see exactly what I meant. It made our discussion much clearer."</i> (AR15)
Device and app-stability constraints	Learning flow and equity depended on device capability; sharing/borrowing devices and app freezing sometimes disrupted the activity.	One student commented: <i>"I couldn't launch the AR app on my phone. It said my device wasn't compatible."</i> (AR12). Another added: <i>"My phone doesn't have enough memory to run the app properly. I had to borrow my friend's phone."</i> (AR18). A third noted: <i>"The app froze several times during the session. I had to restart it and lost some time."</i> (AR22)

*Student comments are direct translations from French; translations preserve learner voice as closely as possible while ensuring readability in English. Each excerpt is identified by an anonymous participant code (ARxx).

Theme 1: Improved 2D-to-3D mapping and functional understanding

Learners repeatedly reported that AR helped them turn DT1/DT2 (2D representations) into a clearer 3D picture of how parts work together and what they do. Observation notes showed that learners frequently used rotation and zoom to check spatial relationships before answering questions about classifying stators and rotors or justifying joints. This theme plausibly explains why AR users were able to complete the decoding tasks more coherently at posttest (see RQ1). Additional learner comment: *"Before using the model, I could identify some parts, but I could not understand how they were connected. The AR view helped me see the relationships between components."* (AR08)

Theme 2: Engagement and sustained attention during decoding

Learners reported that AR made the task more engaging and interactive, which supported sustained effort throughout the session, for example, by repeatedly returning to components they had not yet understood. This theme corresponds with the elevated acceptance ratings noted in RQ2 (high PEOU/ATU/ITU), indicating that ease of interaction and perceived value may facilitate sustained effort during challenging decoding tasks.

Theme 3: Collaboration through a shared visual reference

Both written comments and structured observation notes indicated that the AR model functioned as a shared reference that facilitated peer communication and coordination. Students often pointed to the same part on-screen to coordinate technical terminology and reasoning about joints and the kinematic chain. This collaborative affordance was not measured in the TAM model but emerged as a salient classroom benefit.

Additional learner comment: *“When we discussed the assembly together, it was easier because everyone could look at the same part and explain what they understood.”* (AR05)

Theme 4: Device and app-stability constraints (access and continuity)

A critical constraint concerned device heterogeneity in a BYOD context. Some AR remediation group students’ smartphones could not run the eDrawings AR application effectively due to insufficient RAM, processing capacity, or compatibility limitations. In practice, this required borrowing or sharing devices, including those from students in standard-pathway groups, resulting in unequal access time for AR remediation learners. Additionally, the workflow was interrupted by lagging and freezing, requiring the system to be restarted. This theme demonstrates that classroom effectiveness depends on more than instructional approach alone; it also depends on minimum device specifications and application compatibility within the deployment environment.

An integrated synthesis linking findings from RQ1–RQ3 is presented in the next section.

SUMMARY OF FINDINGS LINKED TO THE RESEARCH QUESTIONS

Findings from the performance, acceptance, and qualitative strands converge on a coherent account of how AR-supported remediation operated in this classroom context. For RQ1, a strictly comparable pre–post analysis was conducted on the component identification dimension (0–55 converted to per cent). The AR remediation group improved substantially from pretest to posttest identification ($\Delta M = 49.75$ percentage points, $t(24) = 18.10$, $p < .001$, Cohen’s $d_z = 3.62$), and this improvement was supported by a robustness check using the Wilcoxon signed-rank test ($Z = -4.38$, $p < .001$) (Table 4). Because the full posttest decoding score is broader in construct coverage than the diagnostic pretest, changes on the overall decoding score are interpreted as end-of-session competency rather than a directly comparable gain. At posttest, all AR remediation learners scored at or above the 66/100 proficiency threshold (minimum = 66/100), indicating that below-threshold learners reached an acceptable competency level by the end of the session (Table 3), and posttest subcomponent scores indicate mid-to-high performance on kinematic decoding elements (Table 5). Between-group comparisons are reported only for benchmarking due to cutoff-based grouping (Table 6).

For RQ2, learners reported a very high level of acceptance of the AR tool (Table 7). The measurement model demonstrated satisfactory reliability and validity (Appendix D, Tables D1–D3 and D6). Structurally, three of four hypothesized TAM paths were supported (Table 8): perceived ease of use predicted perceived usefulness ($\beta = 0.703$, $p < .001$) and attitude toward using ($\beta = 0.550$, $p = .020$), and attitude toward using predicted intention to use ($\beta = 0.444$, $p = .002$). The perceived usefulness to attitude path was not statistically significant ($\beta = 0.241$, $p = .297$). The model explained moderate variance in PU ($R^2 = 0.494$) and ATU ($R^2 = 0.547$), and a smaller proportion of variance in ITU ($R^2 = 0.197$) (Appendix D, Table D4), suggesting that additional determinants of adoption may shape intention in this classroom context.

For RQ3, Theme 4 (device and application stability constraints) suggests that immediate usability experiences and technical friction among AR remediation group participants may have shaped attitudes during this first-exposure, single-session activity (Table 9). Themes 1 and 2 (enhanced 2D-to-3D mapping and sustained engagement through interactive inspection) provide a plausible explanation consistent with the theoretical framework adopted in this study and with Cognitive Load Theory (Sweller et al., 2019). Theme 3 (shared visual reference) highlights a collaborative pathway in which

AR served as a common manipulable referent supporting peer reasoning, a pathway that the quantitative design was not equipped to isolate and that warrants dedicated investigation in future work.

DISCUSSION

Assembly drawing decoding sits at the intersection of spatial reasoning, technical literacy, and functional understanding of mechanical systems. Despite growing interest in augmented reality as a pedagogical tool for engineering graphics, most published studies have concentrated on introductory visualization or isolated spatial tasks rather than on the cognitively demanding work of interpreting a full assembly diagram (Tiware & Bhagat, 2024). Reading an assembly drawing involves more than identifying shapes. It requires learners to transition seamlessly between two-dimensional projections and three-dimensional reasoning, to discern how components interconnect, and to analyze which elements are mobile and which remain stationary. Many reviews have acknowledged that augmented reality (AR) typically produces favorable learning results in STEM fields; however, they also emphasize that researchers seldom clarify the cognitive mechanisms underlying these results or specify the particular conditions in which AR is advantageous (Akçayır & Akçayır, 2017; Garzón et al., 2019; Mystakidis et al., 2022). Positioned in a technical high school (STM baccalaureate) context, this study is guided by three specific research questions aimed at addressing the explanatory gap: whether augmented reality (AR) enhances decoding performance in struggling learners (RQ1), how these learners perceive the technology according to the Technology Acceptance Model TAM (Davis, 1989) (RQ2), and what experiential themes emerge during AR-assisted practice (RQ3).

NOVELTY AND CONTRIBUTIONS TO NEW KNOWLEDGE

The present study contributes new knowledge in three explicit ways.

- (i) **Theoretical contribution (for researchers):** It operationalizes complex assembly decoding as a representational integration problem and explains AR effects through a unified lens combining Cognitive Load Theory (Sweller et al., 2019), the Cognitive Theory of Multimedia Learning (Mayer, 2021), and scaffolding theory (Wood et al., 1976). This provides a principled rationale for why specific AR affordances, including interactive 3D manipulation, internal inspection through transparency and cut views, and simultaneous 2D-to-3D comparison, should support decoding rather than merely increase engagement. Prior AR research in engineering education has typically invoked these frameworks in isolation or as post-hoc interpretive lenses. The present study applies them jointly and prospectively, using the combined framework to generate specific, falsifiable predictions about which AR affordances should matter and why. This shift from generic endorsement of AR toward mechanistic prediction distinguishes the conceptual synthesis offered here from existing contributions in the field.
- (ii) **Empirical contribution (for researchers):** It provides mixed-method evidence from a real classroom remediation context showing that learners below proficiency can reach a curriculum-relevant decoding threshold after AR-supported practice, while also documenting acceptance through TAM and learner-experience themes that clarify boundary conditions and plausible mechanisms. The quantitative strand shows that learners who began below the diagnostic proficiency threshold achieved substantial posttest gains and universally reached the curriculum-relevant threshold in a single AR-supported session. The TAM strand confirms that acceptance was high and that key adoption pathways were operative in this population. The qualitative strand identifies learner-experience themes that elucidate the mechanisms and boundary conditions of these outcomes. Taken together, these three strands provide triangulated, multi-perspective evidence that AR remediation can serve a practically meaningful function for struggling engineering graphics learners, a population and instructional purpose that prior research has largely overlooked.

- (iii) **Practical contribution (for practitioners):** It translates AR integration into an implementable instructional approach by linking AR interactions to decoding objectives and by identifying concrete implementation constraints, notably device capability and app stability, that instructors must plan for. Rather than advocating for AR as a generic supplement, the findings support a structured scaffolding model in which specific AR interactions are explicitly tied to decoding objectives and sequenced to match the representational demands of the assessment rubric. This means that instructors can adopt the approach within a single practical session by organizing AR use around ordered sub-tasks, such as component identification, rotor and stator grouping, joint classification, and coherence verification, and by preparing backup protocols for the technical disruptions that learners in this study reported as a recurring concern.

Beyond demonstrating the potential relevance of the integrated framework, the findings may also refine it. Specifically, the observed improvements were obtained among learners who began below the curriculum proficiency threshold. This pattern is consistent with the interpretation that representational support may be particularly valuable when learners face substantial demands for reconstruction and possess less-developed decoding schemas. Although this possibility cannot be tested directly in the present design, it suggests a theoretically meaningful direction for future research examining whether AR-related benefits differ according to learners' initial proficiency levels.

PLAUSIBLE MECHANISMS UNDERLYING THE OBSERVED PERFORMANCE IMPROVEMENTS (RQ1)

The AR remediation group demonstrated substantial improvement when performance was evaluated using a strictly comparable pre–post measure. Because the diagnostic pretest assessed only component identification (0–55, converted to per cent), we extracted the posttest identification subscore (0–55) and computed a parallel Posttest ID% measure. On this comparable identification dimension, the AR remediation group improved by 49.75 percentage points from pretest to posttest identification ($t(24) = 18.10$, $p < .001$, Cohen's $d_z = 3.62$). A Wilcoxon signed-rank test yielded the same conclusion ($Z = -4.38$, $p < .001$), supporting the robustness of the observed improvement. In addition, all AR remediation learners scored at or above the curriculum proficiency threshold on the full decoding posttest (minimum = 66/100), indicating that below-threshold learners reached an acceptable level of end-of-session decoding competence.

The magnitude of improvement is noteworthy, although practice effects, regression toward the mean, and the diagnostic-remediation structure itself cannot be ruled out as contributing factors. The integrated theoretical lens proposed in this study provides such an explanation by linking specific AR affordances to the cognitive demands of assembly decoding. Consider what happens when a learner faces an assembly drawing armed only with paper views. Hidden geometry must be inferred from dashed lines, and the spatial relationships between rotor and stator components must be reconstructed mentally. This reconstruction consumes working-memory resources that could otherwise support functional and kinematic reasoning. The observed improvements are consistent with the interpretation that AR may alter task conditions by allowing AR remediation learners to rotate, zoom, and inspect internal structures in a manipulable 3D model. Such affordances may externalize part of the reconstruction process and enable learners to verify spatial hypotheses perceptually rather than relying exclusively on mental reconstruction.

From a Cognitive Load Theory perspective, assembly decoding involves high element interactivity, requiring learners to coordinate geometry, hidden structures, part relationships, and joint constraints concurrently. When 3D reconstruction must be performed entirely in working memory, the resources available for schema acquisition become constrained (Sweller et al., 2019). Accordingly, the AR affordances used here are best interpreted as supports that may reduce unnecessary demands on mental reconstruction, a plausible source of extraneous load for novice learners, rather than as evidence of a measured reduction in cognitive load. From a multimedia learning perspective, AR can support coherent mental model construction by helping learners map 2D drawing cues to their 3D

referents and by reducing split attention across representational formats (Mayer, 2021). Qualitative Theme 1 (enhanced 2D-to-3D mapping and functional comprehension) aligns with this mechanism and helps explain why learners reported greater clarity about part relationships and assembly function during the task.

From a scaffolding standpoint, AR may have provided provisional, task-aligned support that enabled learners to perform decoding operations beyond their unaided competence at the diagnostic stage (Wood et al., 1976). This interpretation is consistent with prior evidence that AR is most effective when its affordances are aligned with learners' needs and the representational demands of the task rather than implemented as generic visualization (Garzón et al., 2019; Vanneste et al., 2024). Nonetheless, the present design does not establish whether the observed gains are durable beyond the session; retention and transfer therefore remain key targets for future research.

Benchmark comparisons indicated that the standard-pathway group retained higher performance on kinematic subcomponents and on overall posttest outcomes. Because group membership was determined by a diagnostic cutoff rather than random assignment, these between-group differences should be interpreted as benchmarking rather than differential treatment effects. The findings are consistent with the interpretation that AR may have served as a temporary scaffold for learners initially struggling in this particular session and context. However, the present design does not permit strong causal claims about the mechanisms underlying the observed improvements.

Assessment-related considerations. The study addressed the nonparallel nature of the diagnostic pretest and the full posttest by reporting pre–post change on a strictly comparable identification measure (0–55 converted to per cent), strengthening inferences about progress on that dimension. However, kinematic reasoning components were assessed only at posttest; therefore, development in higher-order decoding should be interpreted via posttest outcomes and subcomponent profiles rather than as a direct pre–post gain estimate. Future studies should employ fully parallel pretest and posttest measures that include both identification and kinematic reasoning, along with delayed posttests, error-pattern analyses, and task-time measures to strengthen inferences about learning progression and generalizability.

Alternative explanations and boundary conditions. Alternative explanations should also be considered. Because the study used a quasi-experimental diagnostic-remediation design rather than random assignment, the observed improvements cannot be attributed exclusively to AR. Practice effects, novelty effects associated with first-time AR use, peer collaboration, instructor guidance, and the remediation structure itself may also have contributed to the outcomes. Consequently, the mechanisms discussed above should be interpreted as plausible explanations consistent with the integrated theoretical framework rather than as demonstrated causal pathways. Future studies should seek to isolate these influences using more controlled designs.

TECHNOLOGY ACCEPTANCE AND SUSTAINABILITY IMPLICATIONS (RQ2)

Participants indicated a highly positive reception of the AR tool across all four TAM components, with mean scores at or exceeding 4.5 on a 5-point scale. The PLS-SEM findings validated the reliability and validity of the measurement model (Hair et al., 2021), with three of the four proposed structural routes substantiated. Perceived ease of use strongly forecasted both perceived usefulness ($\beta = 0.703$) and attitude toward usage ($\beta = 0.550$), while attitude toward usage significantly forecasted intention to use ($\beta = 0.444$, $p = .002$) (Table 8). These findings are consistent with the critical pathways from Perceived Ease of Use (PEOU) to Perceived Usefulness (PU) and from PEOU to Attitude Toward Use (ATU) established in seminal Technology Acceptance Model (TAM) research (Davis, 1989) and provide preliminary support for their applicability to a mobile Augmented Reality (AR) context for assembly decoding, an intersection that has received limited attention in the engineering graphics field.

The non-significant relationship between perceived usefulness and attitude toward use ($\beta = 0.241$, $p = .297$) indicates a notable departure from traditional TAM predictions and requires careful analysis. Three explanations for this pattern deserve consideration. First, limited variability in usefulness ratings – heavily concentrated at the upper end of the scale – may have weakened the predictive relationship by leaving insufficient variance for the model to detect a genuine association. Second, during a brief first-exposure classroom intervention, the immediacy of the usability experience may carry greater weight than reflective judgments about instrumental value in shaping attitudes (Venkatesh & Davis, 2000). When learners are simultaneously working through a demanding decoding task and navigating an unfamiliar interface, the felt smoothness or friction of the interaction is likely to play a particularly prominent role in attitudinal formation, more so than in longitudinal studies or voluntary adoption settings where users have time to develop considered views about usefulness. If the application freezes or the device overheats, the frustration that follows will color the learner's attitude even when that learner recognizes, at an intellectual level, that the tool has genuine educational value. Theme 4 from the qualitative strand, which identified device limitations and software instability as recurring concerns among AR remediation group participants, supports this interpretation. Third, the small sample size ($n = 25$) limits statistical power and increases the likelihood of a Type II error for paths of moderate effect size, meaning that a real but modest relationship between usefulness and attitude may have gone undetected in this study.

The low explained variance in intention to use ($R^2 = 0.197$; Appendix D, Table D4) further suggests that constructs outside the basic TAM model may be particularly relevant in mandatory classroom settings where volitional adoption logic does not fully apply. Facilitating conditions and social influence, both of which are examined in TAM2 and in the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), are plausible candidates. Peer dynamics, device availability, and the way the instructor frames the activity are all factors that these extended models incorporate but that went unmeasured in the present study. Recognizing this gap matters for anyone hoping to predict whether students will actively seek out AR tools after the structured session ends.

Taken together, the TAM findings indicate that mobile AR for assembly decoding is perceived as both usable and useful, and that attitudinal pathways to adoption intention are operative in this population. However, the full adoption picture in classroom settings is likely more layered than the basic TAM is able to capture on its own. Future research should therefore incorporate extended TAM constructs or draw on alternative acceptance frameworks to map the factors shaping classroom adoption more fully and to clarify under what conditions perceived usefulness begins to exert the stronger attitudinal influence that the original model predicts.

WHAT STRATEGIES APPEAR MOST EFFECTIVE, AND WHY? (RQ3 INTEGRATED)

The qualitative strand offers distinctive value for interpreting the plausible processes underlying the quantitative outcomes, because the themes address a question that performance data alone cannot answer: what, specifically, about the AR experience mattered to learners? Each theme maps onto a theoretically identifiable function; taken together, they provide a plausible explanatory account of learners' reported experiences with AR during assembly drawing decoding.

Theme 1: Enhanced 2D-to-3D Mapping and Functional Comprehension

Learners were not passively viewing a 3D model. They were actively alternating between the drawing and the model, verifying whether a feature identified in projection corresponded to what could be seen and manipulated virtually. A student may observe a dashed line indicating concealed geometry in the orthographic view, then rotate the AR model to verify whether that geometry corresponds to a specific interior surface. This intentional cross-referencing is consistent with the representational mapping that Mayer (2021) designates as fundamental to profound multimedia learning. This theme suggests that augmented reality (AR) may have functioned primarily as a representational translation framework, assisting learners in addressing particular projective problems rather than merely offering

generic visual enhancement. This distinction carries theoretical weight: it positions AR as a tool that may reduce unnecessary demands on mental reconstruction (a likely source of extraneous load) at the specific stage where 2D-to-3D correspondence must be constructed, rather than as a motivational supplement.

Theme 2: Sustained Engagement Through Interactive Inspection

Interactive manipulation appeared to support task persistence by allowing learners to verify spatial hypotheses through repeated physical interaction with the model rather than guessing and disengaging. In the context of assembly decoding, where the number of component-level decisions is high and the risk of premature task closure is real, the capacity to repeatedly return to ambiguous regions of the model is a functionally important affordance. A learner unsure about a joint classification could rotate, zoom, and section the model several times before committing to an answer, a process that static reference materials simply do not support. From a CTML perspective, this sustained engagement is plausibly linked to the generative processing thought to support deeper schema formation (Mayer, 2021), rather than merely to extended time on task.

Theme 3: AR as a Shared Referential Anchor for Peer Discussion

The AR model functioned as a shared manipulable object that reduced communicative ambiguity during peer reasoning. Rather than describing a hidden surface or a joint configuration verbally, a learner could rotate the model and point directly to the relevant feature, grounding the conversation in a concrete visual referent. For a task in which imprecise language can readily produce misidentification of joints or motion types, this grounding function is consequential. The shared external representation literature suggests that common referential anchors support more accurate collaborative reasoning by reducing the inferential gap between interlocutors (Tiwari & Bhagat, 2024). This collaborative dimension has received limited attention in the assembly decoding literature and suggests that instructional designs that explicitly structure AR as a collaborative referential tool, through assigned roles and argumentation protocols, may yield learning benefits beyond those of individual AR use alone.

Theme 4: Device and Application Stability Constraints

Application instability and device limitations disrupted the learning flow for a portion of participants, reinforcing a concern that Akçayır and Akçayır (2017) documented systematically and that the field has yet to resolve. The present findings extend that prior work by specifying the instructional consequences: device failures during the session introduced differential access to AR affordances across learners and potentially compromised the homogeneity of the intervention. Such technical constraints deserve explicit attention in AR research designs because they create differential access to core AR affordances during key decoding moments (e.g., resolving projective ambiguities when mapping 2D views to the 3D model). This finding reframes technical reliability not as a peripheral implementation issue but as a moderating variable with direct implications for learning equity within the session. Future implementations should treat minimum device specifications and contingency protocols as components of intervention fidelity rather than as optional logistical considerations.

Integrated reading of the four themes

Reading the four themes in relation to one another yields a coherent practical lesson. The findings are consistent with the interpretation that AR may be most productive when its affordances are deliberately directed toward specific cognitive sub-tasks of decoding, such as resolving projective ambiguities and aligning orthographic views with the assembly's 3D structure.

IMPLICATIONS FOR PRACTICE (ACTIONABLE GUIDANCE)

For technical drawing instructors, the findings of this study translate into five actionable recommendations. These recommendations are grounded in convergent evidence from the quantitative, TAM, and qualitative strands rather than any single data source, and are intended to support the integration of AR into assembly decoding instruction within a single practical session.

First, instructors should use structured prompts that require explicit 2D-to-3D mapping. Rather than allowing learners to explore the AR model freely, each prompt should ask the learner to locate a specific component in the 2D drawing, identify the same component in the 3D model, and then use a concrete drawing cue, such as a section view, a reference number, or a contact surface, to justify their kinematic classification. This prompt structure implements the representational mapping process outlined in Theme 1 and directs AR use toward the specific operations targeted by the assessment rubric, ensuring that engagement with the model fulfills a stated cognitive objective.

Second, the decoding task must be structured into consecutive steps that align with the rubric. A productive process progresses from component identification to the grouping of rotors and stators, followed by the identification of primary and secondary joints, and ultimately concludes with coherence verification. This framework limits unregulated exploration, ensures that augmented reality interactions conform to learner evaluation standards, and reduces the cognitive burden associated with deciding on subsequent actions. Students aware of their current step might allocate their cognitive resources to the content of that step instead of task management.

Third, internal visualization features should be deployed purposefully rather than left on by default. Transparency and cross-sectional views are effective tools for uncovering concealed geometry and elucidating joint configurations; however, indiscriminate activation may introduce unnecessary visual complexity. Limiting these features to the regions where they are most essential, specifically hidden geometry and joint interfaces, directs attentional resources towards the most pertinent elements for kinematic reasoning and prevents inundating learners with extraneous information unrelated to the current sub-task.

Fourth, educators ought to designate organized collaborating responsibilities. Appointing one learner as the navigator, tasked with managing the AR model, and another as the explainer, charged with articulating reasoning and linking observations to the 2D drawing, formalizes the shared referential function identified in Theme 3 as critical for the quality of peer discussions. This role structure ensures that collaborative thinking is grounded in a shared external representation and that both partners are actively involved in complementary facets of the decoding process, rather than merely observing one partner perform the task.

Fifth, technological readiness must be planned for consistently rather than treated as a logistical afterthought. Instructors must define minimal device specifications before the session, implement a concise, standardized familiarization strategy to minimize time lost due to interface ambiguity, and, when feasible, provide backup devices for learners whose equipment malfunctions during the activity. Theme 4 made it clear that device and application instability can disrupt the flow of learning and introduce unequal access to AR affordances among learners. Treating technical preparation as a component of intervention fidelity, rather than an optional convenience, is essential to realizing the pedagogical benefits the other four recommendations are designed to support.

LIMITATIONS AND FUTURE RESEARCH

Several methodological limitations constrain the conclusions and deserve candid acknowledgment. The sample was drawn from a single technical high school (STM track) using convenience sampling, which limits generalizability across contexts. The diagnostic cutoff used to form groups reflects authentic classroom remediation practice but is not equivalent to random assignment; therefore, between-group comparisons should be interpreted strictly as benchmarks rather than treatment-effect estimates. Regression toward the mean remains a plausible partial explanation for some gains among learners selected for low baseline performance.

In addition, cross-contamination cannot be completely ruled out because students were in the same educational setting, and informal exchanges between groups may have occurred outside the intervention activities. Possible novelty effects associated with first exposure to AR also cannot be ruled out

and may have contributed to learner engagement during the session. Finally, although the same instructor taught both groups using a common instructional protocol, instructor-related influences cannot be completely eliminated.

A key measurement limitation concerns the nonparallel structure of the diagnostic pretest and the full posttest. The pretest assessed only component identification, whereas the posttest assessed both identification and kinematic reasoning. To mitigate this concern, the study reported pre–post change on a strictly comparable identification measure by extracting the posttest identification subscore (0–55) and converting it to a percent. However, kinematic reasoning was assessed only at posttest; therefore, development in higher-order decoding should be interpreted through posttest outcomes and subcomponent profiles rather than as a direct pre–post gain estimate. In addition, the single-session design captures immediate performance but does not establish whether benefits were sustained over time or transferred to unfamiliar assemblies. Performance scoring followed explicit rubric rules but relied on a single-rater procedure; therefore, inter-rater reliability could not be reported. Finally, device heterogeneity and occasional application instability may have affected the continuity of AR use for some learners, which should be considered when interpreting implementation feasibility. Because gain distributions in remediation contexts may depart from normality, the study complemented paired-samples *t* tests with Wilcoxon signed-rank tests as a robustness check, which supported the same pre–post conclusion on the comparable identification measure.

For the TAM analysis, the AR group size ($n = 25$) limits statistical power and the stability of coefficients in PLS-SEM. This constraint may have contributed to the non-significant $PU \rightarrow ATU$ path and the modest explained variance in intention to use ($R^2 = 0.197$; Appendix D, Table D4), suggesting that acceptance findings should be treated as preliminary and context-specific. These limitations are consistent with broader patterns in AR education research, where single-institution, short-duration designs with small samples are common, providing ecological validity but constraining generalization (Bermejo et al., 2023).

Three research priorities follow. First, stronger causal inference requires randomized or matched comparisons of AR versus non-AR remediation under equivalent time-on-task conditions within the below-proficiency cohort. Second, retention and transfer should be examined using delayed posttests and novel assembly tasks, with fully parallel pretest and posttest measures that include both identification and kinematic reasoning. Third, the framework’s predictions should be empirically tested by comparing alternative scaffolding designs (e.g., guided prompts vs. freer exploration, stepwise inspection, and targeted annotations) and by adding process-sensitive measures such as interaction logs, cognitive load ratings, and fine-grained error analysis. For instance, the framework predicts that interactive rotation should particularly benefit learners struggling with mental reconstruction. In contrast, internal inspection through sectioning may be more critical for those challenged by hidden joint configurations. This would move the framework from a theoretical proposal toward an evidence-based instructional guideline (Vanneste et al., 2024). The representational integration methodology may also be validated in neighboring technical domains such as GD&T, hydraulic schematic interpretation, and electrical circuit analysis.

CONCLUSION

This study addressed a persistent challenge in technical drawing education: helping learners decode complex assembly drawings that require coordinated 2D interpretation, 3D reconstruction, and functional and kinematic reasoning. Drawing on mixed-methods evidence collected in an authentic classroom setting, the findings provide preliminary evidence that a mobile AR-supported instructional workflow may support learners who begin below curriculum proficiency thresholds in decoding assembly drawing.

The study contributes to the literature in two important ways. First, it extends research on AR in engineering graphics by focusing on remediation for struggling learners engaged in advanced assembly-

decoding tasks rather than on introductory visualization skills alone. Second, it offers a theoretically grounded explanation of the observed outcomes through an integrated framework combining Cognitive Load Theory, the Cognitive Theory of Multimedia Learning, and scaffolding theory. Within this framework, AR affordances such as interactive 3D manipulation, internal visualization, and 2D-to-3D mapping are conceptualized as supports that may facilitate representational integration during decoding activities.

Across the quantitative, technology-acceptance, and qualitative strands, the findings were associated with substantial improvement on the comparable identification measure, high learner acceptance of the AR tool, and learner-reported benefits related to 2D-to-3D understanding, engagement, and collaboration. At the same time, learners also identified practical constraints, particularly device heterogeneity and application stability, highlighting the importance of implementation planning in classroom settings.

The findings should be interpreted in light of several limitations, including the quasi-experimental design, lack of random assignment, small AR-group sample, single-session intervention, non-parallel pretest and posttest measures, and the possibility of novelty, instructor, and contextual influences. Consequently, the study does not establish causal effects but instead offers plausible support for the value of AR-assisted remediation within this educational context.

Future research should strengthen causal inference through randomized or matched designs, examine retention and transfer through delayed post-tests and longitudinal interventions, and replicate the study across educational contexts and technical domains. Further work should also investigate adaptive AR systems and compare AR-supported remediation with alternative instructional approaches, including CAD environments, simulation-based learning, virtual reality, and physical models. Such research would help clarify for whom, under what conditions, and through which mechanisms AR most effectively supports assembly drawing decoding.

REFERENCES

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- Akçayır, M., & Akçayır, G. (2017). Advantages and challenges associated with augmented reality for education: A systematic review of the literature. *Educational Research Review*, 20, 1–11. <https://doi.org/10.1016/j.edurev.2016.11.002>
- Bermejo, B., Juiz, C., Cortes, D., Oskam, J., Moilanen, T., Loihas, J., Govender, P., Hussey, J., Schmidt, A. L., Burbach, R., King, D., O'Connor, C., & Dunlea, D. (2023). AR/VR teaching-learning experiences in higher education institutions (HEI): A systematic literature review. *Informatics*, 10(2), 45. <https://doi.org/10.3390/informatics10020045>
- Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), 77–101. <https://doi.org/10.1191/1478088706qp063oa>
- Buchner, J., & Kerres, M. (2023). Media comparison studies dominate comparative research on augmented reality in education. *Computers & Education*, 195, 104711. <https://doi.org/10.1016/j.compedu.2022.104711>
- Campbell, D. T., & Stanley, J. C. (1963). *Experimental and quasi-experimental designs for research*. Houghton Mifflin.
- Chester, I. (2007). Teaching for CAD expertise. *International Journal of Technology and Design Education*, 17, 23–35. <https://doi.org/10.1007/s10798-006-9015-z>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). Sage.
- Criollo-C, S., Abad-Vásquez, D., Martic-Nieto, M., Velásquez-G, F. A., Pérez-Medina, J.-L., & Luján-Mora, S. (2021). Towards a new learning experience through a mobile application with augmented reality in engineering education. *Applied Sciences*, 11(11), 4921. <https://doi.org/10.3390/app11114921>
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>

- De Jong, T., Linn, M. C., & Zacharia, Z. C. (2013). Physical and virtual laboratories in science and engineering education. *Science*, 340(6130), 305–308. <https://doi.org/10.1126/science.1230579>
- Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs – Principles and practices. *Health Services Research*, 48(6pt2), 2134–2156. <https://doi.org/10.1111/1475-6773.12117>
- Field, A. (2018). *Discovering statistics using IBM SPSS Statistics* (5th ed.). Sage.
- Fraenkel, J. R., Wallen, N. E., & Hyun, H. H. (2019). *How to design and evaluate research in education* (10th ed.). McGraw-Hill Education.
- Garzón, J., Pavón, J., & Baldiris, S. (2019). Systematic review and meta-analysis of augmented reality in educational settings. *Virtual Reality*, 23(4), 447–459. <https://doi.org/10.1007/s10055-019-00379-9>
- Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, 18(1), 59–82. <https://doi.org/10.1177/1525822X05279903>
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage. <https://doi.org/10.1007/978-3-030-80519-7>
- Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139–152. <https://doi.org/10.2753/MTP1069-6679190202>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Hidayat, R., & Wardat, Y. (2024). A systematic review of augmented reality in science, technology, engineering and mathematics education. *Education and Information Technologies*, 29(8), 9257–9282. <https://doi.org/10.1007/s10639-023-12157-x>
- Leins, N., Gonnermann-Müller, J., & Teichmann, M. (2024). Comparing head-mounted and handheld augmented reality for guided assembly. *Journal on Multimodal User Interfaces*, 18(4), 313–328. <https://doi.org/10.1007/s12193-024-00440-1>
- Lin, Y., & Yu, Z. (2023). A meta-analysis of the effects of augmented reality technologies in interactive learning environments (2012–2022). *Computer Applications in Engineering Education*, 31(4), 1111–1131. <https://doi.org/10.1002/cae.22628>
- Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. Sage. [https://doi.org/10.1016/0147-1767\(85\)90062-8](https://doi.org/10.1016/0147-1767(85)90062-8)
- Makransky, G., & Petersen, G. B. (2021). The Cognitive Affective Model of Immersive Learning (CAMIL): A theoretical research-based model of learning in immersive virtual reality. *Educational Psychology Review*, 33(3), 937–958. <https://doi.org/10.1007/s10648-020-09586-2>
- Mayer, R. E. (2021). *Multimedia learning* (3rd ed.). Cambridge University Press. <https://doi.org/10.1017/9781108894333.003>
- Ministry of National Education, Higher Education, Staff Training and Scientific Research. (2006). *Curriculum 1ère année et 2ème année, cycle de baccalauréat. Sciences et Technologies Mécaniques (STM), Sciences de l'Ingénieur* [Curriculum for the first and second years of the baccalaureate cycle. Mechanical Sciences and Technologies (STM), Engineering Sciences]. https://www.academia.edu/14299572/ROYAUME_DU_MAROC_Curriculum_1_%C3%A8re_ann%C3%A9e_et_2_%C3%A8me_ann%C3%A9e_CYCLE_DE_BACCALAU-REAT
- Mystakidis, S., Christopoulos, A., & Pellas, N. (2022). A systematic mapping review of augmented reality applications to support STEM learning in higher education. *Education and Information Technologies*, 27(2), 1883–1927. <https://doi.org/10.1007/s10639-021-10682-1>
- Ozyurt, H., & Ozyurt, O. (2025). Decoding educational augmented reality research trends: A topic modeling analysis. *Education and Information Technologies*, 30(1), 57–87. <https://doi.org/10.1007/s10639-024-12943-1>

- Saif, N., Khan, S. U., Shaheen, I., ALotaibi, F. A., Alnfai, M. M., & Arif, M. (2024). Chat-GPT; validating Technology Acceptance Model (TAM) in education sector via ubiquitous learning mechanism. *Computers in Human Behavior*, 154, Article 108097. <https://doi.org/10.1016/j.chb.2023.108097>
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J.-H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*, 53(11), 2322–2347. <https://doi.org/10.1108/EJM-02-2019-0189>
- Sirakaya, M., & Alsancak Sirakaya, D. (2022). Augmented reality in STEM education: A systematic review. *Interactive Learning Environments*, 30(8), 1556–1569. <https://doi.org/10.1080/10494820.2020.1722713>
- Sorby, S. A. (2007). Developing 3D spatial skills for engineering students. *Australasian Journal of Engineering Education*, 13(1), 1–11. <https://doi.org/10.1080/22054952.2007.11463998>
- Sweller, J., Van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review*, 31(2), 261–292. <https://doi.org/10.1007/s10648-019-09465-5>
- Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (7th ed.). Pearson.
- Tiwari, A. S., & Bhagat, K. K. (2024). Comparative analysis of augmented reality in an engineering drawing course: Assessing spatial visualisation and cognitive load with marker-based, markerless and web-based approaches. *Australasian Journal of Educational Technology*, 40(6), 19–36. <https://doi.org/10.14742/ajet.9217>
- Tiwari, A. S., Bhagat, K. K., & Lampropoulos, G. (2024). Designing and evaluating an augmented reality system for an engineering drawing course. *Smart Learning Environments*, 11, Article 1. <https://doi.org/10.1186/s40561-023-00289-z>
- Uttal, D. H., Meadow, N. G., Tipton, E., Hand, L. L., Alden, A. R., Warren, C., & Newcombe, N. S. (2013). The malleability of spatial skills: A meta-analysis of training studies. *Psychological Bulletin*, 139(2), 352–402. <https://doi.org/10.1037/a0028446>
- Vanneste, P., Dekeyser, K., Ullauri, L. A. P., Debeer, D., Cornillie, F., Depaepe, F., Raes, A., Van den Noortgate, W., & Said-Metwaly, S. (2024). Towards tailored cognitive support in augmented reality assembly work instructions. *Journal of Computer Assisted Learning*, 40(2), 797–811. <https://doi.org/10.1111/jcal.12916>
- Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>
- Wood, D., Bruner, J. S., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry*, 17(2), 89–100. <https://doi.org/10.1111/j.1469-7610.1976.tb00381.x>
- Younes, Z., Younes, Z., Salah, N., El Houssine, E.-C. M., & Khalifa, M. (2025a). A mobile application based on augmented reality for orthogonal projection. In M. E. Auer & T. Rüttmann (Eds.), *Futureproofing engineering education for global responsibility* (Vol. 1281, pp. 41–51). Springer. https://doi.org/10.1007/978-3-031-83520-9_4
- Younes, Z., Younes, Z., Salah, N., El Houssine, E.-C. M., & Khalifa, M. (2025b). The impact of augmented reality on the understanding of assembly drawings: Case study of a gear train. *Proceedings of the 5th International Conference on Innovative Research in Applied Science, Engineering and Technology*, Fez, Morocco, 1–6. <https://doi.org/10.1109/IRASET64571.2025.11008342>
- Younes, Z., Younes, Z., Salah, N., & Khalifa, M. (2025). Enhancing technical drawing education: A study of augmented reality versus physical models. In M. E. Auer & T. Rüttmann (Eds.), *Futureproofing engineering education for global responsibility* (Vol. 1281, pp. 52–63). Springer. https://doi.org/10.1007/978-3-031-83520-9_5
- Zhang, X., & Zhou, M. (2024). Factors affecting university students' intention to use mobile apps for intercultural competence development: A mixed-method approach. *Education and Information Technologies*, 29(6), 6991–7026. <https://doi.org/10.1007/s10639-023-12106-8>

APPENDIX A: DIAGNOSTIC OBSERVATION GRID FOR TECHNICAL DRAWING DECODING

Diagnostic Assessment Rubric: Pump Motor Technical Drawing Decoding

Documents: DT1; DT2; DT3; DT4.
Duration: 45 minutes
Proficiency threshold: 66/100

ASSESSMENT CRITERIA	DESCRIPTION	SCALE	POINTS
PART 1: COMPONENT IDENTIFICATION (55 pts)			
Component identification (No. 1 to 55)	Using DT1, DT2 and DT3, Identify each component by its standardized technical name • Correct terminology = 1 pt • Approximate terminology = 0.5 pt • Error/Missing = 0 pt	1 pt × 55	___/55
PART 2: KINEMATIC ANALYSIS AND COLORIZATION (45 pts)			
2.1 Functional Assembly Colorization			
STATOR assembly (fixed parts)	Color in GREEN : casing, bearings, fixed seals, frame, covers... Criteria: comprehensiveness, accuracy, clarity	15 pts	___/15
ROTOR assembly (moving parts)	Color in RED : shaft, impeller, keys, inner rings... Criteria: comprehensiveness, accuracy, clarity	15 pts	___/15
2.2 Mechanical Joint Justification			
Primary Rotor/Stator joint	Identification and justification (e.g., pivot joint with DOF) Clarity of technical explanation	5 pts	___/5
Critical secondary joint	Identification of a key joint (e.g., shaft/impeller interference fit) Justification of mechanical function	5 pts	___/5
Overall analysis coherence	Systemic vision of the kinematic chain Logical distribution of functional assemblies	5 pts	___/5
TOTAL SCORE			___/100

☒ **INTERPRETATION AND PEDAGOGICAL GUIDANCE**

SCORE	INTERPRETATION	GUIDANCE
≥ 66/100	Sufficient competencies in technical drawing reading and kinematic analysis	Standard pathway
< 66/100	Significant difficulties in spatial visualization and/or mechanical understanding	Adaptive Remediation (AR)

IDENTIFIED DIFFICULTIES (check if applicable):

☐ **Visual decoding:** Confusion between views, spatial location challenges
☐ **Advanced conceptualization:** Joint nomenclature, functional justifications

☐ **Kinematic understanding:** Mobile/fixed confusion, rotation guidance issues

ADDITIONAL OBSERVATIONS:

DT1-
DT3DT1-
DT4

Note. DT1 = cross-section assembly drawing; DT2 = exploded view; DT3 = nomenclature-to-complete sheet; DT4 = kinematic analysis and justification task sheet (coupling and mechanical seal; 45 points). The **diagnostic pretest** assessed **component identification only** using **DT1–DT3** and was scored on **Part 1 of this rubric (0–55 points)**; the identification score was converted to **Pretest ID% = (score/55) × 100** for grouping purposes. The **posttest** used the **full rubric (0–100 points)** based on **DT1–DT4** (Part 1: identification, 55 points; Part 2: kinematic analysis and justification, 45 points). For the parallel pre–post analysis, the posttest identification subscore (0–55) was extracted and converted to **Posttest ID% = (score/55) × 100**.

APPENDIX B: TECHNOLOGY ACCEPTANCE AND USER EXPERIENCE QUESTIONNAIRE

Assessment of the eDrawings Mobile AR Tool

Assessment of Teaching Tools and Augmented Reality Implementation

NAME (or code): _____ CLASS: _____ DATE: ____/____/____

Instructions: Please answer based on your experience using the eDrawings AR tool during the pump assembly decoding activity.

Response scale: Strongly disagree (1), Disagree (2), Neutral (3), Agree (4), Strongly agree (5).

1 Perceived Ease of Use (PEOU)

PEOU1. Learning to use the eDrawings AR tool was easy for me.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

PEOU2. I found it easy to navigate and manipulate the 3D model in AR.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

PEOU3. My interaction with the AR tool was clear and understandable.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

PEOU4. It was easy for me to become skillful at using the AR tool.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2 Perceived Usefulness (PU)

PU1. The AR tool helped me better understand the technical drawings.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

PU2. Using AR improved my ability to identify components in the pump assembly.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

PU3. The AR tool was useful for understanding the kinematic chain of the pump.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

PU4. I found the AR tool useful for learning assembly drawing decoding.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

3 Attitude Toward Using (ATU)

ATU1. I enjoyed using the AR tool during the decoding task.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

ATU2. Using AR made the learning activity more interesting.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

ATU3. I have a positive attitude toward using AR for technical drawing.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4 Intention to Use (ITU)

ITU1. I would like to use AR again in future practical sessions.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

ITU2. I intend to use AR tools for other engineering subjects.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

ITU3. I would recommend AR to other students for learning technical drawing.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5 Challenges Encountered (Implementation note, not part of TAM model)

TECH1. I experienced technical difficulties (device, tracking, or application performance).

☐ 1 Strongly disagree ☐ 2 Disagree ☐ 3 Neutral ☐ 4 Agree ☐ 5 Strongly agree

6 Comments and Suggestions (Open-ended)

Please share your thoughts, suggestions or any additional feedback here:

Thank you for your participation! Your feedback is valuable for improving our teaching methods.

Note. Items were administered in French; this figure presents an English translation for reporting.

APPENDIX C: *CLASSROOM IMPLEMENTATION PHOTOS* (FIGURE C1)



APPENDIX D: *PLS-SEM DETAILED OUTPUTS (SMARTPLS 4)*

This appendix reports detailed PLS-SEM outputs for the TAM analysis conducted with SmartPLS 4 on the AR remediation group ($n = 25$). The model used reflective measurement for all constructs. Bootstrapping was performed with 5,000 subsamples, and predictive relevance was assessed using PLSpredict with 10 folds and 10 repetitions.

Table D1. Outer loadings for the reflective measurement model with bootstrapping

Construct	Item	Loading (PLS-SEM)	STDEV	T	P	95% CI
Perceived Ease of Use (PEOU)	PEOU1	0.781	0.121	6.444	< .001	[0.427, 0.929]
	PEOU2	0.886	0.035	25.351	< .001	[0.808, 0.945]
	PEOU3	0.796	0.116	6.849	< .001	[0.446, 0.938]
	PEOU4	0.811	—	—	—	[0.511, 0.939]
Perceived Use- fulness (PU)	PU1	0.892	0.121	7.391	< .001	[0.551, 0.969]
	PU2	0.897	0.114	7.898	< .001	[0.582, 0.970]
	PU3	0.782	0.111	7.059	< .001	[0.429, 0.905]
	PU4	0.848	—	—	—	[0.410, 0.960]
Attitude Toward Using (ATU)	ATU1	0.910	0.052	17.518	< .001	[0.771, 0.972]
	ATU2	0.924	0.028	33.303	< .001	[0.851, 0.966]
	ATU3	0.893	0.047	18.967	< .001	[0.770, 0.959]

Construct	Item	Loading (PLS-SEM)	STDEV	T	P	95% CI
Intention to Use (ITU)	ITU1	0.822	0.163	5.048	< .001	[0.327, 0.955]
	ITU2	0.942	0.083	11.315	< .001	[0.545, 0.977]
	ITU3	0.870	0.110	7.879	< .001	[0.525, 0.961]

Note. All loadings exceed the recommended threshold of .70, supporting indicator reliability. Loadings are from the PLS-SEM algorithm; STDEV, t, p, and confidence intervals are from bootstrapping. Items with “—” reflect values not displayed in the exported bootstrapping table; BCa confidence intervals are reported as available.

Table D2. Cross-loadings matrix

ITEM	PEOU	PU	ATU	ITU
PEOU1	0.781	0.455	0.573	0.748
PEOU2	0.886	0.722	0.714	0.351
PEOU3	0.796	0.551	0.463	0.322
PEOU4	0.811	0.537	0.576	0.397
PU1	0.572	0.892	0.438	0.021
PU2	0.573	0.897	0.440	0.042
PU3	0.689	0.782	0.703	0.113
PU4	0.515	0.848	0.486	0.097
ATU1	0.661	0.513	0.910	0.377
ATU2	0.675	0.655	0.924	0.384
ATU3	0.625	0.538	0.893	0.375
ITU1	0.491	0.019	0.324	0.822
ITU2	0.549	0.135	0.417	0.942
ITU3	0.408	0.060	0.370	0.870

Note. Bold values indicate each item's loading on its intended construct. All items load highest on their intended construct, supporting discriminant validity.

**Table D3. Discriminant validity:
Heterotrait–Monotrait ratio (HTMT)**

Construct pair	HTMT	Interpretation
ITU ↔ ATU	0.498	Discriminant validity established (< 0.85)
PEOU ↔ ATU	0.819	Discriminant validity established (< 0.85)
PEOU ↔ ITU	0.608	Discriminant validity established (< 0.85)
PU ↔ ATU	0.678	Discriminant validity established (< 0.85)
PU ↔ ITU	0.113	Discriminant validity established (< 0.85)
PU ↔ PEOU	0.786	Discriminant validity established (< 0.85)

Note. All HTMT values are below the conservative threshold of 0.85, confirming discriminant validity among all constructs (Henseler et al., 2015).

Table D4. Effect sizes (f^2) and explained variance (R^2)

Path	f^2	Interpretation	Endogenous construct	R^2	Adjusted R^2	Interpretation
PEOU $\rightarrow$ PU	0.975	Large	PU	0.494	0.472	Moderate
PEOU $\rightarrow$ ATU	0.339	Medium	ATU	0.547	0.506	Moderate to substantial
PU $\rightarrow$ ATU	0.065	Small	ATU	—	—	—
ATU $\rightarrow$ ITU	0.246	Medium	ITU	0.197	0.163	Weak to moderate

Note. f^2 interpretation follows Cohen (1988): 0.02 = small, 0.15 = medium, 0.35 = large. R^2 interpretation follows Hair et al. (2011): 0.25 = weak, 0.50 = moderate, 0.75 = substantial. R^2 is reported at the construct level; therefore, it is shown once per endogenous construct.

Table D5. Predictive relevance (Q^2_{predict})

Endogenous construct	Q^2_{predict}	Predictive relevance
Perceived Usefulness (PU)	0.413	Positive
Attitude Toward Using (ATU)	0.482	Positive
Intention to Use (ITU)	0.211	Positive

Note. $Q^2_{\text{predict}} > 0$ indicates predictive relevance (Shmueli et al., 2019). Values are from PLSpredict (10 folds; 10 repetitions).

Table D6. Construct reliability and convergent validity

Construct	Cronbach's α	Composite reliability (ρ_a)	Composite reliability (ρ_c)	Average variance extracted (AVE)
ATU	0.895	0.896	0.935	0.826
ITU	0.854	0.898	0.911	0.773
PEOU	0.837	0.860	0.891	0.672
PU	0.879	0.890	0.916	0.733

Note. All reliability coefficients exceed .70, and all AVE values exceed .50, supporting internal consistency reliability and convergent validity.

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