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The impact of virtual reality on practical skills for students in science and engineering education: a meta-analysis

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Abstract

Virtual reality (VR) has emerged as a promising tool for enhancing practical skills of students in science and engineering education. However, the effectiveness of VR in this context remains unclear due to inconsistent findings across studies. This meta-analysis aimed to synthesize the existing literature and investigate the overall impact of VR on practical skills among science and engineering students. A comprehensive literature search was conducted, yielding 37 empirical studies published between 2000 and 2022 that met the inclusion criteria. The analysis included 72 effect sizes, and the random-effects model was employed to account for heterogeneity among studies. The results revealed a significant moderate positive effect of VR on practical skills ($g = 0.477$). Moderator analyses indicated that the disciplinary category significantly influenced the effect size, with medical students demonstrating the largest improvement in practical skills. Additionally, using the practice approach combining with traditional methods yielded the highest effect size among the instructional approaches. The study also considered potential reasons behind the observed results and acknowledged certain constraints. Additionally, it proposed avenues for further inquiry to advance the understanding of the subject matter.

Keywords Engineering education, Hands-on experience, Higher education, Science education, Simulation-based training, Virtual reality environments

Introduction

Practical skills refer to the abilities that students need to carry out practical work effectively and efficiently (Hayward, 2003). In science and engineering education, these skills primarily involve the proficiency in manipulating apparatus and equipment, conducting experiments, and analyzing data (Panuluh, 2022). Previous research has established the vital role of practical skills in applying theoretical knowledge to real-world scenarios; they serve as a critical link between classroom learning and practical application (Jou & Wang, 2013). Moreover, practical skills are essential for understanding and solving complex concepts in science and engineering disciplines. These disciplines often require practical experience to fully grasp complex concepts (Paszkiewicz et al., 2021), particularly for engineering students who are expected to excel in designing and analyzing complex systems—a skill traditionally honed through hands-on experience in laboratory settings (Rio & Rodriguez, 2022).

Researchers have made various explorations into cultivating the practical skills and learning outcomes of science and engineering students. For instance, Chiu and Li (2023) discussed the affordances and challenges of emerging technologies in designing and implementing STEM education. Wang et al. (2022) conducted a systematic review of integrating STEM education into K-12 curricula, providing valuable insights into this educational approach. Additionally, Gui et al. (2023) explored the effectiveness of digital educational games

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and game design in STEM learning. Webber et al. (2024) examined the benefits of work-related experiences and their impact on career competencies for STEM students. Another notable approach is the utilization of educational robots, as demonstrated by Ouyang and Xu (2024), which integrates hands-on experience with theoretical knowledge to enhance students' understanding and application of STEM concepts. Nevertheless, due to the limited access to specialized equipment, safety concerns regarding hands-on experimentation, and the escalating costs associated with maintaining laboratories, some researchers have endeavored to enhance students' practical skills in virtual reality (VR) environments. These settings offer a virtual environment that can simulate real-world conditions, providing students with immersive experiences (Maksimenko et al., 2021; Pottle, 2019). A paradigm shift in science and engineering education is underway, driven by the increasing demand for skilled professionals in these fields and the continuous evolution of VR technology.

Despite the growing interest in the use of VR in science and engineering education, the existing literature on its impact on practical skills presents a mixed picture. While many studies highlight VR's positive effects on enhancing students' practical skills (Omori et al., 2023; Park et al., 2019; Ros et al., 2021; Singh et al., 2015), others report no significant improvement in VR environments (Darrah et al., 2014; Lorenzo-Alvarez et al., 2019). This inconsistency in outcomes suggests that a more comprehensive understanding of VR's effectiveness is needed to inform educational policy and practice. Accordingly, it is essential to obtain definitive data from a novel quantitative perspective to assess the comprehensive influence of VR on students' proficiency in practical abilities.

This study makes two main contributions. First, it presents the most extensive compilation of data thus far regarding the impact of VR technology on the enhancement of practical skills among science and engineering students. This evidence serves as valuable references for educators and curriculum developers, as they offer evidence-based insights into the conditions under which VR is most beneficial. Second, this study delves into the examination of various factors that could potentially influence the correlation between the application of VR and the development of practical skills. By exploring a range of moderating variables, the research addresses inconsistencies observed in previous studies, and it provides a clearer understanding of how different elements can modify the effectiveness of VR in an educational context.

Previous works

VR on practical skills

VR is a computer-generated three-dimensional immersive environment that can simulate a fictional universe and the real world, thus making it applicable in various fields (Elmqaddem, 2019). Currently, with the development of technology, VR technology has penetrated highly diverse fields and sectors, such as language learning (Hua & Wang, 2023), surgical education (Singh et al., 2015), cultural heritage (Chong et al., 2021), and sports training (Richlan et al., 2023). Powered by graphics technology and specific devices (Lin, 2021), VR systems enable egocentric navigation, in which the user observes the virtual world from within the environment itself, fostering a heightened sense of presence, immersion, and an increased perception of reality as the scene dynamically updates through head turns or body movements (Masnadi et al., 2022; Slater, 2018). Leveraging these features, an increasing number of higher education institutions are adopting VR to improve practical skills among college students (Soliman et al., 2021).

In science and engineering education, VR technology is increasingly being adopted to act as virtual simulations or virtual labs to enhance the practical skills of college students. For instance, Paxinou et al. (2020) present the integration of three different teaching scenarios during biology laboratory lessons. They highlight the potential predominant effectiveness of teaching and improvement in students' learning through the use of the three-dimensional VR educational tool, Onlabs. The study provides evidence in favor of the application of VR. Similarly, Omori et al. (2023) used VR and lectures as two different learning methods for hand hygiene and personal protective equipment training for medical students. They found that VR could be a useful tool for learning and practicing infection control procedures. Furthermore, Wells and Miller (2020) studied the effect of VR technology on welding skills' performance in gas metal arc welding training. They found that VR training group improved their welding skill, as measured by American Welding Society standards. They suggested that VR has great potential in welding training. Despite the benefits, challenges such as usability issues with low-cost VR headsets may negatively affect the overall user experience. Nonetheless, the immersive and authentic nature of VR experiences is preferred by students and is seen as a valuable addition to higher education curricula.

Previous reviews and meta-analyses

While previous reviews and meta-analyses have evaluated the impact of VR on science and engineering learning outcomes, many have focused narrowly on cognitive or affective results like knowledge, attitudes, and motivation (Asad et al., 2021; Cromley et al., 2023; Hamilton et al., 2020; Yu & Xu, 2022; Zhou & Li, 2019). Furthermore, most reviews and meta-analyses focusing on practical skills concentrate on a single discipline, such as medicine (Chen et al., 2020; Lau et al., 2023), agriculture (Wells & Miller, 2020), engineering (Di Lanzo et al., 2020; Huang & Roscoe, 2021), and science (Durukan et al., 2020; Wang, 2021).

Two meta-analyses have investigated the impact of VR on practical skills among science and engineering students, but they have certain limitations. Angel-Urdinola et al. (2021) found an overall positive impact, attributed this to VR's capacity for immediate feedback, engagement, and real-world transfer. However, their analysis lacked an examination of key moderating factors such as *immersiveness* of VR during VR training. In contrast, Ma et al. (2022) considered moderators like measurement methods, prior experience, and supplementary techniques, and also found a significantly positive effect. Nevertheless, their focus was solely on one aspect of practical skills—technical proficiency—and did not provide a comprehensive discussion of practical skills as a whole.

In summary, current meta-analytic perspectives on VR's effectiveness for building practical skills among college science and engineering students are limited. Although offering initial positive indicators, the existing reviews have yet to comprehensively account for factors like instructional design variations. A more rigorous, expansive synthesis accounting for key moderators would provide vital clarity regarding how VR instruction amplifies technical abilities.

Moderator variables

This study considered identifying a set of moderator variables that could serve as a direct reference for educators in the use of VR for enhancing practical skills. The selection of moderator variables was rigorously grounded in the existing literature, drawing extensively from prior research (Di & Zheng, 2022; Ma et al., 2022). We pinpointed level of immersion, instructional approach, disciplinary category, learning cycle duration, and pretraining as moderators. These variables were chosen because of their frequent examination in the experimental designs of the selected literature and their relative ease of quantification.

Level of immersion

The level of immersion in VR environments plays a crucial role in determining the effectiveness of VR applications for various purposes. Lin (2021) classified VR into low immersion VR (LiVR) and high immersion VR (HiVR) based on the level of immersion experienced by users. HiVR typically involves the use of head-mounted displays (HMDs) that provide a more immersive experience by allowing users to interact with the virtual environment in a more realistic and engaging manner. On the other hand, LiVR utilizes devices such as PC monitors, tablets, or mobile phones, which offer a less immersive experience compared to HMDs.

Instructional approach

Instructional approach has been the focus of previous studies (Scherer et al., 2020). Three main approaches have been identified: practice, presentation, and independent (Mayer, 2008). The practice approach involves a combination of traditional learning methods followed by practical exercises using VR technology. The presentation approach utilizes VR to demonstrate complex concepts or knowledge to aid student learning. The independent approach entails students learning solely through VR without the integration of traditional methods. These instructional approaches are crucial as they align with evidence-based principles for designing effective multimedia instruction. The relationship between theory and practice in instructional methods is essential for ensuring that teaching strategies are consistent with research-based theories of learning.

Disciplinary category

VR has shown promise in enhancing education across disciplines. According to Ma et al. (2022), the disciplinary category comprising biology, geography, mathematics, physics, and chemistry is classified under 'Natural Science.' Engineering and architecture are combined into 'Engineering Technology,' while medicine, nursing, and anatomy fall under 'Medical Science. Another group is agriculture. The effectiveness of VR teaching has also been studied in various disciplines, such as science (Hu et al., 2021; Paxinou et al., 2020), engineering (Singh et al., 2020), agriculture (Wells & Miller, 2020), and medicine (Omori et al., 2023). The variations in disciplines may contribute to different experimental outcomes. Furthermore, studies differ significantly in their learning cycle duration.

Learning cycle duration

The duration of the learning in VR has been a topic of interest in educational research. Dai et al. (2022) discussed varying perspectives on the optimal duration for learning in VR, with some studies suggesting longer durations may be beneficial for learning, particularly in contexts like surgical skill performance, while other research proposes that shorter durations could be more effective (Jensen & Konradsen, 2018). By reviewing the empirical studies and meta-analyses, we categorized learning cycle duration into five groups: 0 to 1 day, 1 to 15 days, 15 to 30 days, and over 1 month.

Pre-training

Pre-training in VR has been a subject of interest in enhancing practical skills for college students in science and engineering education. Previous studies have examined the moderating role of pre-training, but have not reached a consistent conclusion. Meyer et al. (2019) found positive effects of pre-training principles in immersive VR, suggesting its potential to improve learning outcomes. Pre-training can reduce students' cognitive load to a certain extent, which may also positively impact their learning results. Therefore, we recorded whether there is pre-training in the included literature.

Purpose of this meta-analysis

The burgeoning field of VR holds substantial promise for augmenting practical skills in science and engineering education. Despite this potential, there are inconsistent research findings about the effectiveness of VR on practical skills, and there is also a lack of systematic review to shed light on the inconsistent findings from these empirical studies. Therefore, this study aimed to thoroughly examine the effect sizes of VR on practical skills among science and engineering students from 2000 to 2022. By serving as a robust reference for both researchers and educators, this work endeavors to bridge the existing knowledge gap.

To achieve this objective, we employ a meta-analysis approach to synthesize the results of existing studies. Meta-analysis synthesizes data across studies addressing the same conceptual question by extracting each study's effect size (Glass, 1976). Additionally, our analysis of moderators contributed to an exploration of the relationships between potential variables and practical skills. Therefore, this study employed a meta-analysis method to investigate the impact of VR on practical skills. The two research questions are as follows.

1. How effective is VR in enhancing the practical skills of students in science and engineering?
2. How do various moderator variables, such as level of immersion, instructional approach, disciplinary category, learning cycle duration, and pre-training, influence the effects of VR?

Method

This study utilized meta-analysis as the research method to examine the impact of VR on the practical skills of college students in science and engineering. We collected data from controlled experiments by employing comparative methods, sample sizes, and p values to assess the impact of VR on practical skills. This study followed a rigorous research process to collect, analyze, and summarize empirical evidence related to the research questions. In particular, the analysis followed the meta-analysis criteria proposed by Glass (1976) and referred to the procedure outlined by Page et al. (2021).

Literature search

To conduct the meta-analysis on the role of practical skills in VR and immersive learning environments, we conducted a comprehensive search across multiple databases, including Educational Resource Information Center, Springer Link, Web of Science, Science Direct, and China National Knowledge Infrastructure. The keywords included "virtual reality," "immersive learning environment," and "practical skills." In addition, these keywords were also searched in the databases using the Boolean operator "AND" in combination with the term "meta-analysis". This approach helped us to find relevant literature in some meta-analysis articles that were consistent with our study, thus further ensuring the comprehensiveness of the literature search. The search was limited to studies published between 2000 and 2022. After screening the titles and abstracts, we included relevant studies that met the predefined inclusion criteria.

Literature selection and inclusion criteria

Through the literature search, we identified that VR teaching has gained significant traction in K-12 and higher education, particularly in the context of practical simulation training. To ensure objective conclusions, we established specific exclusion rules for the literature screening process:

(1) It must have no duplication.
(2) It must include the impact of VR-based teaching on the learning effect of practical skills.
(3) It must be an empirical research article and a controlled experiment.
(4) Participants must be college students of science and engineering.
(5) Complete data that can be used to calculate effect sizes must be provided.

Ultimately, 37 articles met the inclusion criteria and were included in the analysis. The selection process flowchart for the entire search process and outcomes is shown in Fig. 1.

Coding framework

Several salient characteristics, as described under "Moderator variables", were coded into different levels based on the possibility that they could have influenced the

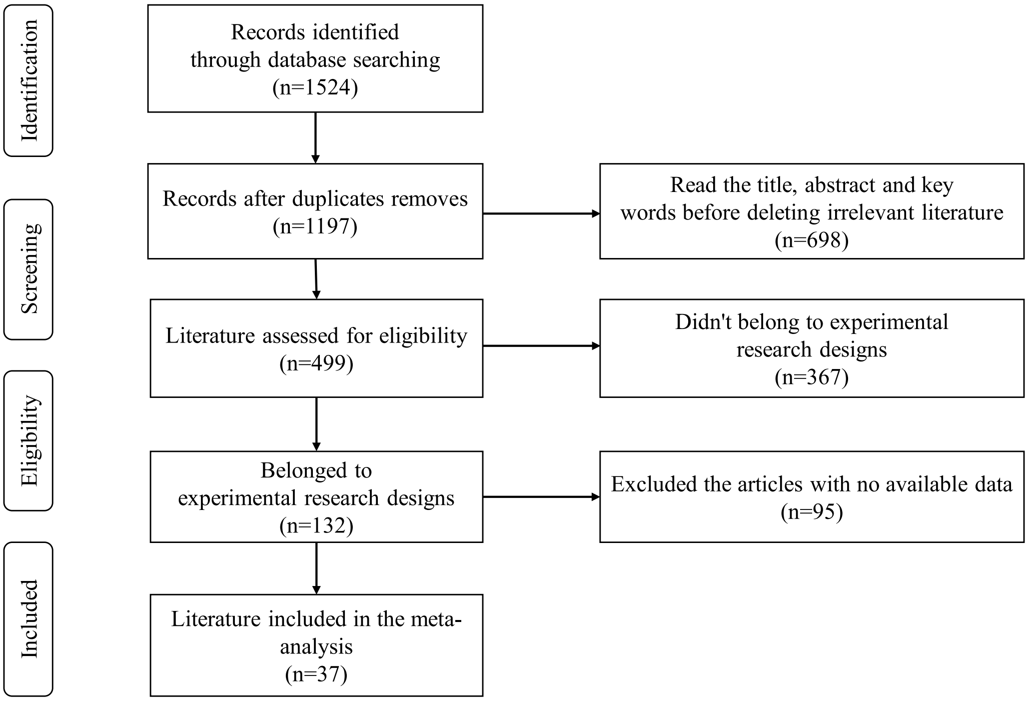


Fig. 1 Flowchart of literature screening

findings across the primary studies. To ensure the reliability of the coding, three researchers independently coded 25 randomly selected primary studies (20% of all studies). The coding consistency coefficient among the three coders was calculated and the coding results were highly reliable ($\kappa = 0.81$). Differences arising in the process of coding were negotiated among the three coders by consulting the original literature. Once the coding procedures were established, differences among the coders were resolved, and the coding reliability established, the remaining studies were then randomly divided into three groups, with each coder independently coding one group of the studies.

This coding scheme was developed through two steps. The first step was to select super dimensions based on the analysis framework of previous studies (Di & Zheng, 2022; Ma et al., 2022). The second step was to refine subdimensions through the research method sections of the selected articles. In this coding scheme, there are five potential moderators identified, since they might lead to a variance in effect sizes. Therefore, information extracted from the literature includes authors' names, year of publication, number of participants, and research result data. In addition, moderator variables, such as level of immersion, instructional approach, disciplinary category, learning cycle duration, and pre-training, also needed to be extracted and coded from the literature (see Table 1). To ensure the objectivity of the coding process, two researchers in this study independently conducted the coding for the 37 empirical research articles included in the meta-analysis. The consistency of the coding results was assessed using SPSS 25, and the calculated kappa value was 0.860, exceeding 0.8, indicating a high level of coding consistency. Any discrepancies were resolved through discussion and, if necessary, mediated by a third author to achieve consensus.

Data analysis

To assess publication bias, the funnel plot method was employed for qualitative analysis. The funnel plot can detect possible bias in a more intuitive way, but the analysis of results is subjective, so Egger et al.'s (1997) test, the trim-and-fill method, and the fail-safe N test were used for quantification. The intercept term in Egger analysis represents the relationship between effect size and precision. If the intercept term is not equal to zero, it indicates the presence of publication bias. The trim-and-fill method (Duval & Tweedie, 2000) was utilized to identify potential asymmetry possibly caused by publication bias. Additionally, this study employed the fail-safe N, as suggested by Rosenthal (1979). When the fail-safe N exceeds $5K+10$, insignificant results are unlikely to impact the average effect size of the meta-analysis conducted in this study. Here, K denotes the total number of articles included.

Table 1 Characteristics of studies included in the meta-analysis

Authors (year)	*N*	Level of immersion	Instructional approach	Disciplinary category	Learning cycle duration	Pre-training
İsmailoğlu et al. (2020)	60	L	ID	Medicine	0–1 day	Y
Al-Azawei et al. (2019)	32	H	ID	Engineering	0–1 day	N
Başer and Durmus (2010)	80	L	ID	Science	15 days to 1 month	N
Bayram and Caliskan (2019)	86	L	PT	Medicine	1–15 days	Y
Chau et al. (2013)	105	L	PT	Engineering	> 1 month	Y
Chu et al. (2020)	151	H	PT	Medicine	> 1 month	Y
Crochet et al. (2011)	22	H	ID	Medicine	> 1 month	Y
Cruz et al. (2013)	20	L	PT	Medicine	0–1 day	N
Darrah et al. (2014)	49/45/51/47	L	ID/PT	Science	> 1 month	Y
Dubovi et al. (2017)	129	L	ID	Medicine	0–1 day	N
Goderstad et al. (2020)	23/21	H	ID	Medicine	> 1 month	Y
Hu et al. (2021)	53	H	ID	Science	0–1 day	Y
Liu et al. (2021)	51	H	ID	Science	0–1 day	Y
Lo et al. (2022)	77	L	PS	Medicine	0–1 day	Y
Lorenzo-Alvarez et al. (2019)	156	L	PS	Medicine	15 days to 1 month	Y
Madan and Frantzides (2007)	31/33	L	ID	Medicine	1–15 days	N
Mansoory et al. (2022)	50	H	PS	Medicine	> 1 month	Y
Meyer et al. (2019)	57/61	H	ID	Science	1–15 days	Y/N
Miller et al. (2021)	203	H	PS	Science	> 1 month	Y
O’Connor and Rainford (2023)	191	H	ID	Medicine	> 1 month	N
Okutsu et al. (2013)	136	L	ID	Engineering	> 1 month	Y
Omlor et al. (2022)	101	H	PS	Medicine	1–15 days	N
Omori et al. (2023)	42	H	PS	Medicine	0–1 day	Y
Park et al. (2019)	72	H	ID	Medicine	> 1 month	N
Parong and Mayer (2018)	55	H	ID	Science	0–1 day	N
Paxinou et al. (2020)	54/53	L	ID	Science	0–1 day	Y
Qi et al. (2021)	60	H	PS	Medicine	1–15 days	N
Ros et al. (2021)	89	H	PS	Medicine	0–1 day	Y
Singh et al. (2015)	16	H	ID	Medicine	1–15 days	Y
Singh et al. (2020)	65	L	PS	Engineering	0–1 day	Y
Smith and Hamilton (2015)	20	L	PT	Medicine	> 1 month	N
Sultan et al. (2019)	169	H	PS	Medicine	> 1 month	N
Wells and Miller (2020)	51/50	H	ID/PT	Agronomy	> 1 month	Y
Youngblood et al. (2005)	30/33	H	ID	Medicine	1–15 days	N
Yu et al. (2021)	50	H	ID	Medicine	> 1 month	N
Zhang et al. (2021)	30	L	ID/PT	Medicine	1–15 days	Y
Zhou et al. (2011)	48	L	ID	Engineering	0–1 day	Y

N sample size, *L* LiVR, *H* HiVR, *PT* practice, *PS* presentation, *ID* independent, *Y* yes, *N* no

We assessed the homogeneity of effect sizes by calculating the Q statistics and determined an I^2 statistic to indicate the proportion of variability between studies attributable to true heterogeneity rather than sampling error (Higgins & Thompson, 2002). This step was essential for subsequent analyses. We employed the random-effects model for the entire calculation. Larger Q statistics indicate greater heterogeneity in effect sizes, with threshold values of I^2 for low, medium, and high heterogeneity set at 0.25, 0.50, and 0.70, respectively. All quantitative analyses were performed using CMA 3.0.

As previously mentioned, the objective of a meta-analysis is to synthesize the quantitative information collected from different studies. This meta-analysis intended to estimate the impact of VR on practical skills for students in science and engineering education and, with this aim, a pooled estimate of effect size was stated as Hedges' *g*. Hedges' *g* is a slightly more conventional derivative of Cohen's *d* (Cohen, 1992), and it contains a correction for biases due to sample size (Hedges, 1981). Cohen (1992) established benchmarks in which effect sizes of 0.2, 0.5, and 0.8 are interpreted as small, medium, and large, respectively.

To address the first research question of how VR enhances the practical skills of science and engineering students, this study incorporated 72 effect sizes from 37 empirical research papers and assessed them using Hedges' *g* values. Regarding the second research question, which explores how potential moderating variables affecting the effectiveness of practical skills, disciplinary category, learning cycle duration, and pre-training were identified as sources of heterogeneity that may lead to differences in effect sizes. Moreover, the level of immersion and instructional approach are crucial for understanding the impact of VR-based science and engineering education on students' practical skills.

Results

The results are presented in two parts. The first part focuses on the overall effect size, while the subsequent part delves into moderator analysis, considering the variables level of immersion, instructional approach, disciplinary category, learning cycle, and pre-training. These moderators are essential factors in empirical research (Wu & Zumbo, 2008) as they influence the effectiveness of VR in enhancing the practical skills of science and engineering students.

Overall effectiveness

This study included 72 different effect sizes from 37 empirical research papers. As shown in Fig. 2, the effect sizes of most of these studies are clustered in the funnel plot, with a few studies that are slightly skewed to the right. Egger analysis revealed an intercept of 2.49531 ($p = 0.00356 < 0.05$), thus suggesting publication bias. Nevertheless, the combined effect sizes before and after using the random-effects model remained unchanged after employing the trim-and-fill method. The effect sizes based on the fixed-effect model were 0.35498 and 0.22851, respectively. These results indicated that the random-effects model can effectively reduce potential publication bias. The fail-safe N, which was larger than "$5K + 10$" ($K = 72$), was 3234, thus suggesting that an additional 3234 unpublished studies would be needed to reverse the results (Rothstein et al., 2005). Therefore, this study did not have significant publication bias.

The meta-analysis included 37 literature sources published between 2000 and 2022. Figure 3 presents the forest plot, which displays the effect sizes and their 95% confidence intervals for each paper. The forest plots showed significant heterogeneity with $I^2 = 83.691\%$ (> 75%) and $Q = 435.350$ ($p < 0.001$), thus indicating a high

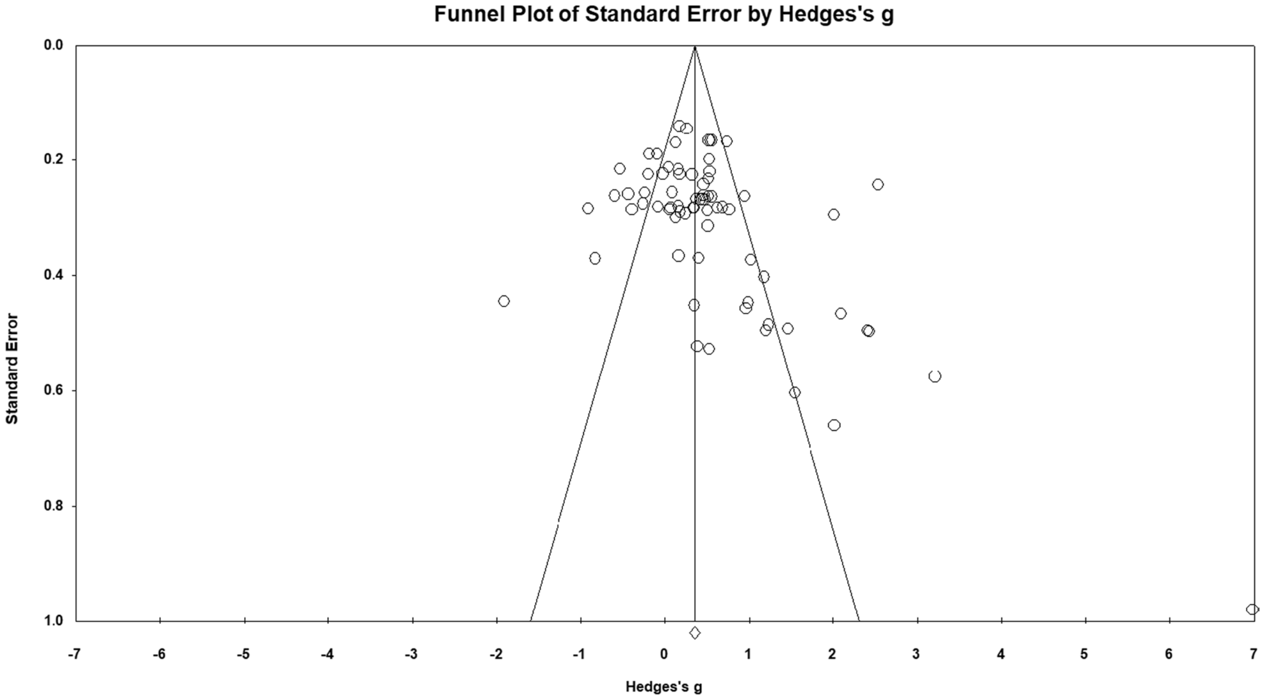
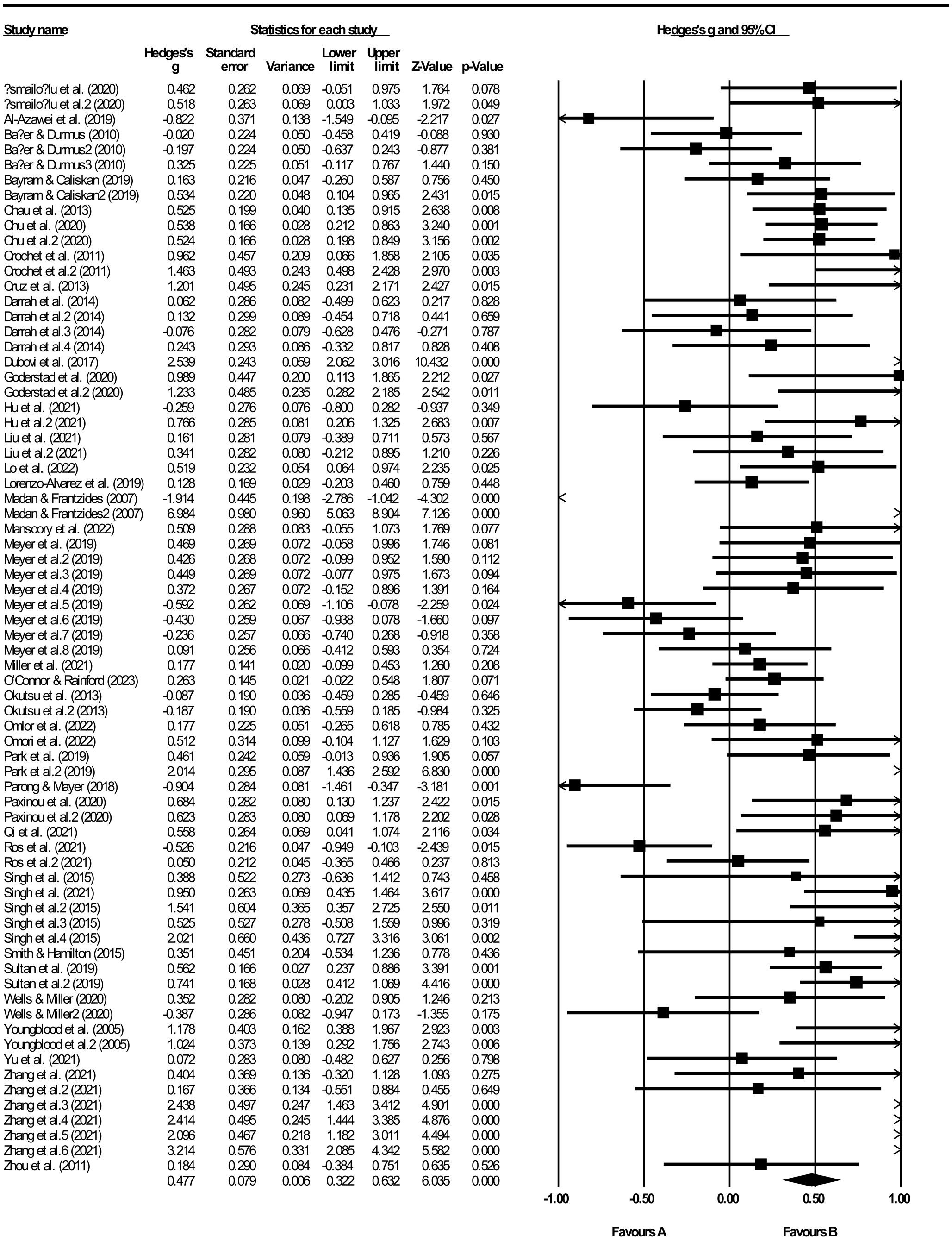


Fig. 2 Publication bias funnel plot



Study name	Hedges's g	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value
?smailo?lu et al. (2020)	0.462	0.262	0.069	-0.051	0.975	1.764	0.078
?smailo?lu et al.2 (2020)	0.518	0.263	0.069	0.003	1.033	1.972	0.049
Al-Azawei et al. (2019)	-0.822	0.371	0.138	-1.549	-0.095	-2.217	0.027
Ba?er & Durmus (2010)	-0.020	0.224	0.050	-0.458	0.419	-0.088	0.930
Ba?er & Durmus2 (2010)	-0.197	0.224	0.050	-0.637	0.243	-0.877	0.381
Ba?er & Durmus3 (2010)	0.325	0.225	0.051	-0.117	0.767	1.440	0.150
Bayram & Caliskan (2019)	0.163	0.216	0.047	-0.260	0.587	0.756	0.450
Bayram & Caliskan2 (2019)	0.534	0.220	0.048	0.104	0.965	2.431	0.015
Chau et al. (2013)	0.525	0.199	0.040	0.135	0.915	2.638	0.008
Chu et al. (2020)	0.538	0.166	0.028	0.212	0.863	3.240	0.001
Chu et al.2 (2020)	0.524	0.166	0.028	0.198	0.849	3.156	0.002
Crochet et al. (2011)	0.962	0.457	0.209	0.066	1.858	2.105	0.035
Crochet et al.2 (2011)	1.463	0.493	0.243	0.498	2.428	2.970	0.003
Cruz et al. (2013)	1.201	0.495	0.245	0.231	2.171	2.427	0.015
Darrah et al. (2014)	0.062	0.286	0.082	-0.499	0.623	0.217	0.828
Darrah et al.2 (2014)	0.132	0.299	0.089	-0.454	0.718	0.441	0.659
Darrah et al.3 (2014)	-0.076	0.282	0.079	-0.628	0.476	-0.271	0.787
Darrah et al.4 (2014)	0.243	0.293	0.086	-0.332	0.817	0.828	0.408
Dubovi et al. (2017)	2.539	0.243	0.059	2.062	3.016	10.432	0.000
Goderstad et al. (2020)	0.989	0.447	0.200	0.113	1.865	2.212	0.027
Goderstad et al.2 (2020)	1.233	0.485	0.235	0.282	2.185	2.542	0.011
Hu et al. (2021)	-0.259	0.276	0.076	-0.800	0.282	-0.937	0.349
Hu et al.2 (2021)	0.766	0.285	0.081	0.206	1.325	2.683	0.007
Liu et al. (2021)	0.161	0.281	0.079	-0.389	0.711	0.573	0.567
Liu et al.2 (2021)	0.341	0.282	0.080	-0.212	0.895	1.210	0.226
Lo et al. (2022)	0.519	0.232	0.054	0.064	0.974	2.235	0.025
Lorenzo-Alvarez et al. (2019)	0.128	0.169	0.029	-0.203	0.460	0.759	0.448
Madan & Frantzides (2007)	-1.914	0.445	0.198	-2.786	-1.042	-4.302	0.000
Madan & Frantzides2 (2007)	6.984	0.980	0.960	5.063	8.904	7.126	0.000
Mansoory et al. (2022)	0.509	0.288	0.083	-0.055	1.073	1.769	0.077
Meyer et al. (2019)	0.469	0.269	0.072	-0.058	0.996	1.746	0.081
Meyer et al.2 (2019)	0.426	0.268	0.072	-0.099	0.952	1.590	0.112
Meyer et al.3 (2019)	0.449	0.269	0.072	-0.077	0.975	1.673	0.094
Meyer et al.4 (2019)	0.372	0.267	0.072	-0.152	0.896	1.391	0.164
Meyer et al.5 (2019)	-0.592	0.262	0.069	-1.106	-0.078	-2.259	0.024
Meyer et al.6 (2019)	-0.430	0.259	0.067	-0.938	0.078	-1.660	0.097
Meyer et al.7 (2019)	-0.236	0.257	0.066	-0.740	0.268	-0.918	0.358
Meyer et al.8 (2019)	0.091	0.256	0.066	-0.412	0.593	0.354	0.724
Miller et al. (2021)	0.177	0.141	0.020	-0.099	0.453	1.260	0.208
O'Connor & Rainford (2023)	0.263	0.145	0.021	-0.022	0.548	1.807	0.071
Okutsu et al. (2013)	-0.087	0.190	0.036	-0.459	0.285	-0.459	0.646
Okutsu et al.2 (2013)	-0.187	0.190	0.036	-0.559	0.185	-0.984	0.325
Omlor et al. (2022)	0.177	0.225	0.051	-0.265	0.618	0.785	0.432
Omori et al. (2022)	0.512	0.314	0.099	-0.104	1.127	1.629	0.103
Park et al. (2019)	0.461	0.242	0.059	-0.013	0.936	1.905	0.057
Park et al.2 (2019)	2.014	0.295	0.087	1.436	2.592	6.830	0.000
Parong & Mayer (2018)	-0.904	0.284	0.081	-1.461	-0.347	-3.181	0.001
Paxinou et al. (2020)	0.684	0.282	0.080	0.130	1.237	2.422	0.015
Paxinou et al.2 (2020)	0.623	0.283	0.080	0.069	1.178	2.202	0.028
Qi et al. (2021)	0.558	0.264	0.069	0.041	1.074	2.116	0.034
Ros et al. (2021)	-0.526	0.216	0.047	-0.949	-0.103	-2.439	0.015
Ros et al.2 (2021)	0.050	0.212	0.045	-0.365	0.466	0.237	0.813
Singh et al. (2015)	0.388	0.522	0.273	-0.636	1.412	0.743	0.458
Singh et al. (2021)	0.950	0.263	0.069	0.435	1.464	3.617	0.000
Singh et al.2 (2015)	1.541	0.604	0.365	0.357	2.725	2.550	0.011
Singh et al.3 (2015)	0.525	0.527	0.278	-0.508	1.559	0.996	0.319
Singh et al.4 (2015)	2.021	0.660	0.436	0.727	3.316	3.061	0.002
Smith & Hamilton (2015)	0.351	0.451	0.204	-0.534	1.236	0.778	0.436
Sultan et al. (2019)	0.562	0.166	0.027	0.237	0.886	3.391	0.001
Sultan et al.2 (2019)	0.741	0.168	0.028	0.412	1.069	4.416	0.000
Wells & Miller (2020)	0.352	0.282	0.080	-0.202	0.905	1.246	0.213
Wells & Miller2 (2020)	-0.387	0.286	0.082	-0.947	0.173	-1.355	0.175
Youngblood et al. (2005)	1.178	0.403	0.162	0.388	1.967	2.923	0.003
Youngblood et al.2 (2005)	1.024	0.373	0.139	0.292	1.756	2.743	0.006
Yu et al. (2021)	0.072	0.283	0.080	-0.482	0.627	0.256	0.798
Zhang et al. (2021)	0.404	0.369	0.136	-0.320	1.128	1.093	0.275
Zhang et al.2 (2021)	0.167	0.366	0.134	-0.551	0.884	0.455	0.649
Zhang et al.3 (2021)	2.438	0.497	0.247	1.463	3.412	4.901	0.000
Zhang et al.4 (2021)	2.414	0.495	0.245	1.444	3.385	4.876	0.000
Zhang et al.5 (2021)	2.096	0.467	0.218	1.182	3.011	4.494	0.000
Zhang et al.6 (2021)	3.214	0.576	0.331	2.085	4.342	5.582	0.000
Zhou et al. (2011)	0.184	0.290	0.084	-0.384	0.751	0.635	0.526
	0.477	0.079	0.006	0.322	0.632	6.035	0.000

Fig. 3 Forest plot of selected studies

degree of variability among the samples. Consequently, a random-effects model was employed for correlation analysis to account for the heterogeneity. The potential sources of heterogeneity might include factors, such as level of immersion, instructional approach, disciplinary category, learning cycle duration, and pre-training. These findings highlighted the need for moderator analysis to examine the impact of VR on practical skills.

This study included 72 effect sizes from 37 empirical research papers, as shown in Table 2. The comprehensive effect size of VR on the practical skills learning of science and engineering students was 0.477, thus indicating that

Table 2 Main effect test

Model	Number of studies (*k*)	ES	SE	σ^2	95% CI		Two-tailed test		Heterogeneity		
					Lower	Upper	*Z*	*P*	*Q*	*df(Q)*	*p*
Fixed	72	0.355	0.101	0.001	0.295	0.415	11.580	0.000	254.181	33	0.000
Random	72	0.477	0.031	0.010	0.322	0.632	6.035	0.000			

Table 3 The effect sizes of categories and their related moderator variables

Moderator	*k*	*g*	*z*	95% CI	Q_B
Level of immersion					2.817
1. LiVR	31	0.615	5.039***	[0.376, 0.854]	
2. HiVR	41	0.377	3.586***	[0.171, 0.583]	
Instructional approach					4.822
1. Practice	14	0.842	4.560***	[0.480, 1.204]	
2. Presentation	12	0.357	1.936	[−0.004, 0.719]	
3. Independent	46	0.406	4.023***	[0.208, 0.604]	
Disciplinary category					20.447***
1. Science	23	0.113	0.864	[−0.142, 0.365]	
2. Engineering	6	0.115	0.457	[−0.377, 0.607]	
3. Agronomy	2	−0.017	−0.038	[−0.888, 0.854]	
4. Medicine	41	0.790	7.628***	[0.587, 0.993]	
Learning cycle duration					4.072
1. 0–1 day	18	0.385	2.444*	[0.076, 0.695]	
2. 1–15 days	26	0.675	4.795***	[0.399, 0.951]	
3. 15–30 days	4	0.060	0.187	[−0.568, 0.688]	
4. More than 1 month	24	0.443	3.758**	[0.175, 0.710]	
Pre-training					0.723
1. Yes	48	0.527	5.372***	[0.335, 0.719]	
2. No	24	0.383	2.788**	[0.114, 0.653]	

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

the overall effect was significant and moderately positive (Cohen, 1992).

Moderator analysis

This study analyzed how personalized learning was moderated by five variables, including level of immersion, instructional approach, disciplinary category, learning cycle duration, and pre-training. Table 3 shows the results of five moderator variables analyzed by the random-effects model. The following sections illustrate the moderator variables one by one.

Level of immersion

The results show that the use of LiVR has a greater impact on students' practical skills ($g = 0.615$, 95% CI [0.376, 0.854], $p < 0.001$) than HiVR ($g = 0.377$, 95% CI [0.171, 0.583], $p < 0.001$). However, Q_B did not reach statistical significance ($Q_B = 2.817$, $p > 0.05$). Therefore, there were no significant differences in effect sizes between LiVR and HiVR.

Instructional approach

Instructional approach is categorized into three types. Among them, the practice approach ($g = 0.842$, 95% CI [0.480, 1.204], $p < 0.001$) and the independent approach ($g = 0.406$, 95% CI [0.208, 0.604], $p < 0.001$) both reach the requirement of statistical significance. The presentation approach ($g = 0.357$, 95% CI [−0.004, 0.719], $p > 0.05$) did not have statistical significance. Meanwhile, the Q_B did not achieve statistical significance ($Q_B = 4.822$, $p > 0.05$), indicating that the average effect sizes did not differ significantly among the three types of instructional approach.

Disciplinary category

The data revealed that the practical skills of medical students had the highest effect size with VR ($g = 0.790$, 95% CI [0.587, 0.993], $p < 0.001$), followed by engineering students ($g = 0.115$, 95% CI [−0.377, 0.607], $p > 0.05$), and science students ($g = 0.113$, 95% CI [−0.142, 0.365], $p > 0.05$). However, there was no positive promotion effect observed for agronomy students ($g = -0.017$, 95% CI [−0.888, 0.854], $p > 0.05$). In the field of medicine, the results were statistically significant. Additionally, the Q_B analysis indicated statistical significance ($Q_B = 20.447$, $p < 0.001$), suggesting that the average effect sizes differed significantly among the four disciplinary categories.

Learning cycle duration

With respect to learning cycle duration, the effect sizes, which were ranked from high to low, were 1–15 days ($g = 0.675$, 95% CI [0.399, 0.951], $p < 0.001$), more than 1 month ($g = 0.443$, 95% CI [0.175, 0.710], $p < 0.01$), 0–1 day ($g = 0.385$, 95% CI [0.076, 0.695], $p < 0.05$), and 15–30 days ($g = 0.060$, 95% CI [−0.568, 0.688], $p > 0.05$). The effect of 15–30 days did not reach a statistically significant level. The Q_B did not achieve statistical significance ($Q_B = 4.072$, $p > 0.05$), indicating that the average effect sizes did not differ significantly among different learning cycle duration.

Pre-training

Finally, the effect size for students with pre-training was 0.527 (95% CI [0.335, 0.719], $p < 0.001$). For students without pre-training, the size was 0.383 (95% CI [0.114, 0.653], $p < 0.01$). Both cases demonstrated significant differences. However, Q_B did not reach statistical significance ($Q_B = 0.723$, $p > 0.05$).

Discussion

How effective is VR in enhancing the practical skills of students in science and engineering?

This meta-analysis corroborates the effectiveness of VR as a significant tool for improving practical skills among students in science and engineering disciplines. The findings indicate a moderate, positive impact of VR on practical skills. This aligns with findings from previous reviews showing the benefits of immersive VR technology for procedural training across medical, technical, and scientific domains (Angel-Urdinola et al., 2021; Ma et al., 2022).

In line with conclusions by Angel-Urdinola et al. (2021), the findings here also highlight the nuanced factors influencing experimental outcomes and demonstrate the vital ability of VR technology to complement traditional teaching and expand practical skills training in more cost-effective and scalable ways. This exploration aims to identify diverse strategies for integrating VR optimally, thereby unlocking its enhanced potential. This could indicate even greater potential for realistic, scenario-based VR experiences to enable science and engineering students to bridge conceptual knowledge with tangible skills' mastery.

The present study expands on this prior work by focusing specifically on college students in science and engineering fields. The aggregated results across 72 randomized-controlled trials show that VR training consistently improves skills performance compared to more traditional teaching methods. This suggests that meaningful learning gains can be achieved by incorporating VR tools as supplements to standard lab work, experimentation, and knowledge application in technical coursework. Further research can continue to explore optimal integration of VR tools in science and engineering curricula to drive positive learning outcomes.

How do the features of studies, such as level of immersion, instructional approach, disciplinary categories, learning cycle duration, and pre-training, moderate the effect?

With regard to level of immersion, LiVR and HiVR experiences have been found to have positive effects on student learning. However, it is worth noting that the effect size of LiVR surpasses that of HiVR in the context of learning. A possible reason for this difference is that LiVR and HiVR have distinct technical features and usage conditions. As mentioned by Hamilton et al. (2020), the novelty of HMDs and immersive VR might hinder learning outcomes and classroom applications, especially for individuals unfamiliar with or new to this technology. The accessibility and lower interface burdens of LiVR systems potentially lessen extraneous cognitive load during complex psychomotor tasks, enabling heightened focus on skills practice itself. Conversely, despite their superior realism, HiVR may overwhelm working memory resources. Further research should continue investigating specific VR features and implementation methods that optimize practical skill training without overburdening student working memory.

In terms of instructional approach, VR demonstrated optimal practical skill improvements as a supplementary tool for reinforcing concepts initially introduced via traditional teaching, consistent with the findings of Ma et al. (2022). This suggests that when the use of VR is combined with the traditional teaching method, it promotes effective student learning (Xu et al., 2018). Such a strategy allows students to form foundational knowledge through traditional means before engaging in immersive practice sessions, thereby fostering a more seamless integration and consolidation of knowledge (Villena-Taranilla et al., 2022). Using VR tools independently as primary teaching platforms was less impactful, suggesting full substitution remains premature. Additionally, passively viewing VR content rarely surpasses gains from participatory simulations and physical learning. Findings indicate that VR's flexibility allows variability in usage from expansive labs to focused reinforcement. Yet exclusively relying on synthetic environments or passive observation risks disconnect from grounded learning contexts. Further research should continue investigating optimal integration techniques.

Concerning the disciplinary category, a substantially larger effect size was found for VR practical skills training in medicine compared to science, engineering, and agronomy, aligning with the conclusions of Shen et al. (2020) and Zhou and Li (2019). The early prioritization of immersive simulation in medicine for high-risk procedural development has led to a more mature pedagogical use of VR in this field. Conversely, technical limitations around implementing complex mechanical/chemical reactions likely constrain VR's impact in emerging areas like engineering and agriculture. However, the negligible effect found for agronomy learning warrants careful interpretation due to the very limited sample size. Similarly, the smaller science/engineering effect size, while significant, still indicates supplementary value for VR incorporation and is likely to grow with improving technology and increased research on optimal integration techniques. While application gaps persist in some fields, sustained investigation of discipline-specific design principles can unleash VR's skill-building potential across spheres.

With respect to learning cycle duration, the study found that the largest effect size for the experimental period is 1–15 days, followed by periods lasting more than 1 month ($g = 0.443$) and periods ranging from 0 to 1 day. The initial efficacy of short < 1-day trials likely reflect curiosity spikes, while insufficient time training with the VR interface may constrain outcomes. Meanwhile, the non-significant impact of 15–30-day periods could stem from declining novelty without yet achieving mastery. For sustained skills reinforcement, pairing interactive VR activities with targeted feedback and benchmarks appears vital. Additionally, the smallest sample of long-term studies may have underpowered detection of effects from prolonged engagement. Overall, tailoring VR supplement duration to scaffold progressive expertise while maintaining student motivation seems crucial. Findings illuminate the double-edged sword of captivation, which can inspire early participation but requires careful upkeep and alignment to pedagogical aims over time.

In terms of pre-training, both scenarios positively affect students' practical skills, with present pre-training outperforming the absence of it. This finding is consistent with the research conducted by Meyer et al. (2019). Pre-training serves to familiarize students with the VR environment and the equipment that they will be using, thus enabling learners to acquire the foundational skills necessary for subsequent learning activities (Meyer et al., 2019). By reducing cognitive load during subsequent learning tasks, pre-training allows students to allocate their cognitive resources effectively toward acquiring the intended content and skills. Additionally, pre-training enhances students' confidence and motivation, thereby promoting their engagement and performance in subsequent learning activities. To advance our understanding of the role of pre-training, future research should delve into exploring the optimal duration and content of pre-training sessions, considering variations in student backgrounds and familiarity with VR technology. Additionally, investigating the sustained impact of pre-training on long-term skill retention and transferability to real-world applications would provide valuable insights. By exploring these aspects, researchers can refine pre-training strategies and maximize their effectiveness in VR-based educational settings.

Implications for theory and practice

This study confirmed that VR can effectively promote practical skills among science and engineering students. Theoretically, these results underscore VR's substantial role in educational psychology and technology-enhanced learning, providing robust evidence that VR interventions can meaningfully improve practical skills. The nuanced analysis of moderator variables, such as level of immersion, instructional approach, and disciplinary category, contributes to a deeper understanding of the design and utilization principles of VR in skill development. By elucidating the specific conditions that maximize the effectiveness of VR, this study not only confirms its value in educational settings but also sheds light on the mechanisms that facilitate learning through VR.

As for practical implications, the findings provide valuable guidance for educators and curriculum developers on how to effectively integrate VR for practical skills training. When considering immersion levels, it seems that LiVR systems may be beneficial for the acquisition of practical skills. Regarding instructional approach, using VR as a supplementary tool to reinforce concepts initially taught through traditional methods appears most effective, allowing students to establish foundational knowledge frameworks before applying immersive practice. Moreover, disciplinary differences should be considered, as fields like medicine have more mature VR pedagogical practices due to their early adoption of immersive simulations. Regarding the learning cycle duration, an optimal duration of 1–15 days seems most beneficial, balancing initial curiosity with sustained skill reinforcement. Additionally, incorporating pre-training sessions to familiarize students with the VR environment and equipment may be more effective in promoting practical skills. Therefore, educators and curriculum developers are encouraged to determine a thoughtful integration of VR in education, leveraging its strengths to enhance practical skills while being mindful of the variability in its effectiveness across different contexts and learner needs.

Conclusions and limitations

The purpose of this meta-analysis was to consolidate findings from various studies examining the impact of VR on practical skills among science and engineering students. By synthesizing data from 37 high-quality empirical studies, this study offers insights into the impact of VR. Overall, VR had a moderate effect on practical skills, with an effect size of 0.477. Furthermore, the disciplinary category emerged as a significant moderator of the effect size, revealing that it differed significantly when comparing medical, engineering, science, and agronomy students. Notably, among different instructional approaches, the practice approach demonstrated the largest effect size.

This meta-analysis has two limitations. First, only articles published in English were included, which may exclude relevant studies in other languages and introduce language or cultural bias. In addition, several experimental studies were omitted due to insufficient and unanalyzable statistical information, which may affect the meta-analysis results. In summary, while recognizing these limitations, this meta-analysis represents an important step in synthesizing quantitative evidence regarding impacts of VR on practical skills.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40594-024-00487-2.

Supplementary Material 1.

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Author contributions
CY: conceptualization, methodology, resources, formal analysis, data curation, writing (original draft, review, and editing), visualization, and project management. JZ: resources, formal analysis, data curation, and writing (original draft, review, and editing). YH: resources, investigation, data curation, formal analysis, and writing (original draft, review, and editing). XY: conceptualization, writing (review and editing), and supervision. MC: writing (review and editing). MS: writing (review and editing). LL: writing (review and editing).

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Availability of data and materials
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no competing interests.

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