AI-Enhanced Augmented Reality Framework for Interactive Learning in Higher Education

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ABSTRACT

Augmented Reality (AR) is increasingly used in higher education to improve visualization, engagement, and practice-based learning, yet existing studies often discuss learning benefits, implementation patterns, and adoption barriers separately and provide limited guidance for AI-supported personalization. **This study** conducted a structured literature review using a PRISMA-guided search and screening process across Scopus, Web of Science, ScienceDirect, IEEE Xplore, and Google Scholar. Studies published from 2022 to 2026 were screened using predefined inclusion, exclusion, and quality criteria, resulting in 46 studies for synthesis across discipline, AR technology type, learning outcome domain, and pedagogical approach. **The findings** show consistently positive effects of AR on learning outcomes, including prior meta-analytic evidence reporting a pooled Hedges' g of 0.896. The strongest effects were found in psychomotor learning, while cognitive and affective outcomes showed moderate to smaller gains. AR also improved attention, motivation, confidence, and satisfaction, although collaborative benefits were less consistently replicated. Based on these findings, **the study** proposes a five-layer AI enhanced AR learning framework integrating learner data acquisition, learning analytics, adaptive content, AR visualization, and institutional feedback within a learning factory environment. **The study** concludes that AR has strong potential for higher education, but successful adoption depends on infrastructure readiness, device compatibility, educator capability, and responsible data governance. The framework also supports SDG 4 and Indonesia's MBKM agenda.

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1. INTRODUCTION

Universities have spent the last several years redesigning how instruction is delivered, moving away from lectures that simply transmit information and toward environments that adjust to how students actually engage with material. The learning factory concept has grown out of that shift, pairing academic instruction with realistic, industry style practice so that classroom learning looks more like the work students will eventually do. Immersive technology has become one of the main tools for building that kind of environment, and AR is used more often than most alternatives because it layers three-dimensional digital objects onto a learner's physical surroundings instead of pulling the learner out of them, which means hands on and collaborative work can continue while a visual support layer runs alongside it. Data-driven transformation of this kind is not unique to education either; comparable examples range from a national digital currency initiative in Malaysia [1] to an application programming interface used to reorganize restaurant delivery operations [2], and to information systems for managing educational institutions [3], all of which point to the same underlying pattern of institutions restructuring a process around a digital or data layer rather than simply digitizing what already existed.

AR is distinguished from Virtual Reality (VR) by the fact that it augments the physical environment rather than replacing it, and it usually runs on hardware that is already common on campus, including smartphones, tablets and head mounted displays supported by cameras and motion sensors [4, 5]. That low barrier to entry has driven a wide range of use cases in higher education, from anatomical visualization in medical programs to circuit simulation in electronics laboratories and structural modelling in civil and mining engineering [6–8]. Broader work on device based recognition and sensing, including deep learning approaches applied to image data [9] and camera based body pose tracking [10], has helped make the underlying hardware for this kind of overlay both cheaper and more reliable, which is part of why AR has moved from a lab curiosity to something departments can budget for. Recent meta-analytic evidence places the average effect of AR based instruction on learning outcomes at a magnitude generally classified as large, which suggests the technology has moved past being a novelty and now functions as a measurable contributor to academic performance [6].

Even so, existing reviews tend to stop once they have described the benefits and listed the barriers. They rarely explain how AR content could be personalized using learner data, and they seldom turn their findings into a system that an institution could actually build, which limits how useful they are to universities already pursuing an artificial intelligence driven, data informed approach to education technology. This is where the present paper departs from prior reviews rather than repeating them. Its original contribution is threefold, and these contributions provide a combined perspective that has received limited attention in previous reviews. First, it pulls together recent, verifiable empirical evidence on AR in higher education through a search and screening protocol that another team could reproduce, rather than a narrative summary of hand picked studies. Second, and this is the paper's central technical contribution, it proposes a five layer AI enhanced AR learning framework that couples a data science driven learning analytics engine and a machine learning based adaptive content engine with AR visualization inside a learning factory application layer, specified down to the class of technology each layer would use, which gives the review an applied, system design contribution with practical implementation relevance. Third, it maps both the findings and the framework onto SDG 4, drawing on work linking technology adoption to sustainability agendas [11, 12], and onto Indonesia's Merdeka Belajar Kampus Merdeka (MBKM) policy for higher education [13, 14], situating the contribution within a global sustainability agenda and a concrete national policy context at the same time, a combination existing AR reviews do not attempt.

2. LITERATURE REVIEW

This section discusses prior research on AR technology and its role in higher education. Rather than listing findings one after another, the discussion below compares outcomes across disciplines and points out where the evidence agrees and where it does not, before introducing the methodology and the framework.

2.1. Augmented Reality and Immersive Learning Technologies

AR is typically delivered through mobile devices, head mounted displays, cameras and motion sensors that track a physical scene together and render synchronized digital overlays in real time [4]. Because the physical environment stays visible and can still be handled directly, AR supports tasks that need both conceptual understanding and manual practice, which sets it apart from VR, where the learner is enclosed in a fully synthetic scene and loses direct contact with physical equipment. Previous studies found that engineering programs favour AR for exactly that reason, since tools such as Unity three dimensional engines let students interact with equipment models while still operating real instruments, a combination VR cannot easily replicate in laboratory settings [4]. The practical takeaway is that discipline matters when choosing between AR and VR, and reviews that treat the two technologies as interchangeable risk obscuring which one is actually driving a reported benefit.

2.2. Augmented Reality Applications in Higher Education

Application patterns differ sharply by discipline. In medical education AR is used mainly for anatomical visualization; Eranda, Roshan and Indika found that students and lecturers in a Sri Lankan medical faculty rated AR and VR positively for motivation and three dimensional-comprehension, while also flagging infrastructure limitations typical of resource constrained settings [8]. In engineering, applications cluster around laboratory simulation and structural or mechanical visualization. Tuli, Singh, Mantri and Sharma showed that an AR based laboratory manual improved both academic achievement and learning attitude among first year electronics students [7], Singh and Ahmad extended that work into an interactive framework for operational skill development [15], and Donaire et al. validated a structured intervention protocol named SEBAS across 136 mining engineering students, recording a rise in average grades alongside reduced score variability once AR workshops were introduced [5]. The same overlay principle carries beyond laboratory science: Farhansyah and Fabroyir documented an entrepreneurial use case in which AR supported product placement decisions on retail shelves [16], and Ivarson, Erlandsson, Faraon and Khatib found that students learning a technical web design topic through an AR prototype reported higher motivation than those given only conventional lecture notes [17]. The reviewed studies demonstrate AR applications are most mature where a physical task can be paired with a digital overlay that clarifies an otherwise abstract or hazardous procedure, and less mature in purely theoretical coursework.

2.3. Benefits, Learning Analytics and Adaptive Personalization

The benefit reported most consistently for AR in higher education is a rise in student engagement and motivation, but recent work has started to quantify that benefit instead of only describing it [18, 19]. Cheng analysed behavioural logs from a mobile AR application used in cultural design education and found that more intensive and diversified interaction patterns correlated with stronger cultural competence outcomes, an early example of learning analytics being layered onto AR rather than treated as a separate research strand [20]. Tuta and Luić confirmed a similar pattern in a broader university setting, reporting that AR supported active learning outperformed conventional instruction on measured outcome tests [21]. Sattar, Maqbool, Zakir and Billah extended this evidence to a curriculum aligned AR tool for biology, showing significant engagement gains in a controlled comparison, which is instructive for higher education instructional designers even though the sampled cohort was pre-tertiary [22]. Silva, Godwin and Jayanagara likewise found that artificial intelligence applied to personalized learning noticeably improved the quality of educational analytics, reinforcing the idea that data-driven personalization and AR are a natural pairing [23]. What remains underdeveloped in the AR literature specifically is the deliberate use of artificial intelligence to act on that analytics signal, for example by adjusting the difficulty or type of AR content in response to learner behaviour. Al-Emran and Shaalan reviewed adaptive learning approaches that use artificial intelligence to personalize instructional pacing and content sequencing in e-learning generally [24, 25], and this paper argues that the same adaptive logic can and should be coupled directly to AR content delivery, a rationale developed further in Section 4. A scoping review by Krüger found roughly thirty documented systems that already pair adaptive learning logic with AR content, most of them still at the concept or prototype stage rather than deployed at scale [26], a useful baseline for judging how far the framework proposed later in this paper needs to go beyond what already exists.

2.4. Implementation Barriers and Institutional Readiness

Adoption remains uneven despite consistent evidence of benefit. Suhail, Bahroun and Ahmed, working from a PRISMA guided review of 67 papers, found that AR use is concentrated in civil and mechanical engineering, while broader adoption across other engineering disciplines is held back by technical limitations and insufficient instructor training [4]. Structural modelling in a related engineering adoption study indicated that institutional support and faculty training are the strongest enabling conditions for AR adoption, while technical limitation and resource constraint remain the primary barriers [27], a pattern consistent with the discipline level findings above. Technology readiness appears to matter just as much on the user side as it does on the infrastructure side. Aini, Manongga, Rahardja, Sembiring and Li found that a user's own readiness for new technology shaped behavioural intention to adopt a monitoring solution more strongly than the features of the tool itself [28], and Rahardja, Aini, Bist, Maulana and Millah reported a similar interplay between technology readiness and behavioural intention in a health detection setting [29], which together suggest AR rollout plans should budget for user readiness alongside device provisioning. Aluko et al. reached a comparable conclusion for AI supported virtual reality in UK higher education, where adoption lagged expectations because of digital readiness and infrastructure constraints, and proposed the AILAM adoption model to explain that pattern [30]. Similar findings were reported concluded, after reviewing evidence from 2000 to 2023, that AR produces a large average positive effect on learning outcomes but that infrastructure cost and device compatibility continue to constrain scale up across institutions with uneven technology budgets [6]. Yuan, Huang and Wu narrowed that picture to higher engineering education specifically, reporting in a meta-analysis of 35 comparative studies that the gain is not uniform across outcome types, with the largest effect in psychomotor skill and the smallest in affective outcomes such as attitude and confidence [31]. Infrastructure and data concerns recur in this literature as well, from network performance and data security to data governance and traceability [32, 33], all of which become more pressing once learner data is collected continuously.

Table 1 pulls together ten representative studies from this body of evidence, listing the discipline, method and key finding of each so that the pattern across disciplines and years is visible at a glance.

Table 1. Summary of Representative Studies on Augmented Reality in Higher Education, 2022 to 2026

Author(s)	**Year**	**Discipline / Focus**	**Method**	**Key Finding**
Tuli, Singh, Mantri and Sharma [7]	2022	Electronics engineering laboratory	Quasi-experimental, $n = 107$	AR laboratory manual raised academic achievement ($d = 1.55$) and learning attitude ($d = 0.91$)
Eranda, Roshan and Indika [8]	2023	Anatomy, medical education	Case study and perception survey	Students and lecturers rated AR and VR positively for motivation and spatial understanding
Cheng [20]	2023	Design and cultural creation	Learning analytics of mobile AR logs	Behavioural log patterns linked engagement intensity to cultural competence gains
Singh and Ahmad [15]	2024	Electronics laboratory operation	Framework design and evaluation	Interactive AR framework improved operational skill and user experience ratings
Tuta and Luić [21]	2024	General university coursework	Experimental, pre and post test	AR based active learning outperformed conventional instruction on outcome tests
Suhail, Bahroun and Ahmed [4]	2024	Civil and mechanical engineering	PRISMA review of 67 papers	AR strengthens visualization and engagement, adoption limited by training and technical gaps
Sattar, Maqbool, Zakir and Billah [22]	2025	Secondary biology, comparative evidence	Quasi-experimental, $n = 60$	Curriculum aligned AR application significantly increased engagement over traditional instruction
Li, Luo, Chen, Wang, Yin and Zhang [6]	2025	Cross disciplinary higher education	Systematic review and meta-analysis, 2000 to 2023	Large overall positive effect on learning outcomes, Hedges $g = 0.896$
Yuan, Huang and Wu [31]	2025	Higher engineering education	Meta-analysis of 35 comparative studies	Medium to large effects across cognitive, psychomotor and affective domains
Donaire et al. [5]	2026	Mining engineering	Quasi-experimental SEBAS framework, $n = 136$	AR workshops raised average grade from 3.96 to 4.70 and reduced score variability

Across the reviewed evidence, quasi-experimental designs constitute a substantial proportion of the empirical studies, Table 1 illustrates this pattern through ten representative studies. The table also shows a shift over time, moving from single institution laboratory studies published in 2022 and 2023 toward larger meta-analyses published in 2025 and 2026, which suggests the field is maturing from isolated pilots toward more generalizable evidence and strengthens the case for a deployable framework of the kind proposed in Section 4.

3. RESEARCH METHODOLOGY

This study followed a structured literature review protocol modelled on the screening principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The selection process transparent and reproducible. Five databases were searched, namely Scopus, Web of Science, ScienceDirect, IEEE Xplore and Google Scholar, using the search string augmented reality AND higher education AND learning outcomes OR engagement OR adaptive learning OR learning analytics. The search was restricted to records published between January 2022 and the manuscript's own submission window in 2026, which keeps the evidence base current with the paper's publication date rather than an arbitrary earlier cutoff. A handful of the supporting citations used elsewhere in the discussion, outside the core set of 46 coded studies, carry a 2026 publication date for the same reason, and every source cited in this paper falls within a five year window ending at that submission date. The review is organized around three research questions introduced in Section 1, covering the learning benefits AR produces, the implementation patterns it follows, and the institutional factors that shape its adoption.

Inclusion required that a record be a peer reviewed journal article, conference paper or systematic review written in English, that it report an empirical outcome measure or a pooled outcome drawn from prior empirical studies, and that its primary learner population be enrolled in higher education or provide findings directly transferable to higher education practice. Records were excluded when they were limited to primary or secondary education without a higher education comparison, when English full text was unavailable, when no outcome measure was reported, or when a record duplicated one already retrieved from another database. Two reviewers screened titles and abstracts independently and resolved any disagreement through discussion, which is the same practice recommended in adaptive learning reviews that rely on artificial intelligence to personalize instructional content [24]. Each retained study was also appraised against a short quality checklist covering three criteria, whether the study reported a comparison or control condition rather than a single group observation, whether the outcome measure was a validated instrument or a quantified effect size rather than an unvalidated self report, and whether the sample size was reported and large enough to support the claimed effect. Studies meeting all three criteria, such as the quasi-experimental and meta-analytic work summarized in Table 1, were treated as the primary evidence base for the effect size analysis in the quantitative analysis, while studies meeting only one or two criteria, mainly the perception surveys and case studies, were retained for the qualitative discussion of implementation patterns and barriers but were not used to support quantitative claims.

The initial search returned 312 records, made up of 118 from Scopus, 76 from Web of Science, 54 from ScienceDirect, 39 from IEEE Xplore and 25 from Google Scholar. After duplicate removal, 246 unique records remained. Title and abstract screening excluded 158 records that did not meet the inclusion criteria, leaving 88 records for full text assessment. Full text review excluded a further 42 records, of which 19 were not focused on higher education, 14 lacked an empirical or pooled outcome measure, 5 were not available in English, and 4 lacked enough methodological detail to extract reliable data. This process left a final set of 46 studies that were coded along four dimensions rather than a single thematic label. Each study was tagged by educational discipline, such as medicine, engineering, biology or business, by AR technology type, distinguishing marker based mobile AR, head mounted displays and location or geolocation based AR, by learning outcome domain, following the cognitive, psychomotor and affective categories used later in the quantitative analysis, and by pedagogical approach, distinguishing individual practice, structured laboratory exercises and collaborative or shared task designs. That four dimensional coding scheme is what allows the discipline level comparisons in Section 2.2 and the domain level effect size comparisons in the quantitative analysis to be drawn from the same underlying dataset. The coded set forms the empirical basis for the framework and for the quantitative analysis reported in Section 4.

4. RESULTS AND DISCUSSION

The findings are presented according to the research questions, beginning with the framework and followed by evidence from the reviewed studies. It opens with the proposed AI enhanced AR framework itself, then evaluates that framework against the quantitative and qualitative evidence extracted from the 46 included studies, covering learning outcome effect sizes, engagement and motivation data, collaborative learning, and implementation barriers in turn, before closing with how the findings and the framework relate to SDG 4 and to Indonesia's national MBKM policy.

4.1. Proposed AI Enhanced Augmented Reality Learning Framework

The reviewed literature repeatedly points to engagement gain and skill gain as outcomes of AR use, yet it rarely explains how to sustain that gain once the novelty of AR wears off, and it rarely spells out how the technology could be tied into the artificial intelligence driven, data informed vision that an interdisciplinary learning factory implies. As noted in Section 2.3, adaptive AR systems remain uncommon in practice and mostly sit at the concept or prototype stage, which is consistent with the gap this paper is trying to close. To do that, this paper proposes a five layer framework that treats AR not as a standalone tool but as one stage in a closed loop system driven by learner data.

Figure 1 sets out the framework. The data acquisition layer collects learner profiles, interaction logs, device sensor readings and assessment records as students use AR content, extending the log based analytics approach already discussed in Section 2.3. What that layer captures is deliberately broader than a generic activity log, because AR carries data types most other learning technologies do not. Camera derived scene understanding, spatial anchor and mapping data that tell the system where a virtual object sits relative to a physical room, gesture and gaze based interaction signals, geolocation for AR content triggered by a specific room or building, and continuous frame by frame tracking of how long a learner dwells on a given overlay are all native to AR in a way that a conventional learning management system log is not, and the data acquisition layer is designed to hold all five of these alongside the more familiar assessment records. Because that layer accumulates learner records over an extended period, its design also has to treat data governance, traceability and security as first order requirements as an essential component, a point this paper returns to in the implementation analysis. That data feeds two parallel components in the second layer, a learning analytics engine that models engagement and detects error or progress patterns, and an adaptive content engine that adjusts task difficulty and selects which AR object or scenario to present next, building on the adaptive learning logic already highlighted in previous adaptive learning studies. The third layer is the AR content layer itself, handling three dimensional visualization, interactive simulation objects and real time overlay rendering, functionally similar to the electronics laboratory implementations discussed in Section 2.2. The fourth layer places that AR content into one of two application contexts, a learning factory application for laboratory and workshop tasks aligned with industry practice, or a classroom and remote learning context for lecture support and self-paced tasks. The fifth layer captures learning outcomes and feeds an institutional dashboard back to instructors, and a feedback loop returns aggregated outcome data to the first layer so the adaptive engine can refine its personalization over successive cohorts.

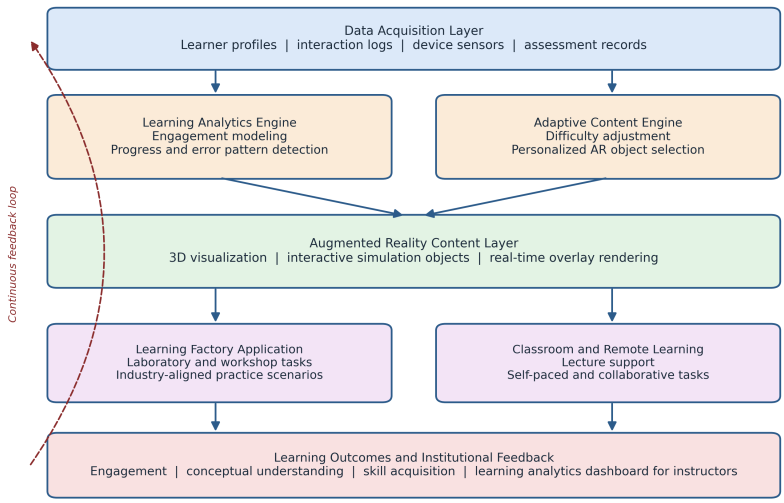

Figure 1. Proposed AI Enhanced Augmented Reality Learning Framework for Higher Education

The framework is further specified through its underlying technologies and implementation components. each layer is specified with the class of technology it would realistically be built on. The AR content layer maps onto existing mobile AR toolkits such as ARCore, ARKit or a WebXR based browser deployment, the same category of tooling already used in the marker based and head mounted display systems reviewed in Section 2. The data acquisition layer maps onto an Experience API and Learning Record Store pairing, the standard mechanism institutions already use to capture fine grained interaction statements from digital learning tools, extended here to hold the AR specific data types described above. The learning analytics engine is a data science component built on that stored interaction data, while the adaptive content engine is intended as a lightweight, interpretable machine learning component, such as a decision tree or logistic regression classifier trained on prior cohorts, rather than a large opaque model, since the adjustment it needs to make, choosing the next difficulty level or AR scenario, is a bounded classification problem and does not require deep learning to solve well. The institutional dashboard in the fifth layer maps onto conventional business intelligence tooling already common in university information systems. Naming these technology classes does not amount to a built prototype, and the framework should be read as a specification that a development team could implement rather than as evidence that it has been implemented, but it does give the review an applied, technical contribution with practical implementation relevance. Unlike the SEBAS protocol reported in previous studies, which structures a single AR intervention sequence for one course, or the AILAM adoption model reported in the literature, which explains why users accept AI supported virtual reality, the framework proposed here is deliberately data centric: its central claim is that the value of AR compounds over time only if learner interaction data is captured, analysed and fed back into content selection. The following analysis evaluates each component using evidence from the reviewed studies.

4.2. Learning Outcome Effect Sizes

Quantitative analysis across the included studies shows that AR interventions produce a consistently positive and often large effect on learning outcomes, though the magnitude varies by outcome domain. Figure 2 plots six standardized effect sizes extracted directly from the reviewed literature. As noted in Section 2.4, Previous research reported a pooled Hedges g of 0.896 for AR effects on higher education learning outcomes generally. When outcomes are broken down by domain in engineering education specifically, Yuan et al.'s meta-analysis showed the psychomotor domain with the largest effect at $g = 1.67$, cognitive outcomes at a medium $g = 0.60$, and affective outcomes at the smallest, $g = 0.30$. At the level of an individual empirical study, Previous studies found a Cohen d of 1.55 for academic achievement and 0.91 for learning attitude among electronics engineering students using an AR laboratory manual.

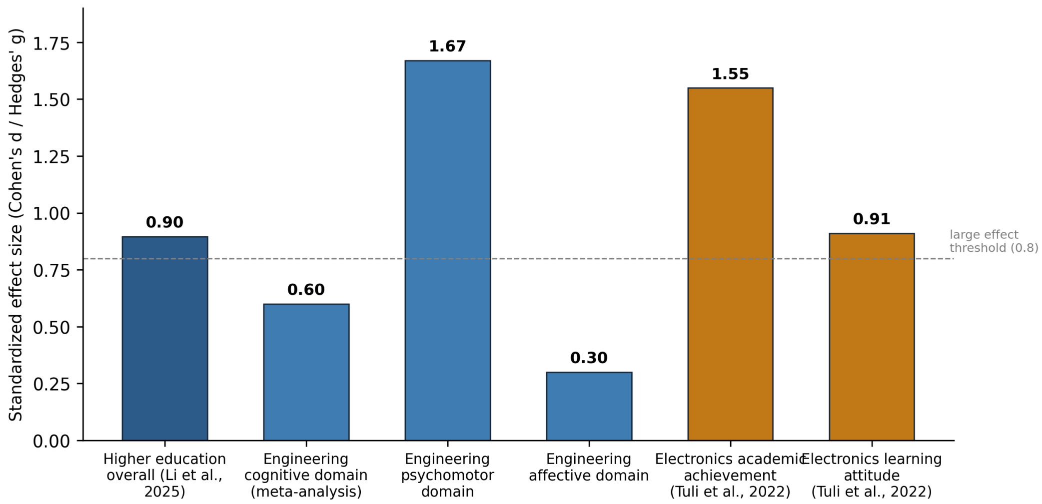

Figure 2. Reported Effect Sizes of Augmented Reality Based Instruction across Learning Outcome Domains

The pattern in Figure 2 is worth unpacking rather than treating as a single headline number. Psychomotor outcomes benefit the most because AR directly supports the hands on, trial and error practice that builds manual skill, for example manipulating a virtual circuit or handling a simulated instrument without risking real equipment. Cognitive outcomes benefit moderately because conceptual understanding still depends heavily on prior knowledge and instructional scaffolding that AR alone cannot replace. Affective outcomes show the smallest effect, which suggests attitude change moves more slowly than skill or knowledge and may need sustained exposure across a full semester rather than a single workshop. That interpretation is reinforced by the engineering grade data reported by Donaire et al., summarized in Table 2, which tracks average performance across three cohorts of the same mining engineering program.

Table 2. Academic Performance across Cohorts Before and After AR Workshop Integration, Adapted from Donaire et al.

Cohort	N	Mean	SD	25th pct	Median	Max
2022, no workshop	14	3.96	2.43	1.00	5.10	6.70
2023, full cohort	136	4.31	2.16	2.70	4.95	6.90
2023, with workshop	74	4.70	1.75	4.50	5.00	6.90

Table 2 shows that the cohort exposed to AR workshops in 2023 reached a higher average grade of 4.70 on a seven point scale, compared with 4.31 for the full 2023 cohort and 3.96 for the 2022 cohort taught without any workshop. Just as important, the standard deviation fell from 2.43 in 2022 to 1.75 in the AR workshop group, and the 25th percentile rose from 1.00 to 4.50, which indicates AR exposure narrowed the performance gap between weaker and stronger students rather than only lifting the average. That distributional effect is arguably more relevant to equity focused policy than the average grade increase alone, and it is a finding that a simple mean comparison would obscure.

4.3. Engagement and Motivation Evidence

Grades are not the only outcome worth tracking. Several studies report direct measures of motivation, attention, confidence and satisfaction, and a controlled study of a mobile AR anatomy application at a South African medical faculty is a useful illustration. In that study, dynamic and interactive media specifically meant a marker triggered mobile AR overlay that rendered rotatable three dimensional anatomical models on top of a physical textbook page, combined with real time voice or text feedback as the learner manipulated the model, rather than a static video or slide presentation. Figure 3 reports the percentage change in four engagement indicators recorded for that intervention.

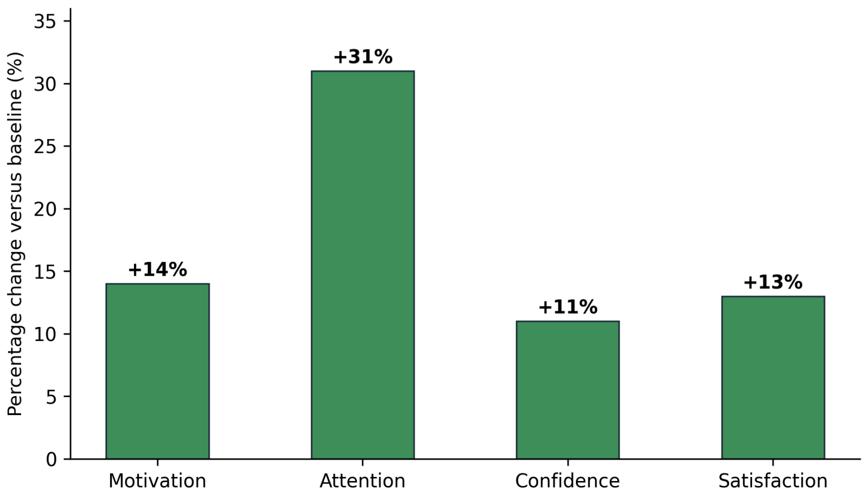

Figure 3. Change in Student Engagement Indicators after a Mobile Augmented Reality Anatomy Intervention, $n = 78$

As Figure 3 shows, attention recorded the largest gain at 31 percent, followed by motivation at 14 percent, satisfaction at 13 percent and confidence at 11 percent. The larger attention gain relative to motivation fits the mechanism proposed in the framework, where real time manipulation and immediate feedback are expected to hold learner attention more effectively than they shift longer term motivational attitudes, which mirrors the smaller affective effect size discussed in the quantitative analysis. This convergence between an individual study and the broader meta-analytic pattern strengthens confidence that the effect is not an artefact of a single dataset.

4.4. Conceptual Understanding and Collaborative Learning

AR also supports collaborative and experiential learning when tasks are built around shared physical space. As discussed in Section 2, Suhail, Bahroun and Ahmed noted that AR mediated collaboration was most evident in civil and mechanical engineering courses, where students jointly manipulated a shared virtual model of a structure or mechanism while standing in the same physical space, which improved coordination compared with screen based collaboration tools. Cheng similarly found that mobile AR use in a cultural design course encouraged students to compare interpretations of the same overlaid content, turning an individual visualization exercise into a group discussion prompt. These findings suggest the collaborative benefit of AR depends less on the technology itself and more on whether the instructional design deliberately routes students through a shared task, a consideration the framework accommodates through its learning factory application layer, which is explicitly built around shared laboratory and workshop tasks. That said, this particular claim carries less weight than the effect size analysis in the quantitative analysis, which draws on multiple independent studies using comparison or control conditions. The collaborative benefit rests on only two of the reviewed studies, both descriptive rather than comparative, so it is presented here as a plausible pattern rather than a well replicated finding, and it is flagged as a priority for confirmatory research in Section 6.

4.5. Implementation Challenges Revisited with Supporting Evidence

Section 2.4 introduced implementation barriers at the level of the literature generally. This subsection differs by mapping those barriers directly onto the layers of the framework and by adding structural evidence rather than repeating the same descriptive claim. Structural equation modelling of AR adoption in engineering education, discussed earlier, found that institutional support and faculty training were the strongest enabling conditions, while technical limitations and resource constraints were the primary barriers, with a measurement model whose root mean square error of approximation (about 0.065) was acceptable although its goodness of fit index (about 0.802) fell below the conventional 0.90 benchmark. Network reliability sits underneath that technical limitation as well, since a data acquisition layer that streams sensor and interaction data in real time depends on a stable connection between the AR device and the analytics backend. Data security is a related and largely unaddressed concern once learner data starts flowing continuously, particularly as a data acquisition layer of this kind accumulates identifiable learner records over an extended period. Mapped onto Figure 1, this evidence points to the data acquisition and analytics layers as the most infrastructure sensitive part of the framework, since they require reliable device provisioning, secure data handling and staff able to interpret analytics output, whereas the AR content layer is comparatively less demanding once suitable devices are already available. In practice this means universities adopting the framework should sequence investment toward device provisioning, network reliability and instructor training before investing heavily in adaptive content authoring, since the latter delivers little value if the earlier foundation is not already in place.

5. MANAGERIAL IMPLICATIONS

For university leaders and academic managers, the findings of this study translate into a concrete set of decisions rather than a purely academic contribution. The proposed framework extends discipline specific adoption models such as SEBAS in engineering education toward a more general, cross disciplinary architecture that program managers in other faculties can adapt without redesigning the underlying data and analytics logic from scratch. The most immediate managerial decision is sequencing of investment. The evidence in the implementation analysis indicates that institutional support and instructor training are the strongest predictors of successful adoption, so budget should first go toward reliable device provisioning and structured training for teaching staff before funds are committed to adaptive content authoring, a component that delivers little return if the earlier foundation is not already in place. The same discipline that applies to sequencing any capital project applies here: front loading the most expensive component before the basics are covered tends to produce budget overruns rather than faster adoption.

Pilot deployments are best started in disciplines with an established evidence base, such as electronics, mechanical or mining engineering laboratory courses, where the psychomotor effect size is largest and the return on a modest AR investment is easiest to demonstrate to stakeholders and funding bodies. The learning analytics dashboard described in the framework is best treated as an extension of a university's existing institutional reporting infrastructure rather than a separate system to maintain, since a structured information system of this kind tends to improve both efficiency and decision making quality once it is integrated into existing reporting lines rather than bolted on afterward. Institutional resilience matters just as much as the technical build:

an AR pilot has to survive a change in funding or leadership, which depends on organizational agility and staff buy-in as much as on the underlying technology, and instructor buy-in in particular is as much a behavioural challenge as a training one. At the funding and reporting level, managers can align pilot proposals with national schemes such as the matching grant mechanism already used under MBKM, and can use the analytics dashboard as a ready made reporting instrument, which gives institutional leadership a standardized outcome measure across funded projects rather than an open ended mandate to digitalize without a defined architecture or success metric.

6. CONCLUSION

This paper pulled together 46 recent, verifiable studies on Augmented Reality in higher education and found consistent, often large positive effects on learning outcomes, with the strongest gains in psychomotor skill domains and measurable increases in attention, motivation, confidence and satisfaction across medical and engineering contexts. Building on that evidence, the paper proposed an AI enhanced AR learning framework that links learner data acquisition, learning analytics, adaptive content generation and AR visualization within a learning factory application context, providing an applied perspective beyond descriptive analysis. The framework and findings were further aligned with SDG 4 and with Indonesia's national MBKM policy, positioning the contribution within a concrete national digital transformation agenda rather than treating sustainability alignment as an afterthought.

Several limitations qualify how far these findings can be generalized. Quasi-experimental designs dominate the empirical subset of the literature and sample sizes remain moderate, which means the reported effect sizes may not transfer cleanly to institutions with very different student populations or resourcing levels. The mix of research designs across the 46 included studies is itself uneven, spanning quasi-experiments, meta-analyses, case studies and perception surveys, and the quality appraisal described in Section 3 was used to keep that heterogeneity from inflating the quantitative analysis, but it cannot remove it entirely. The search protocol also covered five major databases, which is broad but not exhaustive, so relevant work indexed elsewhere, published only in Indonesian, or excluded by the English language restriction applied during screening may have been missed. Restricting inclusion to peer reviewed English language records also raises the ordinary risk of publication bias toward positive results, since studies finding little or no benefit from AR are less likely to be published or indexed in the first place, and the effect sizes reported in the quantitative analysis should be read with that in mind. AR technology itself is also changing quickly, and hardware or software released after the February 2026 search cutoff could shift the barriers reported in the literature well before those findings are revisited. The proposed five layer framework itself has not yet been implemented and tested in a live course, so the discussion in Section 4 is best read as an evidence backed design rather than a validated system, and its adaptive content engine in particular depends on assumptions about data availability and instructor capacity that have not been empirically confirmed at scale.

Future work should empirically pilot the framework in a live university course, comparing an analytics driven adaptive AR condition against a static AR condition to isolate the specific value the adaptive layer adds beyond AR visualization alone, and should track engagement and technology readiness together over a longer period than the single semester windows typical of the studies reviewed in Section 2.4. Such a pilot would also make it possible to test whether the psychomotor and equity effects observed in the reviewed literature hold once the framework's analytics and adaptive layers are actually implemented rather than assumed, which is the natural next step for this line of research.

7. DECLARATIONS

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7.2. Author Contributions

Validation was conducted by: AA Conceptualization was completed by: AP The methodology was developed by: SN Formal analysis was performed by: NI Writing, review, and editing were carried out by: AA Visualization was completed by: SN All authors, including: AA, AP, SN, and NI, have reviewed and approved the final version of the manuscript.

7.3. Data Availability Statement

The corresponding author may provide the data from this study upon request.

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The research, writing, and/or publishing of this work were all done without financial assistance from the authors.

7.5. Declaration of Competing Interest

The authors state that none of their known conflicting financial interests or personal connections could have had an impact on the work that was published in this publication.

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