

Effects of online professional learning on healthcare professionals' knowledge and skill acquisition: A systematic review and meta-analysis

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Declarations of interests

The authors have developed a number of online learning programs for health professionals, but for research purposes only and not for private gain. LC undertakes occasional paid presenting work for StrokeEd, an organisation that provides professional education (including online

learning) to allied health professionals. This role is independent of the research reported in this manuscript, and StrokeEd had no involvement in the study design, analysis, interpretation, or preparation of this manuscript. They have no other conflicts of interest.

Acknowledgements

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) and Claude (Anthropic) to support language editing and improve readability. The authors also used Claude Code and Codex to support drafting and checking code. All AI-assisted outputs were reviewed and edited by the authors, who take full responsibility for the content of the publication.

Data sharing statement

Data and code for reproducing analyses are available at https://osf.io/46zav/?view_only=b1b46e241a9d4ee691d587c6c74a1ebe

Role of the funding source

There was no funding source for this study.

Summary

Background

Online professional learning offers a scalable alternative to traditional face-to-face learning, but there are doubts regarding how well it works and when it works best. This review assessed the effectiveness of online professional learning interventions on healthcare professionals' knowledge and skill acquisition.

Methods

We conducted a systematic review and meta-analysis of randomised controlled trials that compared online professional learning against static controls or face-to-face controls. We searched MEDLINE Complete, Scopus, Embase, CENTRAL, and PsycINFO from inception to January 31, 2025. Eligible studies included practising healthcare professionals in any clinical setting that measured knowledge or skill acquisition related to patient care. Data was extracted in duplicate, with disagreements resolved through discussion or by a third reviewer. We used multilevel meta-analyses to estimate the overall effect size and conducted moderation analyses for pre-specified factors. The study protocol was pre-registered on the Open Science Framework (OSF; <https://osf.io/46zav>).

Findings

Of 55,376 records; 171 studies (391 effects, 25,412 participants) met the inclusion criteria. Online learning significantly improved knowledge and skill acquisition compared to static controls ($g = 0.93$, 95% CI [0.78, 1.07], $p < 0.001$; $I^2 = 89.8\%$), with larger effects in lower-middle income countries ($g = 1.30$, 95% CI [0.88, 1.72]) than in high income ($g = 0.75$, 95% CI [0.63, 0.86]). Online learning also significantly improves outcomes compared to face-to-face instruction ($g = 0.45$, 95% CI [0.31, 0.59], $p < 0.001$; $I^2 = 85.92\%$), with larger effects for

knowledge outcomes ($g = 0.46$, 95% CI [0.33, 0.59]) than skills outcomes ($g = 0.20$, 95% CI [0.04, 0.36]). Effects did not differ significantly by profession, clinician experience, clinical setting, intervention characteristics or the learning design features (all $p > 0.05$). No studies had low overall risk of bias, and some evidence of publication bias was found.

Interpretation

From this body of evidence, we identified that online learning appears to improve healthcare professionals' knowledge and skill acquisition, exceeding traditional teaching methods. Healthcare organisations can be confident implementing or expanding online professional learning to improve knowledge and skill acquisition.

Funding

No funding

Effects of online professional learning on healthcare professionals' knowledge and skill acquisition: A systematic review and meta-analysis

Knowledge translation aims to accelerate the implementation of research into clinical practice. It can be a slow process; research can take an average of 17 years to reach widespread clinical practice¹⁻³, leading to preventable deaths^{4,5} and disability^{6,7}. To close this research-practice gap, continuing professional learning aims to provide healthcare professionals with up-to-date knowledge and skills⁸⁻¹⁰. Traditionally, face-to-face education has been shown to develop practitioners' knowledge and skills^{11,12}. However, face-to-face programs often require significant resources, incur high costs, and present scalability challenges^{2,13,14}. As a result, many healthcare professionals, especially those in remote or low-resource areas, struggle to access professional learning opportunities¹⁵⁻¹⁹. Online learning has emerged as a flexible and cost-effective alternative that allows professionals to access materials at their own pace, regardless of time or location²⁰⁻²³.

Despite widespread adoption^{2,24}, evidence regarding the effectiveness of online learning remains mixed. For instance, Ding et al.²⁵ conducted a meta-analysis of e-learning programs for nurse education on pressure injury management, reporting significant knowledge gains compared to traditional approaches. In contrast, Vaona et al.'s¹⁴ meta-analysis involving licensed healthcare professionals found online learning made little to no difference in knowledge acquisition compared to traditional professional development methods. Rouleau et al.'s²⁶ overview of systematic reviews of nursing continuing education found that while online learning was effective when compared to no intervention, traditional classroom learning was superior in certain clinical skills, particularly drug dose practices. Overall, the variability in findings underscores the need to better understand when and how online learning can be most effective

compared to traditional methods.

Whether online learning is effective or not may depend on the delivery format and design features, such as the level of interactivity²⁷, blended learning, collaboration^{28,29}, or feedback^{21,30}. Yet few reviews have examined how these principles influence knowledge and skills outcomes across healthcare professionals. The aim of our systematic review was to assess the effectiveness of online professional learning interventions on healthcare professionals' knowledge and skill acquisition, and investigate a broad range of online learning design features to determine which, if any, influence knowledge and skills outcomes. Understanding these elements will enable development of evidence-based interventions to effectively bridge the research-practice gap.

Methods

We conducted a systematic review and meta-analysis following Preferred Reporting Items for Systematic Review and Meta-Analysis guidelines (see Supplementary File 1 for PRISMA 2020 checklist)³¹, the Assessing the Methodological Quality of Systematic Review (AMSTAR) 2 tool³², and pre-registered our protocol on the Open Science Framework (OSF; <https://osf.io/46zav>). This report focuses on aims two and three of the protocol, examining outcomes related to knowledge and skill acquisition, while a complementary paper addresses aims one and four³³.

Eligibility Criteria

We included randomised controlled trials of practising healthcare professionals comparing online professional learning with any other professional learning or a control condition whereby the outcomes reported were specific to knowledge or skill development as relevant to patient care. Studies in any language were eligible; non-English reports were translated using Google Translate. Studies needed to present new data (e.g., protocols and reviews were excluded) in a

form that could be used to calculate an effect size (e.g., means, standard deviations, number of events/successes, precise p values). Where data required for effect-size calculation were missing, we contacted study authors and excluded studies if data could not be obtained. Full eligibility criteria are provided in the supplementary materials (see Supplementary File 2).

Search strategy and selection criteria

Our search strategy development began with analysing key terms from an initial sample of relevant papers, including systematic reviews ^{e.g., 14,34} and primary studies ^{e.g., 35,36}. We compiled a list of terms to accurately identify target papers ³⁷, achieving high sensitivity and specificity by successfully capturing all 28 identified primary studies.

We used those terms to search MEDLINE Complete, Scopus, Embase (Ovid), CENTRAL, and PsycINFO from inception to Jan 31, 2025; full strategies are provided in Supplementary File 3. After de-duplication in EndNote, title/abstract records were processed using RobotSearch³⁸ to assist identification of randomised controlled trials ³⁹ and then imported into Covidence for screening. Two reviewers screened records independently at title/abstract and full-text stages, resolving disagreements through discussion or adjudication by a third reviewer (GS, SG, or MN). Forward and backward citation searches were conducted in Scopus on July 19, 2025 (by SG) and screened in duplicate (SG, GS, and KR), with disagreements resolved by discussion.

Data Analysis

Data Items

We extracted study characteristics and outcome data required to calculate effect sizes (as defined in the protocol), independently and in duplicate, with disagreements resolved through discussion or by a third reviewer (SG, GS or MN). When studies presented alternative data in formats that did not directly provide effect sizes (e.g., interquartile range instead of standard

deviations), we calculated the necessary values following guidelines from the Cochrane Handbook for Systematic Reviews of Interventions ⁴⁰. When studies provided only figures, we extracted the relevant data using WebPlotDigitizer ⁴¹.

Risk of Bias

We a priori planned that risk of bias assessments would be conducted independently and in duplicate. Given the high volume of included studies, we modified this process following guidance from AMSTAR 2 ³² and the Cochrane Handbook ⁴⁰ to maintain reliability. We assessed methodological quality of the included randomised studies using the Cochrane Risk of Bias 2 (RoB2), we calibrated reviewers on 29% of studies. Reviewers independently assessed these articles, then met to resolve disagreements and establish decision rules. Once we achieved 80% agreement on all RoB2 domains, reviewers proceeded with individual assessments of remaining studies.

Certainty Assessment

We assessed the certainty of the evidence for each outcome using the Grading of Recommendations Assessment, Development, and Evaluation (GRADE) framework, evaluating risk of bias, inconsistency, indirectness, imprecision, and publication bias ^{40,42}. Assessments were conducted in duplicate (SG, MN), with disagreements resolved through discussion.

Statistical Analysis

We extracted all eligible effect sizes from each study, using the post-test, between-groups standardised mean difference as the primary summary measure. All metrics were converted to Hedges' g ⁴³. Our multilevel meta-analyses examined the effect of online professional learning on knowledge and skill acquisition through two distinct comparisons: online learning versus static controls (e.g., waitlists, electronic or print materials, self-directed textbook reading), and

online learning versus face-to-face instruction. For each comparison, we quantified heterogeneity using I^2 . We tested the influence of this heterogeneity following Mathur and VanderWeele⁴⁴, estimating the proportion of true effects (not due to sampling error) likely to be helpful (interpreted as a small, positive effect; Hedges' $g > 0.2$) or harmful (Hedges' $g < -0.2$).

To explore sources of heterogeneity, we pre-specified a range of moderators (see protocol <https://osf.io/46zav>). To avoid generalising from small samples, we only included moderator levels with at least three studies. For learning design principles, we planned three approaches to moderation analyses, given these design principles may co-occur and interact. First, we modelled the effect of all learning design principles simultaneously (akin to multiple regression). Then, we modelled the effect of each learning design principle, one at a time (akin to running multiple simple regressions), using 99% confidence interval (CI) to mitigate false positives from multiple comparisons. Finally, we used meta-analytic classification and regression trees (meta-CART) to explore possible interactions between moderator effects. The meta-CART analysis was performed using the *metacart* package in R (version 4.3.1)⁴⁵ with default parameters.

Sensitivity and Publication Bias Analysis

We conducted a sensitivity analysis to assess the influence of extreme outliers, testing whether removal of effect sizes exceeding $g > 2.5$ meaningfully altered the pooled effect size estimates. To balance methodological rigour with analytic stability, outliers were retained in the main analysis but excluded from moderator analyses, as extreme effect sizes can disproportionately influence subgroup estimates and produce unstable or misleading moderator effect estimates^{46,47}.

We conducted sensitivity analyses to assess whether the risk of bias in the included studies explained the variance observed in pooled effect size estimates. For each bias domain and

for overall risk of bias, we modelled the effects of studies rated as low risk and compared effects against our overall analysis (including all studies).

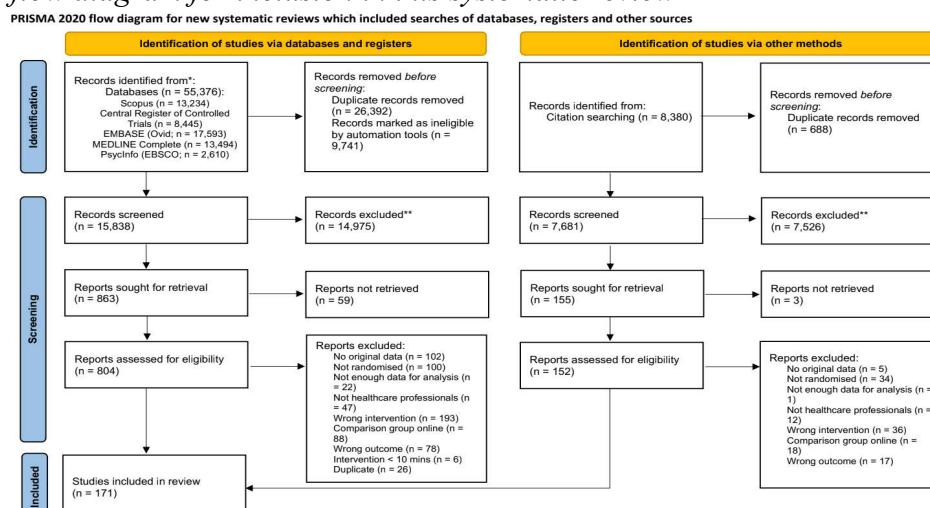
We assessed publication bias using a multi-level meta-analytic Egger's test to determine whether smaller studies reported disproportionately larger effect sizes, suggesting potential small-study effects^{40,48}. This approach assessed whether effect sizes and their standard errors indicated publication bias while controlling for clustering, including a random effect for studies and incorporated delivery type as a categorical moderator to explore whether publication bias varied across control types. Standard error was modelled as a predictor to detect funnel plot asymmetry, an indicator of publication bias.

Results

Our systematic search identified 55,376 titles and abstracts. Given the extensive literature identified, this paper addresses knowledge and skill acquisition, while a complementary paper reports effects on clinical practice³³. After deduplication and screening (detailed in Figure 1; see Supplementary File 1 for PRISMA 2020 checklist³¹; see Supplementary File 4 for excluded full-text studies with reasons), we included 171 studies reporting 391 effect sizes from 25,412 participants. Sex or gender was reported in 123 studies (16,567 participants), of whom 74% were female. Table 1 provides the full characteristics of each included study.

Figure 1

PRISMA flow diagram for inclusion in this systematic review



Effect of Online Learning Versus Static Controls

The effect sizes of learning extracted from individual studies are shown in Figure 2.

Overall, online interactive professional learning significantly improved knowledge and skill acquisition compared against static controls such as waitlist or static dissemination ($g = 0.93$, 95% CI [0.78, 1.07], $n = 103$, $k = 230$, $p < 0.001$). This point estimate demonstrated a high level of heterogeneity that was not explained by sampling error alone ($I^2 = 89.8$). Our models estimated that online learning was likely to be meaningfully better than controls (i.e., $g > 0.2$) for 89% of true effects (95% CI [82%, 93%]). Models suggested online learning would be meaningfully worse (i.e., $g < -0.2$) than controls in 0% of true effects (95% CI [0%, 2%]) of cases.

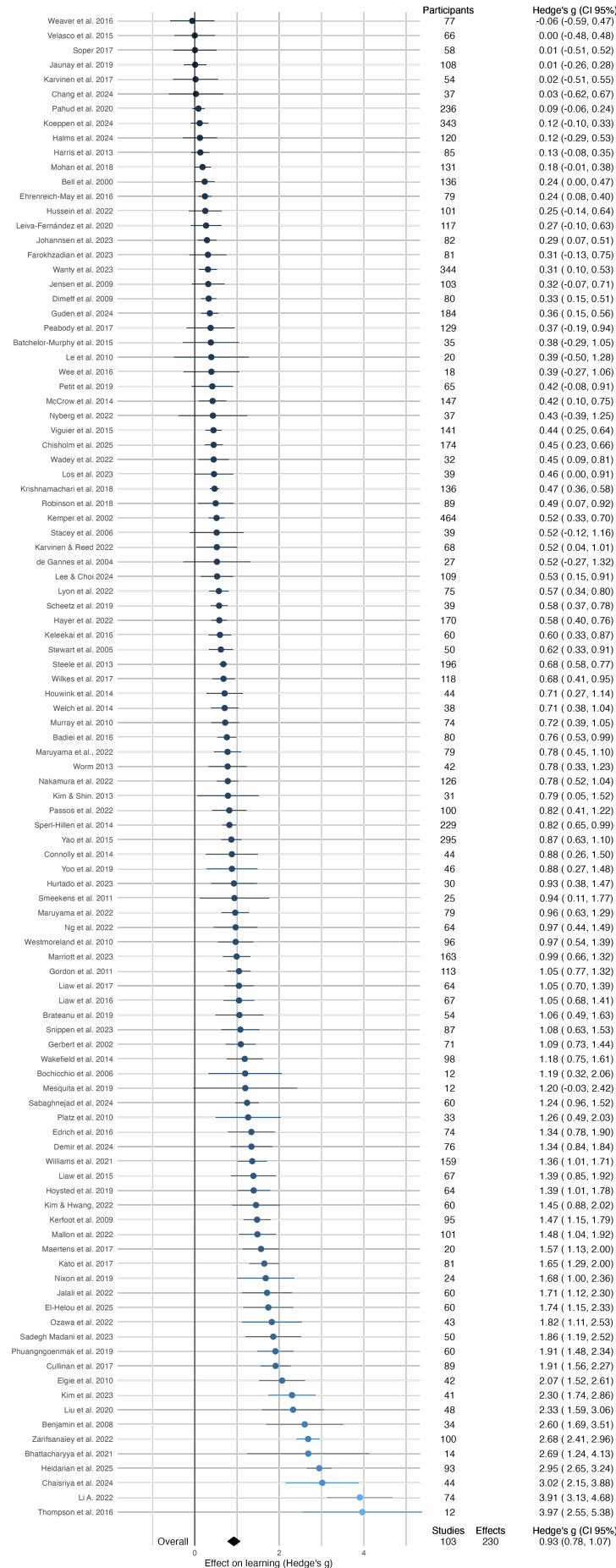
Outlier Consideration

Visual inspection of effect size distributions identified 18 extreme outliers with effect sizes $g > 2.5$ from 12 studies. Sensitivity analysis confirmed that removing these outliers had minimal impact on the pooled effect size ($\Delta g = 0.15$), with overlapping 95% confidence intervals, demonstrating that the main effect estimate was robust to the inclusion of extreme values. All moderator analyses reported below were conducted using the filtered dataset without outliers ($n = 97$, $k = 212$).

Figure 2

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Forest plot of pooled result for online learning compared against static controls



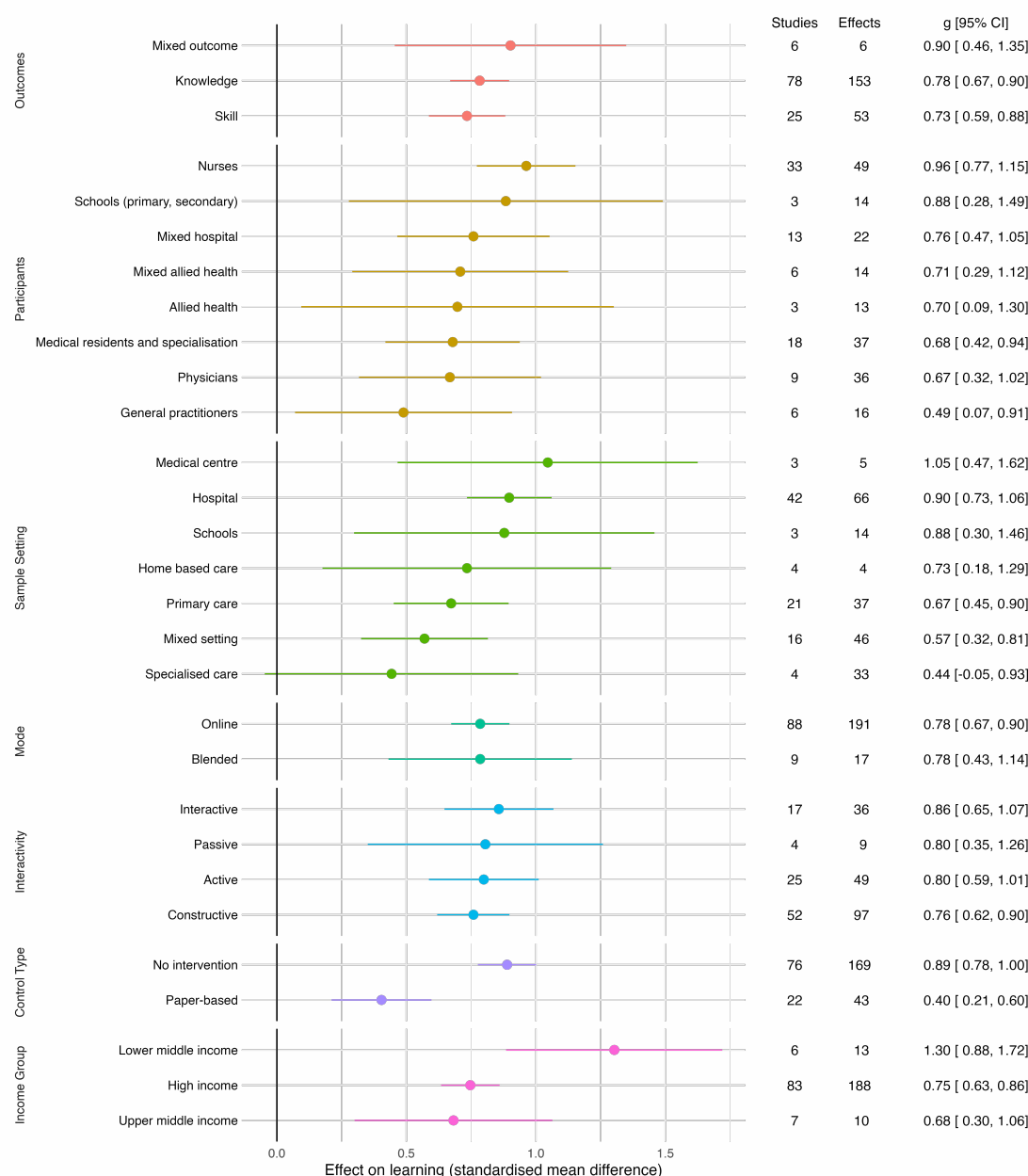
Moderation Analysis for Online Learning Versus Static Controls

Moderation Analysis by Outcome

The type of learning outcome (i.e., knowledge vs skill) assessed did not significantly moderate the effectiveness of online learning in promoting learning ($F(2, 209) = 0.44, p = 0.64$). There was minimal variation in effect sizes for different outcome types (see Figure 3).

Figure 3

Summary of moderation analyses for online learning versus static controls by outcomes, participant, intervention, and comparison.



Moderation Analysis by Follow-up

The time delay between completion of the intervention and follow-up post-test measure was not a significant moderator of the effect of online learning on knowledge and skills acquisition ($F(1,210) = 0.11, p = 0.74$).

Moderation Analysis by Participant

The type of professional ($F(7, 193) = 0.97, p = 0.46$) and length of professional experience was not a significant moderator ($F(1, 107) = 2.54, p = 0.11$).

Moderation Analysis by Sample Setting

The setting (e.g., hospital, medical centre) in which a healthcare professional worked was not a significant moderator of effectiveness ($F(6, 198) = 1.40, p = 0.21$; see Figure 3 for all settings).

Moderation Analysis by Intervention

The length of an online learning program (in hours) was not a significant moderator ($F(1, 130) = 1.36, p = 0.25$).

The type of online learning (blended, or online only) was not a significant moderator ($F(1, 206) = 0.00, p = 1$). As shown in Figure 3, both methods showed significant positive effects on knowledge and skills acquisition.

The degree of interactivity (i.e., passive, active, interactive, constructive) in the online learning intervention did not significantly moderate its overall impact on knowledge and skills acquisition ($F(3,187) = 0.27, p = 0.85$).

Moderation Analysis by Control Type

The type of comparison group was a significant moderator of the effect of online learning on knowledge and skills acquisition ($F(1, 210) = 19.89, p < 0.001$). As shown in Figure 3, online

learning demonstrated a higher effect size compared to no intervention ($g = 0.89$, 95% CI [0.78, 1.00], $n = 76$, $k = 169$, $p < 0.001$) and a smaller but still positive effect compared to paper-based learning ($g = 0.40$, 95% CI [0.21, 0.60], $n = 22$, $k = 43$, $p < 0.001$). These results indicate that online learning consistently outperformed static controls such as waitlist or paper-based educational materials.

Moderation Analysis by Income Groups

The income level of the country where the study was conducted significantly moderated effects ($F(2, 208) = 3.34$, $p = 0.04$). Lower-middle income countries showed substantially larger effects ($g = 1.30$, 95% CI [0.88, 1.72], $n = 6$, $k = 13$, $p < 0.001$) compared to high income ($g = 0.75$, 95% CI [0.63, 0.86], $n = 83$, $k = 188$, $p < 0.001$) and upper middle income countries ($g = 0.68$, 95% CI [0.30, 1.06], $n = 7$, $k = 10$, $p = 0.001$; see Figure 3).

Moderator Analysis by Other Design Features

When considering all learning design components together, there was no significant moderation effect on knowledge and skills acquisition ($F(10, 219) = 1.45$, $p = 0.16$; see Supplementary File 5). When separately modelling the effect of each learning design feature in isolation (see Supplementary File 5), none showed significant effects on knowledge and skill outcomes. Planned analysis using classification and regression trees (meta-CART) did not identify any significant moderators.

Effect of Online Learning Versus Face-to-Face

The effect sizes of learning extracted from individual studies are shown in Figure 4. When compared to face-to-face learning, online learning maintained a significant positive effect ($g = 0.45$, 95% CI [0.31, 0.59], $n = 76$, $k = 162$, $p < 0.001$). The analysis indicated a high level of heterogeneity ($I^2 = 85.92$), which suggests that the variability in effect sizes across studies is not

solely due to sampling error. Accounting for this heterogeneity, approximately 60% of true effects (95% CI [47%, 69%]) were likely to be beneficial (i.e., $g > 0.2$), and only 6% of true effects (95% CI [2%, 15%]) of interventions would be detrimental (i.e., $g < -0.2$).

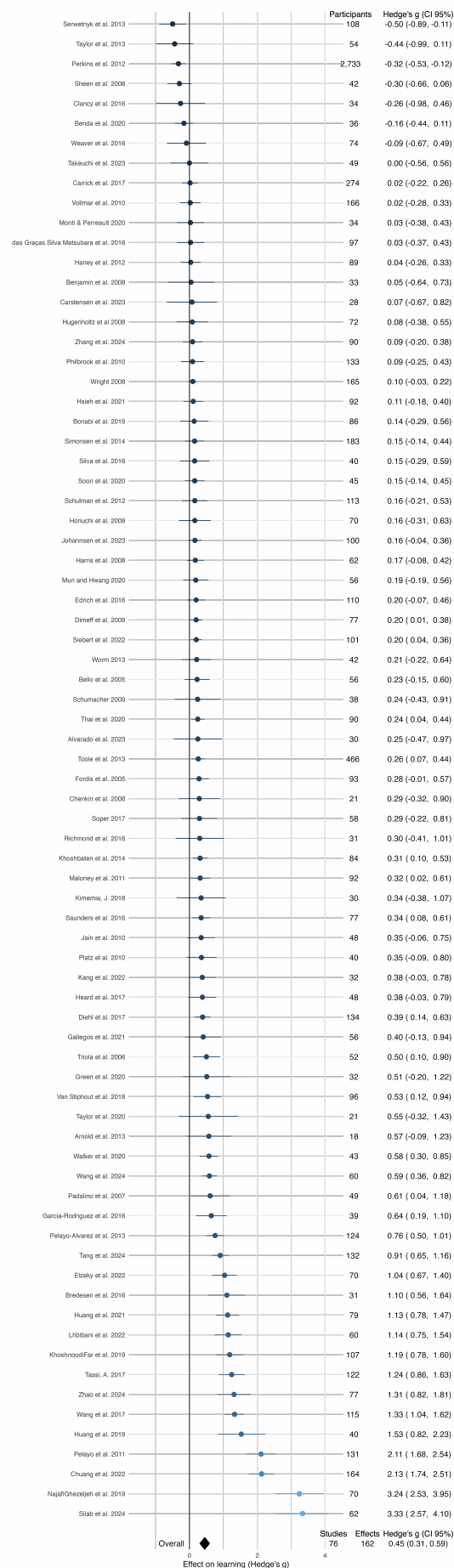
Outlier Considerations

Consistent with the analytical approach for static controls, visual inspection identified 3 extreme outliers ($g > 2.5$) from three studies. Sensitivity analysis confirmed that removing these outliers had minimal impact on the pooled effect size ($\Delta g = 0.07$), with overlapping 95% confidence intervals, demonstrating that the main effect estimate was robust to the inclusion of extreme values. All moderator analyses reported below were conducted using the filtered dataset without outliers ($n = 74$, $k = 159$).

Figure 4

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Forest plot of pooled result for online learning compared against face-to-face controls



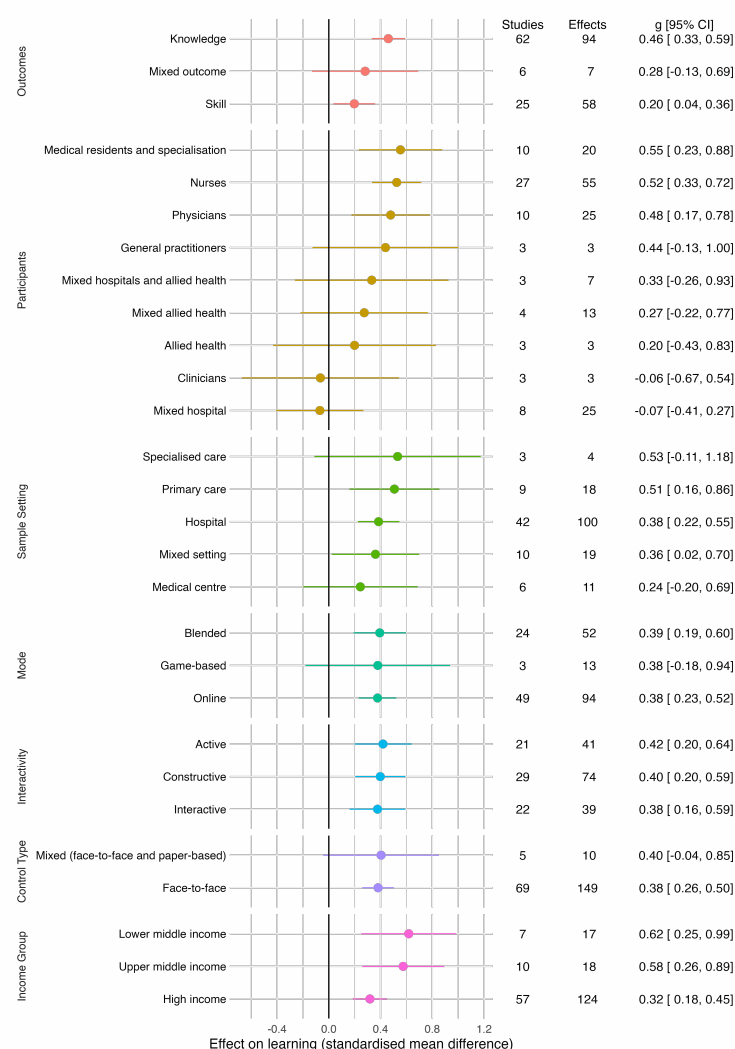
Moderation Analysis for Online Learning Versus Face-to-Face

Moderation Analysis by Outcome

The type of learning outcome assessed (i.e., knowledge, skills, or mixed) significantly moderated the effectiveness of online learning in promoting knowledge and skills acquisition ($F(2, 156) = 7.03, p = 0.001$; See Figure 5). Online learning showed a significant positive effect for knowledge acquisition ($g = 0.46, 95\% \text{ CI } [0.33, 0.59], n = 62, k = 94, p < 0.001$) and skills acquisition ($g = 0.20, 95\% \text{ CI } [0.04, 0.36], n = 25, k = 58, p = 0.017$), while mixed outcomes ($g = 0.28, 95\% \text{ CI } [-0.13, 0.69], n = 6, k = 7, p = 0.179$) were positive but not statistically significant.

Figure 5

Summary of moderation analyses for online learning versus face-to-face by outcomes, participant, intervention, and comparison



Moderation Analysis by Follow-up

The length of follow-up was not a significant moderator of the effect of online learning on knowledge and skill outcomes ($F(1, 157) = 0.41, p = 0.52$).

Moderation Analysis by Participant

The type of professional ($F(8, 145) = 1.67, p = 0.11$) and length of professional experience was not a significant moderator of effects ($F(1, 67) = 0.44, p = 0.51$).

Moderation Analysis by Sample Setting

The setting (e.g., hospital, medical centre) in which the online learning took place did not significantly moderate its effectiveness in improving knowledge and skill acquisition ($F(4, 147) = 0.27, p = 0.9$; See Figure 5).

Moderation Analysis by Intervention

The longer online learning programs (i.e., > 80 hours) appeared to lead to smaller effects ($F(1, 104) = 7.78, p = 0.01$). However, after removing two outliers where the online learning intervention exceeded 80 hours, moderation by length was no longer significant ($F(1, 101) = 2.77, p = 0.1$). The next longest intervention in the dataset was 20 hours (spread over days or months), suggesting that within this more typical range, intervention length does not substantially influence effectiveness.

The type of online learning (i.e., blended, game-based, or online only) did not significantly influence its effectiveness compared to face-to-face learning ($F(2, 156) = 0.01, p = 0.99$). Similarly, the degree of interactivity (i.e., passive, active, interactive, constructive) in the online learning intervention did not significantly moderate its impact on knowledge and skills acquisition ($F(2, 151) = 0.04, p = 0.96$).

Moderation Analysis by Control Type

The type of comparison group (i.e., face-to-face or face-to-face with paper-based) was not a significant moderator on knowledge and skill outcomes ($F(1,157) = 0.01, p = 0.92$).

Moderation Analysis by Income Groups

The income-level of the country where the study was conducted did not significantly moderate the effect of online learning on knowledge and skill outcomes ($F(2, 156) = 1.98, p = 0.14$).

Moderator Analysis by Learning Design Features

When considering all learning design components together, there was no significant moderation effect on knowledge and skill outcomes (see Supplementary File 6; $F(7, 151) = 0.86, p = 0.54$). When separately modelling the effect of each learning design feature in isolation (see Supplementary File 6), none showed significant effects on knowledge and skill outcomes. Planned analysis using classification and regression trees (meta-CART) did not identify any significant moderators.

Sensitivity Analyses

Sensitivity analysis was conducted to evaluate the impact of Cochrane's Risk of Bias domains on the observed effect sizes. Full consensus ratings for each included study are presented in Supplementary File 7. As illustrated in Figure 6, no studies were categorised as having a low overall risk of bias. Therefore, we ran separate sensitivity analyses for each Risk of Bias criterion, when at least three studies met the low-risk threshold. Effect estimates were smaller in studies at low risk of selective reporting for both comparisons (Figure 7 and 8), and smaller in studies at low risk of deviations from intended interventions for the face-to-face comparison.

Figure 6

Risk of bias summary plot

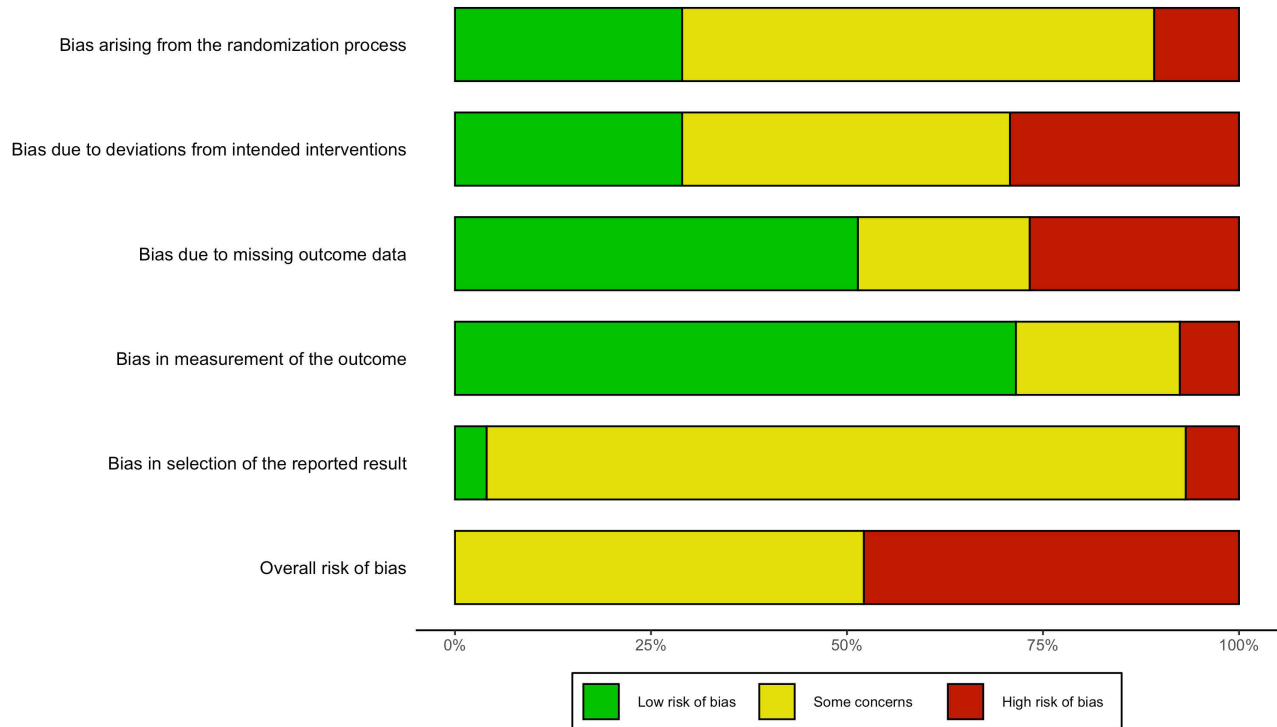


Figure 7

Sensitivity analysis for static comparison studies with low risk of bias vs main analysis

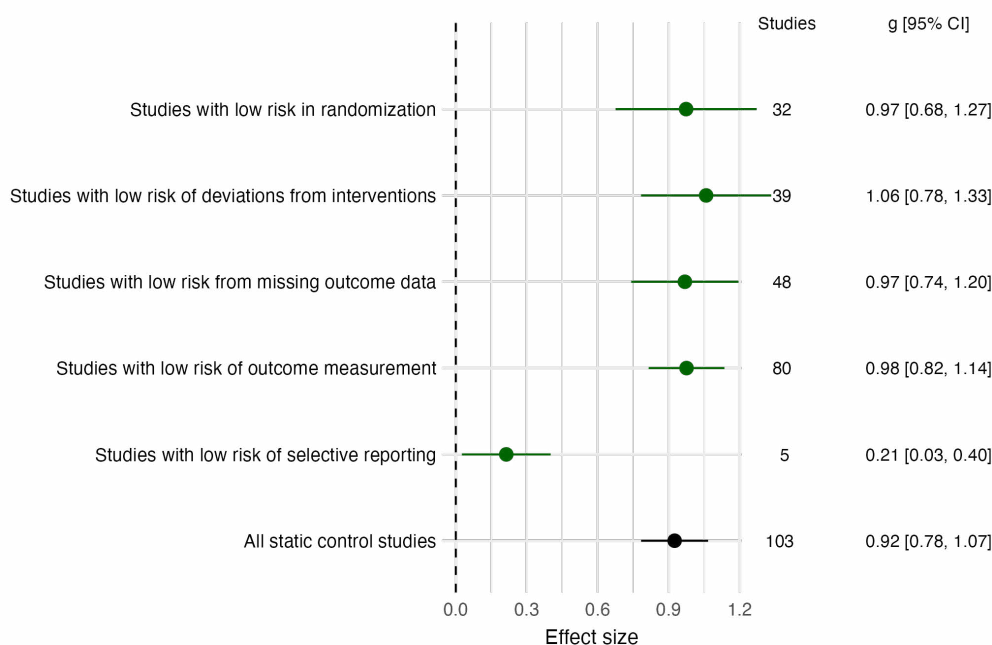
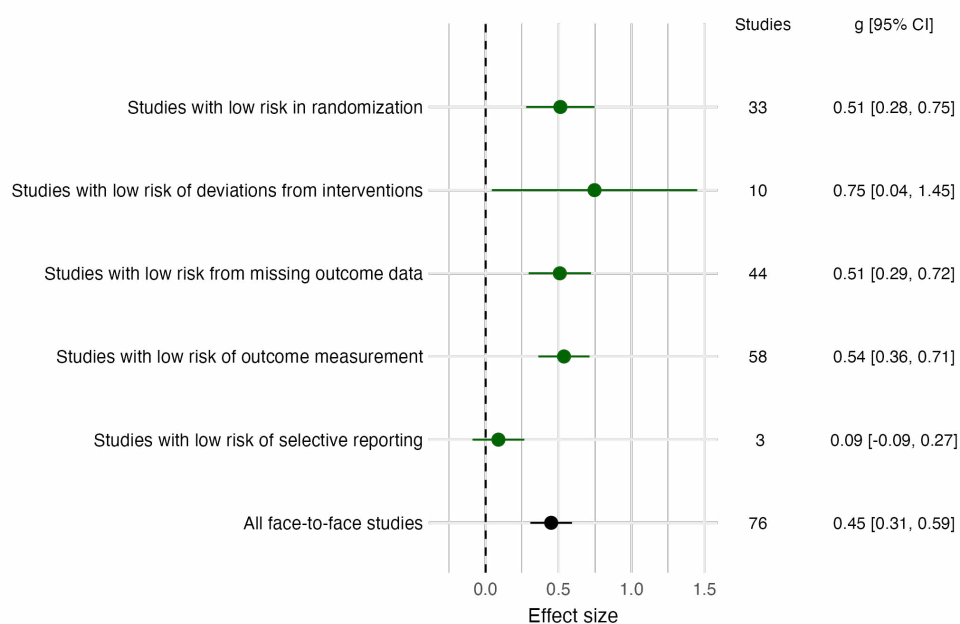


Figure 8

Sensitivity analysis for face-to-face comparison studies with low risk of bias vs main analysis

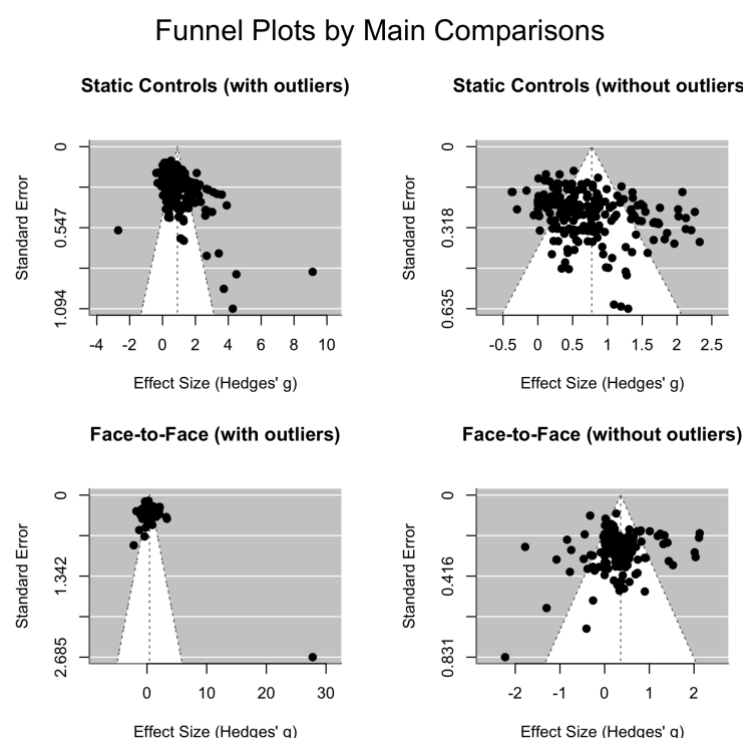


Publication Bias

We plotted effect sizes against standard errors using a funnel plot (Figure 9). These plots show some asymmetry driven by the outliers described above ($g > 2.5$). The multi-level meta-analytic Egger's test detected the presence of small-study effects for online versus static controls ($QM(df = 1) = 22.47, p < 0.001$) and online versus face to face ($QM(df = 1) = 7.23, p = 0.007$). Removing the outliers ($g > 2.5$), there was lower asymmetry detected by Egger's test for comparisons with static controls ($QM(df = 1) = 12.91, p < 0.001$) and non-significant asymmetry for comparisons with face-to-face instruction ($QM(df = 1) = 1.36, p = 0.243$).

Figure 9

Funnel plots moderated by main effects analyses



Certainty Assessment

We assessed the certainty of the evidence for each outcome using the GRADE framework (Table 2). Overall, comparisons against face-to-face controls was ‘low’ certainty for knowledge acquisition. Skill acquisition was ‘very low’, as were both knowledge and skills outcomes comparing online learning to static controls. Evidence was generally downgraded for not having studies of low-risk of bias, and high levels of unexplained heterogeneity.

Table 2

Summary of Findings for Certainty Assessment for the Effects of Online Professional Learning on Healthcare Professionals’ Knowledge and Skill Acquisition

Population: Practising healthcare professionals in any clinical setting, **Intervention:** Online professional learning,

Comparison: Static controls (waitlist, no intervention, paper-based materials) or face-to-face controls

GRADE domain assessment								
Outcome	Studies (effects)	Hedges' g (95% CI)	Risk of bias	Inconsistency	Indirectness	Imprecision	Publication bias	Certainty of evidence
Static Controls (waitlist, no intervention paper-based materials)								
Knowledge acquisition	78 (153)	0.78 (0.67, 0.90)	Serious ^a	Serious ^b	Not serious	Not serious	Serious ^c	⊕○○○ Very low
Skill acquisition	25 (53)	0.73 (0.59, 0.88)	Serious ^a	Serious ^b	Not serious	Not serious	Serious ^c	⊕○○○ Very low
Face-to-Face Controls								
Knowledge acquisition	62 (94)	0.46 (0.33, 0.59)	Serious ^a	Serious ^b	Not serious	Not serious	Not serious	⊕⊕○○ Low
Skill acquisition	25 (58)	0.20 (0.04, 0.36)	Serious ^a	Serious ^b	Not serious	Some concerns ^d	Not serious	⊕○○○ Very low

Note. All included studies were randomised controlled trials; evidence therefore begins at High certainty and is downgraded for concerns in each domain. A positive Hedges’ g indicates online learning outperforms the comparator. Certainty ratings: ⊕⊕○○ Low; ⊕○○○ Very low. ^a Downgraded one level due to risk of bias.

^b Downgraded one level due to inconsistency. ^c Downgraded one level due to publication bias. ^d Downgraded one level due to imprecision.

Discussion

We found 171 randomised controlled trials meeting our criteria for examining online learning for healthcare professionals' knowledge and skills acquisition. Overall, online learning demonstrated large positive effects when compared to static controls (e.g., waitlists, self-directed textbook reading, electronic or print materials) and small but significant positive effects compared to face-to-face instruction. Results seemed consistent regardless of the learning design, intervention characteristics, professional group, clinician experience, or clinical setting. Overall, the findings suggest that online programmes may be more effective than traditional methods for improving healthcare professionals' knowledge and skills, with the added advantages of scalability and flexibility for healthcare professional development ²⁰⁻²³.

Prior reviews of online learning were small e.g., ¹⁴ or focused on a single skill or context ^{25,26,30}. In contrast, our findings show that online learning is effective across diverse professional groups, experience levels, practice settings, and income classifications (Figures 3 and 5). These consistent findings across different contexts establish online learning as a reliable approach for healthcare professional development. Our broad inclusion criteria also gave us the power to test a large number of potential moderators. Few of these moderators demonstrated consistent effects. Given the heterogeneity we observed, this means differences between effect sizes are driven by differences we did not or could not assess from the study's report (e.g., the institutional support for online learning ⁴⁹, or the degree of end-user co-design ⁵⁰).

A few significant moderators emerged. Benefits of online learning were particularly pronounced in lower-middle income countries when compared against static controls, likely because there were fewer high-quality alternatives to the training provided by the trials in these

settings^{18,19}. In these contexts, geography and limited infrastructure are key barriers to professional development^{22,26}, and online learning's digital delivery, flexible access, and low cost^{21,23} directly address these constraints. In high-income countries, where professionals have greater resources and access to professional learning, these advantages are less distinctive and the marginal benefit of any single programme is smaller by comparison. Even so, online learning improved knowledge and skill acquisition compared to static control resources and face-to-face delivery across all income settings, suggesting its value is universal but its potential to reduce global health inequalities is greatest where access to professional development is most limited²².

Another moderator of note was the type of outcome assessed, observed only when comparing online learning to face-to-face instruction. Online learning produced larger effects for knowledge acquisition than for skills acquisition, which aligns with evidence that structured digital content is well suited to transferring declarative knowledge. More notably, online learning still outperformed face-to-face instruction for skills acquisition, challenging the assumption that physical presence is the primary driver of procedural development. Other systematic reviews have shown online video leads to bigger improvements in skill acquisition than knowledge development⁵¹, arguably because video can easily show authentic skill demonstrations. Benefits of online learning may reflect the inherent variability of face-to-face clinical training, where the learning experience depends on available cases, supervisors, and setting, meaning practitioners may develop inconsistent levels of competence. Online learning, by contrast, delivers standardised instruction consistently across learners regardless of context, which can mitigate the inconsistencies of traditional professional learning.

Interactivity level did not moderate online learning effectiveness in either comparison, contrary to the Interactive, Constructive, Active, and Passive (ICAP) framework's prediction that

constructive and interactive engagement produce greater learning gains than passive modes ²⁷.

Two explanations are plausible. Conceptually, the lack of a moderating effect may stem from the fact that all engagement levels (i.e., active, constructive, interactive, and passive) produced significant positive effects with tightly clustered effect sizes (Figure 3 & 5). When every delivery format consistently outperforms control conditions, specific differences between categories become difficult to isolate, suggesting that the primary driver of benefit is the online learning itself rather than the specific level of interactivity. Methodologically, interactivity was categorised from published intervention descriptions rather than direct measurement of learner experience, which may have reduced sensitivity to detect meaningful differences. Overall, the findings suggest that even less resource-intensive, passive online learning formats provide a robust and scalable alternative to traditional professional development for advancing professional knowledge and skills.

It remains unclear whether any learning design principles such as feedback, scaffolding, simulation, and group collaboration, enhance the effects of online learning on knowledge and skill acquisition. This may be an artefact of our design's sensitivity to detect between-study moderators. Studies in our review covered different content for different audiences, measuring different outcomes. It might therefore be difficult to detect effects of studies using specific learning design principles. Robust assessments of these learning design principles exist, for example, where the same training is conducted with and without online videos ⁵¹. Learning designers should use design principles supported by existing systematic reviews, such as letting learners collaborate ^{28,29}, use quizzes ^{52,53}, design clear multimedia ⁵⁴, scaffold the training ⁵⁵ or provide authentic simulations ⁵⁶.

Limitations of the included research

Several limitations of the included studies and the available evidence should be considered when interpreting these findings. When we conducted sensitivity analyses for each risk of bias domain, effect sizes appeared robust. However, a major limitation of this review is that none of the included studies were classified as having a low overall risk of bias (see Figure 6), primarily because most studies did not have clear blinding of participants, did not follow intention-to-treat principles, incompletely concealed allocation, or lacked pre-registration. While sensitivity analyses indicated no significant differences in effect sizes between studies rated as ‘low’ risk and the main analysis for most domains (see Figure 7 & 8), effects were smaller when controlling for selective reporting. Few studies pre-registered their protocols, and when they did, effects were lower. This effect is not uncommon, which is why pre-registration is becoming the norm⁵⁷. In combination with funnel plot asymmetry and significant Eggers test, the data raises concerns of selective reporting and publication bias. Authors of future trials should be expected to prospectively register their protocols prior to data collection.

We initially planned to conduct a Two-Stage Structural Equation Model (TSSEM) to assess whether knowledge and skill acquisition mediate the relationship between online learning and clinical practice. However, our analysis was limited by available data: none reported the necessary correlation between participant’s learning and behaviour change. Due to the insufficient number of studies reporting this correlation, we were unable to proceed with the planned analysis. Reporting this correlation in the future would allow for useful tests of the hypothesised causal structure.

Our analysis did not include studies conducted in low-income settings because no eligible studies from these contexts were identified, despite studies in any language being eligible. While

conclusions could be drawn for studies of other income levels, the absence of data from low-income settings leaves a gap in our understanding for the most resource-constrained contexts. Challenges unique to these settings, such as limited technology infrastructure and internet accessibility, are likely to influence outcomes and must be considered for future research. Addressing this gap is essential, as online learning has high potential to overcome traditional barriers to education and professional development in low-income countries. Future studies should prioritise evaluating online learning in these environments to better inform scalable and inclusive strategies.

Limitations of this review

Our review provides strong evidence for the efficacy of online learning, yet policymakers require more than effectiveness evidence to justify adoption. Online learning is assumed to be cost-efficient at scale, as once developed, programmes can reach large numbers of learners at low marginal cost. In practice, however, upfront investment in content development, platform infrastructure, and facilitation can be substantial, and these costs may only be recovered when programmes are delivered at sufficient scale. Future reviews should examine cost alongside effectiveness through formal economic evaluations to better inform investment decisions across diverse healthcare settings.

Finally, we used intention-to-treat effect sizes where available, but we did not assess course completion rates, which serve as an important indicator of the overall success and sustainability of online learning programmes²². Barriers to engagement (e.g., time constraints, technical difficulties, or lack of motivation) were not examined but remain critical for understanding how to optimise online learning experiences²². Addressing these factors in future

research will help identify strategies to improve course completion and engagement rates, particularly in diverse and resource-limited healthcare environments.

Conclusion

Our findings support online learning as an effective tool for professional learning, delivering strong positive effects on knowledge and skills acquisition for all health professional groups. Online learning not only outperforms static controls, but also proves more effective than traditional face-to-face learning. Results suggest that modern online platforms can replicate many benefits of face-to-face learning by incorporating features like virtual simulations, real-time feedback, and interactive case studies. Yet, we found that no single design element guarantees greater knowledge and skill acquisition outcomes.

Healthcare organisations can use online learning to deliver high-quality training across diverse settings, including resource-limited environments. Its scalability, accessibility, and cost-efficiency make it a practical solution for professional development, ensuring healthcare professionals can acquire essential knowledge and skills without relying on face-to-face instruction. Despite challenges such as publication bias, the evidence supports online learning as a reliable and effective method for enhancing healthcare professionals' knowledge and skill acquisition.

Study Characteristics Table of the Included Studies (N =171)

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Alvarado et al. 2023	United States	High income	nurses	Hospital	30	NR	NR (NR)	15.75 (12.51)	Online	NR	Face-to-face	NR	Knowledge	Computer-program
Arnold et al. 2013	United States	High income	nurses	Health care institution	33	25	24.9 (4.4)	0.85 (1.4)	Blended	3.5	Face-to-face	5	Knowledge	Computer-program
Badiei et al. 2016	Iran	Lower middle income	nurses	Hospital (endocrinology and interNRI medicine wards)	123	111	30.04 (5.25)	NR (NR)	Online	NA	Paper-based	NR	Knowledge	Computer-program
Batchelor-Murphy et al. 2015	United States	High income	nurses	Nursing homes	50	34	40 (NR)	NR (NR)	Blended	0.57	No intervention	NA	Knowledge	Computer-program
Bell et al. 2000	United States	High income	medical residents and specialisation	Family and internal medicine at four universities	162	67	29.1 (2.7)	NR (NR)	Online	1.25	Paper-based	1.25	Knowledge	Computer-program
Bello et al. 2005	Italy	High income	physicians	Anesthesiology and Intensive Care Medicine of the Catholic University Medical Center	56	33	28.65 (1.6)	NR (NR)	Online	5	Face-to-face	5	Knowledge	Computer-program
Benda et al. 2020	United States	High income	mixed hospital	Hospital (obstetrical service)	36	30	32.82 (7.38)	2.57 (2.85)	Game-based	NR	Face-to-face	NR	Skill	Observer
Benjamin et al. 2008	United States	High income	mixed hospitals and allied health	Child care health centers	51	49	40.88 (11.98)	3.58 (3.28)	Online	3	Face-to-face	3	Knowledge	Computer-program
Bhattacharyya et al. 2021	United Kingdom	High income	medical residents and specialisation	Hospitals (operating theatre)	14	2	NR (NR)	NR (NR)	Online	NR	Paper-based	NR	Skill	Observer
Bohicchio et al. 2006	United States	High income	medical residents and	University hospital	12	NR	NR (NR)	NR (NR)	Online	NR	No intervention	NA	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Bonabi et al. 2019	Iran	Lower middle income	specialisation general practitioners	Family clinics	107	64	41.74 (7.48)	13.04 (12.43)	Online	NR	Mixed (face-to-face and paper-based)	NR	Knowledge	Computer-program
Brateanu et al. 2019	United States	High income	medical residents and specialisation	Institutional Clinics	54	24	27.4 (2.25)	1.1 (1.1)	Online	NR	Paper-based	NR	Knowledge	Computer-program
Bredesen et al. 2016	Norway	High income	nurses	Acute care hospital or nursing home	50	49	NR (NR)	NR (NR)	Online	0.75	Face-to-face	0.75	Skill	Computer-program
Carrick et al. 2017	United States	High income	mixed hospital	Hospital	274	72	38.5 (NR)	NR (NR)	Online	26	Face-to-face	26	Knowledge	Computer-program
Carstensen et al. 2023	Denmark	High income	medical residents and specialisation	Hospitals	28	19	33 (4)	NR (NR)	Blended	3.5	Face-to-face	NR	Skill	Observer
Chaisriya et al. 2024	Thailand	Upper middle income	clinicians	Medical centres	44	25	32.25 (8.38)	5.5 (7.78)	Online	NR	No intervention	NA	Knowledge	Computer-program
Chang et al. 2024	Taiwan	High income	nurses	Hospital	40	NR	23 (NR)	NR (NR)	Blended	2	Paper-based	NR	Knowledge	Computer-program
Chenkin et al. 2008	Canada	High income	medical residents and specialisation	University hospital	22	8	NR (NR)	NR (NR)	Blended	3	Face-to-face	3	Skill	Observer
Chisholm et al. 2025	South Africa	Upper middle income	nurses	Clinics	466	301	NR (NR)	NR (NR)	Online	1.5	No intervention	NA	Knowledge	Computer-program
Chuang et al. 2022	Taiwan	High income	nurses	Teaching hospital	176	NR	31.28 (6.29)	6.03 (5.52)	Online	1	Face-to-face	1	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Clancy et al. 2016	Australia	High income	clinicians	Mental health services	63	48	NR (NR)	NR (NR)	Blended	18.5	Face-to-face	18.5	mixed outcome	Computer-program
Connolly et al. 2014	Australia	High income	medical residents and specialisation	Children's hospital	56	46	31.4 (3.8)	3.4 (2.3)	Online	4	No intervention	NA	Knowledge	Computer-program
Cullinan et al. 2017	Republic of Ireland	High income	mixed hospital	Hospitals	146	NR	NR (NR)	NR (NR)	Online	1.5	No intervention	NA	Knowledge	Computer-program
Demir et al. 2024	Turkey	Upper middle income	nurses	Hospital (university-affiliated)	76	24	29.65 (3.5)	6.32 (3.28)	Online	3.33	No intervention	NA	Knowledge	Computer-program
Diehl et al. 2017	Brazil	Upper middle income	physicians	Public health care unit	170	83	37.99 (11.82)	4.49 (NR)	Game-based	4	Face-to-face	4	Knowledge	Computer-program
Dimeff et al. 2009	United States	High income	mixed allied health	Mixed (private practice, outpatient clinics, day treatment, residential treatment facility, corrections facility, drug treatment program, and other)	174	121	39.61 (10.78)	5.54 (7.94)	Online	20	Paper-based	NR	Knowledge	Computer-program
Edrich et al. 2016	United States, Austria, Germany	High income	medical residents and specialisation	Teaching hospitals	138	NR	33.77 (8.42)	4.51 (6.64)	Online	0.67	Face-to-face	1.08	mixed outcome	Computer-program
Ehrenreich-May et al. 2016	United States	High income	general practitioners	Mixed	215	161	40.45 (10.64)	9.09 (8.9)	Online	12.9	Paper-based	9.3	Knowledge	Computer-program
El-Helou et al. 2025	Mixed (New Zealand, United Kingdom,	High income	mixed allied health	NR	204	NR	NR (NR)	6 (NR)	Online	1.5	No intervention	NA	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
	Canada, Hong Kong SAR, Ireland, Greece, Republic of South Africa, India, Belgium, Australia)													
Elgie et al. 2010	United States	High income	schools (primary, secondary)	Schools	52	NR	NR (NR)	NR (NR)	Online	NR	No intervention	NA	Knowledge	Computer-program
Elzeky et al. 2022	Egypt	Lower middle income	nurses	Hospitals (Specialised medical hospital and main university hospital)	70	18	28.3 (3.65)	NR (NR)	Online	2.4	Face-to-face	1	Knowledge	Computer-program
Farokhzadian et al. 2023	Iran	Lower middle income	nurses	Specialised trauma hospital	81	61	38.07 (7.26)	NR (NR)	Online	8	No intervention	NA	Knowledge	Computer-program
Fordis et al. 2005	United States	High income	physicians	Primary care clinics	103	46	NR (NR)	NR (NR)	Online	2.2	Face-to-face	4.5	Knowledge	Computer-program
Gallegos et al. 2021	United States	High income	pharmacy	Hospital	56	NR	NR (NR)	NR (NR)	Online	NR	Face-to-face	NR	Knowledge	Observer
Garcia-Rodriguez et al. 2016	Canada	High income	medical residents and specialisation	Univeristy residence service	39	18	NR (NR)	NR (NR)	Online	NR	Face-to-face	NR	Knowledge	Computer-program
Gerbert et al. 2002	United States	High income	physicians	Primary care	71	24	42 (NR)	NR (NR)	Online	NR	No intervention	NA	Skill	Observer
Gordon et al. 2011	United Kingdom	High income	physicians	University hospital	205	NR	NR (NR)	NR (NR)	Online	1.5	No intervention	NA	Skill	Computer-program
Green et al. 2020	United States	High income	nurses	Perinatal patient care setting	80	80	NR (NR)	NR (NR)	Blended	NR	Face-to-face	NR	Skill	Observer

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Guden et al. 2024	Turkey	Upper middle income	general practitioners	Family Health Centers	184	63	48.98 (7.87)	23.9 (7.38)	Online	0.58	No intervention	NR	Knowledge	Computer-program
Halms et al. 2024	Germany	High income	mixed hospital	Mixed (hospitals or departments of psychiatry and psychotherapy)	282	197	37.18 (9.32)	8.24 (7.58)	Online	NR	Paper-based	NR	Knowledge	Computer-program
Haney et al. 2012	United States	High income	mixed hospital	Teaching hospital	89	11	39 (8)	12 (7.46)	Online	NR	Face-to-face	NR	Knowledge	Computer-program
Harris et al. 2008	United States	High income	physicians	General practice	154	21	50.3 (11.35)	NR (NR)	Online	4	Face-to-face	4	Knowledge	Computer-program
Harris et al. 2013	United States	High income	medical residents and specialisation	Adult medicine primary care training programs	170	48	34.07 (8.71)	NR (NR)	Online	2.08	No intervention	NA	Knowledge	Computer-program
Hayer et al. 2022	United States	High income	mixed hospital	Healthcare clinics, hospitals, and CVS minute clinics	177	NR	NR (NR)	NR (NR)	Online	0.5	No intervention	NA	Skill	Observer
Heard et al. 2017	Australia	High income	mixed hospitals and allied health	Hospitals	64	38	30 (NR)	4 (NR)	Blended	1.5	Face-to-face	1.5	Knowledge	Computer-program
Heidarian et al. 2025	Iran	Lower middle income	nurses	Hospitals	100	NR	36.78 (8.06)	8.45 (6.65)	Online	NR	No intervention	NA	Knowledge	Computer-program
Horiuchi et al. 2009	Japan	High income	mixed hospital	Hospitals	93	91	34.64 (NR)	NR (NR)	Online	2	Face-to-face	6	Knowledge	Computer-program
Houwink et al. 2014	Netherlands	High income	general practitioners	University medical centre	80	39	34.5 (NR)	NR (NR)	Online	2	No intervention	NA	Knowledge	Computer-program
Hoysted et al. 2019	Australia, New Zealand	High income	mixed hospital	Hospital emergency	84	79	37.34 (10.39)	13.48 (10.3)	Online	0.25	No intervention	NA	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Hsieh et al. 2021	Taiwan	High income	nurses	Hospital (general ward)	92	84	28 (5.3)	NR (NR)	Online	0.5	Face-to-face	3	Knowledge	Computer-program
Huang et al. 2019	China	Upper middle income	medical residents and specialisation	Hospital (Anesthesiology department)	40	NR	NR (NR)	NR (NR)	Online	NR	Face-to-face	NR	Knowledge	Observer
Huang et al. 2021	Taiwan	High income	nurses	Teaching hospital	82	53	21.7 (1.48)	NR (NR)	Blended	1.12	Mixed (face-to-face and paper-based)	NR	Knowledge	Computer-program
Hugenholtz et al. 2008	Netherlands	High income	allied health	Mixed allied health care	74	33	49.51 (5.56)	16.06 (6.04)	Online	0.5	Face-to-face	0.5	Knowledge	Computer-program
Hurtado et al. 2023	United States	High income	military	Active military duty	56	NR	NR (NR)	NR (NR)	Online	1.5	No intervention	NA	Knowledge	Computer-program
Hussein et al. 2022	Canada	High income	mixed hospital	Pharmacies	120	94	NR (NR)	NR (NR)	Online	NR	Paper-based	NR	Knowledge	Computer-program
Jain et al. 2010	India	Lower middle income	nurses	Tertiary care hospital	49	NR	36.61 (8.87)	13.38 (8.91)	Online	2	Face-to-face	2	Knowledge	Computer-program
Jalali et al. 2022	Iran	Lower middle income	nurses	Hospital (neonatal intensive care units)	70	NR	NR (NR)	NR (NR)	Online	NR	No intervention	NA	Knowledge	Computer-program
Jaunay et al. 2019	France	High income	general practitioners	Family practice	108	57	41 (NR)	NR (NR)	Game-based	0.83	Paper-based	0.25	Knowledge	Computer-program
Jensen et al. 2009	Denmark	High income	physicians	Hospital	103	65	NR (NR)	0.9 (2.3)	Online	NR	No intervention	NA	mixed outcome	Computer-program
Johannsen et al. 2023	Germany	High income	mixed allied health	Hospital (oncology wards)	152	134	44.9 (11.54)	NR (NR)	Online	3	Face-to-face	3	Knowledge	Computer-program
Kang et al. 2022	Korea	High income	medical residents and specialisation	Hospital (emergency department)	32	18	29.5 (3)	NR (NR)	Online	0.33	Face-to-face	0.5	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Karvinen & Reed 2022	Canada	High income	nurses	Hospitals	68	66	42.5 (11.15)	16.4 (11.1)	Online	3	No intervention	NA	Knowledge	Computer-program
Karvinen et al. 2017	Canada	High income	nurses	Hospitals	54	NR	45.4 (10.9)	19.5 (11.4)	Online	3	Paper-based	NR	Knowledge	Computer-program
Kato et al. 2017	Japan	High income	nurses	Perinatal hospitals and obstetric hospitals	81	NR	NR (NR)	NR (NR)	Blended	3.5	No intervention	NA	Skill	Observer
Keleekai et al. 2016	United States	High income	nurses	Hospital	63	54	39.9 (12.6)	11.1 (11.4)	Blended	10	No intervention	NA	Knowledge	Computer-program
Kemper et al. 2002	United States	High income	mixed allied health	Hospitals	537	470	40.48 (10.34)	NR (NR)	Online	1	No intervention	NA	Knowledge	Computer-program
Kerfoot et al. 2009	United States	High income	mixed hospital	Veterans Affairs hospitals	95	57	49.06 (9.15)	NR (NR)	Online	1.5	No intervention	NA	Knowledge	Computer-program
Khoshbaten et al. 2014	Iran	Lower middle income	physicians	Emergency medicine	84	NR	NR (NR)	NR (NR)	Online	6	Face-to-face	6	Knowledge	Computer-program
KhoshnoodiFar et al. 2019	Iran	Lower middle income	general practitioners	Mixed	120	53	41.12 (9.12)	NR (NR)	Blended	NR	Face-to-face	NR	Knowledge	Computer-program
Kim & Hwang, 2022	Korea	High income	nurses	University hospital	60	57	31 (6.12)	NR (NR)	Online	2	Paper-based	NR	Knowledge	Computer-program
Kim & Shin. 2013	Korea	High income	nurses	Hospital (oncology)	32	NR	33.66 (6.34)	10.23 (6.53)	Online	12.33	No intervention	NR	Knowledge	Computer-program
Kim et al. 2023	Korea	High income	nurses	Community mental health and welfare centers	41	17	38 (NR)	6.2 (0.84)	Online	7	No intervention	NA	Knowledge	Computer-program
Kimemia, J. 2018	United States	High income	nurses	Univeristy medical center	40	25	NR (NR)	8.25 (7.59)	Online	NR	Face-to-face	NR	Knowledge	Computer-program
Koeppen et al. 2024	Australia	High income	nurses	General practice	343	318	38 (11)	NR (NR)	Online	NR	Paper-based	NR	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Krishnamachari et al. 2018	United States	High income	physicians	Osteopathic clinics	138	NR	46.92 (12.88)	16.49 (13.34)	Online	NR	No intervention	NA	Knowledge	Computer-program
Le et al. 2010	United States	High income	medical residents and specialisation	Mixed (solo practice, single specialty group practice, hospital clinic, and federal, state, or public health clinic)	24	10	NR (NR)	11.48 (7.82)	Online	2.67	No intervention	NA	Knowledge	Computer-program
Lee & Choi 2024	Korea	High income	nurses	Hospital (COVID-19 unit)	120	112	28.26 (5.58)	13.74 (5.13)	Online	0.72	Paper-based	NR	Knowledge	Computer-program
Leiva-Fernández et al. 2020	Spain	High income	general practitioners	Healthcare centres	117	77	NR (NR)	18.3 (3.4)	Online	1.33	No intervention	NA	Knowledge	Computer-program
Lhibani et al. 2022	Morocco	Lower middle income	nurses	Hospitals	60	44	NR (NR)	NR (NR)	Online	NR	Face-to-face	3	Knowledge	Computer-program
Li A. 2022	United States	High income	general practitioners	NR	122	113	NR (NR)	NR (NR)	Online	NR	Paper-based	NR	Knowledge	Computer-program
Liaw et al. 2015	Singapore	High income	nurses	Hospitals (Acute care)	70	68	25.58 (3.19)	NR (NR)	Online	3	No intervention	NR	Skill	Observer
Liaw et al. 2016	Singapore	High income	nurses	Hospitals (acute care)	70	68	25.58 (3.16)	2.3 (1.4)	Online	3	No intervention	NR	Skill	Observer
Liaw et al. 2017	Singapore	High income	nurses	Hospital (acute care tertiary hospital)	67	63	27.61 (4.15)	2.88 (1.56)	Online	2.5	No intervention	NA	Knowledge	Computer-program
Liu et al. 2020	Taiwan	High income	nurses	Hospitals	48	42	31.4 (5.3)	6.6 (4.4)	Online	16	No intervention	NA	Knowledge	Computer-program
Los et al. 2023	Netherlands	High income	allied health	Companies (Industry)	39	18	50 (NR)	16.8 (10.7)	Online	4.5	No intervention	NA	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Lyon et al. 2022	United States	High income	schools (primary, secondary)	Schools elementary to high	75	68	40 (NR)	NR (NR)	Online	NR	No intervention	NA	Knowledge	Computer-program
Maertens et al. 2017	Belgium	High income	medical residents and specialisation	Hospitals	32	16	NR (NR)	NR (NR)	Blended	NR	No intervention	NA	Knowledge	Computer-program
Mallon et al. 2022	United States	High income	general practitioners	Private pediatric practices	101	65	48.29 (NR)	17.51 (NR)	Online	6.5	Paper-based	NR	Knowledge	Computer-program
Maloney et al. 2011	Australia	High income	mixed allied health	Health department, private practice, and community health centres	135	108	NR (NR)	4.16 (1.65)	Online	7	Face-to-face	7	Knowledge	Computer-program
Marriott et al. 2023	United States	High income	clinicians	General practice	163	121	47.9 (11.7)	NR (NR)	Online	10	No intervention	NR	Skill	Observer
Maruyama et al. 2022	Japan	High income	mixed hospital	Mixed (hospital and clinics)	88	NR	38 (8.9)	11.7 (8.1)	Online	3	No intervention	NA	Knowledge	Computer-program
Maruyama et al., 2022	Japan	High income	mixed hospital	Hospitals and independent midwifery clinics	88	88	38 (NR)	11.7 (NR)	Online	3.33	No intervention	NA	Knowledge	Computer-program
McCrow et al. 2014	Australia	High income	nurses	Hospitals (critical care, orthopedic, medical or surgical wards)	147	130	39 (12)	NR (NR)	Online	NR	No intervention	NA	Knowledge	Computer-program
Mesquita et al. 2019	Europe, United States, South America	High income	medical residents and specialisation	Hospitals	12	6	30 (3.53)	NR (NR)	Online	1	No intervention	NA	Skill	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Mohan et al. 2018	United States	High income	physicians	Nontrauma centres	320	93	41.98 (10.52)	8 (9.7)	Game-based	2	No intervention	NA	Skill	Observer
Monti & Perreault 2020	United States	High income	military	U.S. Army Combat Medics	34	NR	NR (NR)	NR (NR)	Blended	4	Face-to-face	4	Knowledge	Computer-program
Mun and Hwang 2020	Korea	High income	nurses	Hospital	56	54	NR (NR)	NR (NR)	Online	1.33	Face-to-face	1	Knowledge	Computer-program
Murray et al. 2010	Canada	High income	mixed hospitals and allied health	Community-based organisations and Hospitals	88	NR	NR (NR)	NR (NR)	Blended	NR	No intervention	NA	Skill	Observer
NajafiGhezeljeh et al. 2019	Iran	Lower middle income	nurses	Hospitals	60	37	28.66 (3.76)	6.16 (3.67)	Online	NR	Face-to-face	NR	Knowledge	Computer-program
Nakamura et al. 2022	Japan	High income	mixed hospital	Hospital and clinics (obstetric wards)	145	NR	NR (NR)	9.74 (7.78)	Online	2.33	Paper-based	NR	Knowledge	Computer-program
Ng et al. 2022	Singapore	High income	pharmacy	Primary care clinics	71	58	35.99 (13.33)	9.24 (9.91)	Online	1	No intervention	NA	Knowledge	Computer-program
Nixon et al. 2019	United States	High income	medical residents and specialisation	University hospital	26	13	NR (NR)	NR (NR)	Online	NR	No intervention	NA	Skill	Observer
Nyberg et al. 2022	Sweden	High income	mixed hospital	Private residential housing and nursing homes	39	35	43.92 (10.46)	13.56 (8.65)	Online	3	No intervention	NA	Knowledge	Computer-program
Ozawa et al. 2022	Japan	High income	nurses	Hospital (Neonatal Intensive and Special Care Units)	64	63	41.19 (5.79)	15.07 (4.59)	Online	1	No intervention	NA	mixed outcome	Computer-program
Padalino et al. 2007	Brazil	Upper middle income	nurses	Hospitals	49	NR	NR (NR)	NR (NR)	Online	0.67	Face-to-face	2	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Pahud et al. 2020	United States	High income	medical residents and specialisation	Mixed (pediatrics, family medicine, and internal medicine-pediatrics)	1444	983	NR (NR)	NR (NR)	Blended	4	No intervention	NA	Knowledge	Computer-program
Passos et al. 2022	Brazil	Upper middle income	nurses	Primary healthcare units	110	97	NR (NR)	NR (NR)	Online	NR	No intervention	NA	Knowledge	Computer-program
Peabody et al. 2017	United States	High income	medical residents and specialisation	Urology	261	NR	50.1 (8.9)	NR (NR)	Online	0.25	No intervention	NA	Skill	Observer
Pelayo et al. 2011	Spain	High income	physicians	Family medicine	164	90	47.46 (6)	18.92 (6.51)	Online	96	Face-to-face	NR	Knowledge	Computer-program
Pelayo-Alvarez et al. 2013	Spain	High income	physicians	Palliative care	NR	NR	NR (NR)	NR (NR)	Online	96	Face-to-face	20	Knowledge	Computer-program
Perkins et al. 2012	United Kingdom, Australia	High income	mixed hospital	Hospitals	3732	NR	31.4 (7.77)	NR (NR)	Blended	12.63	Face-to-face	20	mixed outcome	Observer
Petit et al. 2019	Switzerland, Canada	High income	medical residents and specialisation	Hospitals	65	54	29.8 (3.8)	3.6 (2.7)	Online	NR	No intervention	NA	mixed outcome	Computer-program
Philbrook et al. 2010	United States	High income	clinicians	Hospitals	133	NR	NR (NR)	NR (NR)	Blended	NR	Face-to-face	NR	Knowledge	Computer-program
Phuangngoenmak et al. 2019	Thailand	Upper middle income	nurses	Primary care units	64	62	44.15 (7.6)	7.83 (5.65)	Blended	NR	No intervention	NA	Knowledge	Computer-program
Platz et al. 2010	Germany	High income	physicians	Hospitals	64	23	NR (NR)	NR (NR)	Online	NR	Face-to-face	NR	Knowledge	Computer-program
Richmond et al. 2016	United Kingdom	High income	allied health	Physiotherapy clinics	35	25	NR (NR)	11.99 (9.53)	Online	6.8	Face-to-face	10	Knowledge	Computer-program
Robinson et al. 2018	United States	High income	mixed hospital	Primary care	90	59	NR (NR)	NR (NR)	Online	NR	No intervention	NA	Skill	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Sabaghnejad et al. 2024	Iran	Lower middle income	nurses	Hospital (ICU)	60	56	31.6 (4.74)	8.02 (4.09)	Online	NR	No intervention	NA	Knowledge	Computer-program
Sadegh Madani et al. 2023	Iran	Lower middle income	nurses	Hospitals	50	33	28.5 (4.52)	4 (15.7)	Online	4	No intervention	NA	Knowledge	Computer-program
Saunders et al. 2016	Finland	High income	nurses	University Hospital	85	84	50.11 (9.81)	18.27 (6.36)	Blended	NR	Face-to-face	4	Knowledge	Computer-program
Scheetz et al. 2019	Australia	High income	allied health	Ophthalmology clinics	46	NR	NR (NR)	NR (NR)	Online	NR	No intervention	NA	Skill	Computer-program
Schulman et al. 2012	United States	High income	military	Army training centre	113	NR	NR (NR)	NR (NR)	Online	0.75	Face-to-face	0.75	Knowledge	Computer-program
Schumacher 2009	United States	High income	allied health	Dietetic practice	40	39	NR (NR)	NR (NR)	Online	NR	Face-to-face	NR	Knowledge	Computer-program
Serwetnyk et al. 2013	United States	High income	nurses	Medical center	253	217	35.84 (NR)	NR (NR)	Online	2.58	Face-to-face	4.23	Knowledge	Computer-program
Sheen et al. 2008	Taiwan	High income	nurses	University teaching hospital	54	54	30.55 (NR)	7.84 (NR)	Online	5.5	Face-to-face	5.5	Knowledge	Computer-program
Siebert et al. 2022	Switzerland	High income	mixed hospital	Hospitals	101	92	34.9 (8.45)	10.2 (6.37)	Blended	0.75	Face-to-face	0.33	Skill	Observer
Silab et al. 2024	Iran	Lower middle income	nurses	Hospital	62	50	28.9 (3.75)	5.03 (3.91)	Online	NR	Face-to-face	NR	mixed outcome	Observer
Silva et al. 2016	Brazil	Upper middle income	medical residents and specialisation	Hospital	53	NR	NR (NR)	NR (NR)	Blended	16	Face-to-face	16	Knowledge	Computer-program
Simonsen et al. 2014	Norway	High income	nurses	Mixed (hospitals and primary healthcare)	183	167	42 (9.45)	12.25 (9.45)	Online	NR	Mixed (face-to-face and paper-based)	NR	Knowledge	Computer-program
Smeeckens et al. 2011	Netherlands	High income	nurses	University hospital (emergency department)	25	NR	41 (20)	9 (0.75)	Online	2	No intervention	NA	Skill	Observer

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Snippen et al. 2023	Netherlands	High income	allied health	Mixed (company + self-employed)	110	48	51 (9.6)	NR (NR)	Online	NR	No intervention	NA	Knowledge	Computer-program
Soon et al. 2020	United States	High income	mixed hospital	Hospital (pediatric emergency medicine and pediatric intensive care unit)	45	31	NR (NR)	7 (NR)	Online	0.17	Face-to-face	0.17	Knowledge	Observer
Soper 2017	United States	High income	nurses	Hospitals	87	NR	NR (NR)	NR (NR)	Online	4	Face-to-face	4	Knowledge	Computer-program
Sperl-Hillen et al. 2014	United States	High income	medical residents and specialisation	Mixed (primary care residency programs - hospitals, university medical centres, family medical centres)	341	180	29 (2.96)	NR (NR)	Online	5.2	No intervention	NA	Knowledge	Computer-program
Stacey et al. 2006	Canada	High income	nurses	Healthcare call centre	41	40	NR (NR)	NR (NR)	Blended	6	No intervention	NA	mixed outcome	Observer
Steele et al. 2013	United States	High income	schools (primary, secondary)	Schools	526	520	28.62 (9.35)	9.59 (7.1)	Online	4.8	No intervention	NA	Knowledge	Computer-program
Stewart et al. 2005	Canada	High income	physicians	Family clinics	58	19	NR (NR)	18.27 (NR)	Online	NR	No intervention	NA	Knowledge	Computer-program
Takeuchi et al. 2023	Japan	High income	physicians	Mixed (Medical centre + hospital)	48	7	NR (NR)	5 (NR)	Online	8	Face-to-face	8	Knowledge	Computer-program
Tang et al. 2024	Taiwan	High income	nurses	Tertiary-care medical center	154	NR	32.61 (7.7)	NR (NR)	Game-based	NR	Face-to-face	NR	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Tassi, A. 2017	Saudi Arabia	High income	nurses	Hospitals	180	115	NR (NR)	NR (NR)	Online	NR	Face-to-face	NR	Knowledge	Computer-program
Taylor et al. 2013	Canada	High income	mixed hospital	Hospitals	74	NR	NR (NR)	NR (NR)	Online	0.83	Face-to-face	0.83	mixed outcome	Computer-program
Taylor et al. 2020	United States	High income	mixed allied health	NR	44	NR	NR (NR)	NR (NR)	Online	8	Face-to-face	8	Knowledge	Computer-program
Thai et al. 2020	Vietnam	Lower middle income	physicians	Public primary care clinics	90	23	47.8 (NR)	2.3 (NR)	Blended	NR	Face-to-face	NR	Knowledge	Computer-program
Thompson et al. 2016	United States	High income	allied health	Private practice	18	NR	NR (NR)	NR (NR)	Online	NR	No intervention	NA	Skill	Observer
Toole et al. 2013	United States	High income	nurses	Hospitals	1688	1552	39.96 (12.2)	13.32 (12.03)	Online	NR	Face-to-face	NR	mixed outcome	Practitioner
Triola et al. 2006	United States	High income	mixed hospitals and allied health	University hospital	55	35	NR (NR)	NR (NR)	Blended	2	Face-to-face	2	Skill	Computer-program
Van Stiphout et al. 2018	Netherlands	High income	medical residents and specialisation	Outpatient clinics	NR	554	54.75 (15.88)	NR (NR)	Blended	5	Face-to-face	1	mixed outcome	Computer-program
Velasco et al. 2015	Brazil	Upper middle income	mixed hospital	Pediatric hospital	66	58	NR (NR)	NR (NR)	Online	NR	Paper-based	NR	Knowledge	Computer-program
Viguiet et al. 2015	France	High income	medical residents and specialisation	Mixed (private hospitals, mixed hospitals, and private practice)	141	74	44.9 (11.1)	15.4 (10.5)	Online	1	No intervention	NA	Skill	Computer-program
Vollmar et al. 2010	Germany	High income	general practitioners	General practice	305	87	50.85 (7.15)	NR (NR)	Blended	1.25	Face-to-face	1.25	Knowledge	Computer-program
Wadey et al. 2022	North America	High income	medical residents and specialisation	Family medical clinics	40	NR	NR (NR)	NR (NR)	Online	NR	Paper-based	NR	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Wakefield et al. 2014	United States	High income	nurses	Hospitals	202	NR	NR (NR)	NR (NR)	Online	4.2	No intervention	NA	mixed outcome	Computer-program
Walker et al. 2020	United States	High income	nurses	Trauma and certified comprehensive stroke center	43	NR	NR (NR)	NR (NR)	Online	NR	Face-to-face	NR	Knowledge	Computer-program
Wang et al. 2017	China	Upper middle income	nurses	Community health centers	115	108	30.75 (9.17)	7 (9.63)	Blended	NR	Face-to-face	6	Knowledge	Computer-program
Wang et al. 2024	China	Upper middle income	medical residents and specialisation	Hospital	60	53	24.1 (1.3)	NR (NR)	Blended	NR	Mixed (face-to-face and paper-based)	NR	Knowledge	Computer-program
Wanty et al. 2023	United States	High income	mixed allied health	Primary care + community care	712	NR	47.91 (10.26)	NR (NR)	Online	NR	No intervention	NA	Knowledge	Computer-program
Weaver et al. 2016	South Africa	Upper middle income	clinicians	Primary healthcare clinics	297	NR	NR (NR)	NR (NR)	Online	6	Mixed (face-to-face and paper-based)	NR	Knowledge	Computer-program
Wee et al. 2016	United States	High income	mixed hospital	Medical clinics	22	NR	NR (NR)	NR (NR)	Online	0.67	No intervention	NA	Knowledge	Computer-program
Welch et al. 2014	United States	High income	mixed hospitals and allied health	Mixed (athletic training setting)	473	284	27.61 (5.17)	4.85 (4.26)	Online	4.17	No intervention	NA	Knowledge	Computer-program
Westmoreland et al. 2010	United States	High income	medical residents and specialisation	Hospital	96	46	NR (NR)	NR (NR)	Online	20	Paper-based	8	Knowledge	Computer-program
Wilkes et al. 2017	United States	High income	physicians	General practice	121	49	48.9 (10.1)	21.5 (11)	Online	6	Paper-based	6	Knowledge	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
Williams et al. 2021	United States	High income	mixed allied health	Nursing homes	219	203	42.6 (13.7)	9.2 (9.3)	Online	3	No intervention	NA	Knowledge	Computer-program
Worm 2013	Denmark	High income	nurses	NR	63	NR	NR (NR)	NR (NR)	Online	0.88	Face-to-face	0.75	Knowledge	Computer-program
Wright 2008	United States	High income	nurses	Acute-care medical facility	175	160	41.47 (12.26)	14.48 (11.66)	Online	7	Face-to-face	7	Knowledge	Computer-program
Yao et al. 2015	Australia, China, India, Korea, Malaysia, Singapore, Thailand, Turkey, United Kingdom, Italy, Poland, Portugal, Russia, Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Mexico, Paraguay, Peru, Uruguay, Venezuela)	Upper middle income & High income & Lower middle income	medical residents and specialisation	Mixed	332	NR	NR (NR)	NR (NR)	Online	NR	No intervention	NA	Skill	Computer-program
Yoo et al. 2019	Korea	High income	nurses	Hospitals	50	NR	33.33 (6.18)	9.42 (6.67)	Online	6.67	No intervention	NA	Knowledge	Computer-program
Zarifshanaiey et al. 2022	Iran	Lower middle income	nurses	Urban health centres	150	150	29.05 (3.7)	NR (NR)	Online	16	No intervention	NA	Knowledge	Computer-program
Zhang et al. 2024	China	Upper middle income	nurses	Hospitals	90	85	28.15 (1.24)	NR (NR)	Blended	4	Face-to-face	4	Knowledge	Computer-program
Zhao et al. 2024	China	Upper middle income	medical residents	Hospital (department	77	35	NR	NR	Blended	NR	Face-to-face	NR	mixed outcome	Computer-program

Citation	Country	Income Classification	Profession	Setting	Sample size	Female (n)	Total mean age (SD)	Mean length of experience (SD)	Intervention delivery	Intervention duration (hrs)	Control delivery	Control duration (hrs)	Type of outcome	Person reporting outcome
			and specialisation	of anesthesiology)			(NR)	(NR)						
das Graças Silva Matsubara et al. 2016	Brazil	Upper middle income	nurses	Hospital. Oncology	97	82	31.36 (5.55)	NR (NR)	Online	NR	Face-to-face	18	Knowledge	Computer-program
de Gannes et al. 2004	Canada	High income	physicians	General practice	52	28	NR (NR)	NR (NR)	Online	0.2	No intervention	NA	Knowledge	Computer-program

Note. NA = not applicable. NR = not reported.

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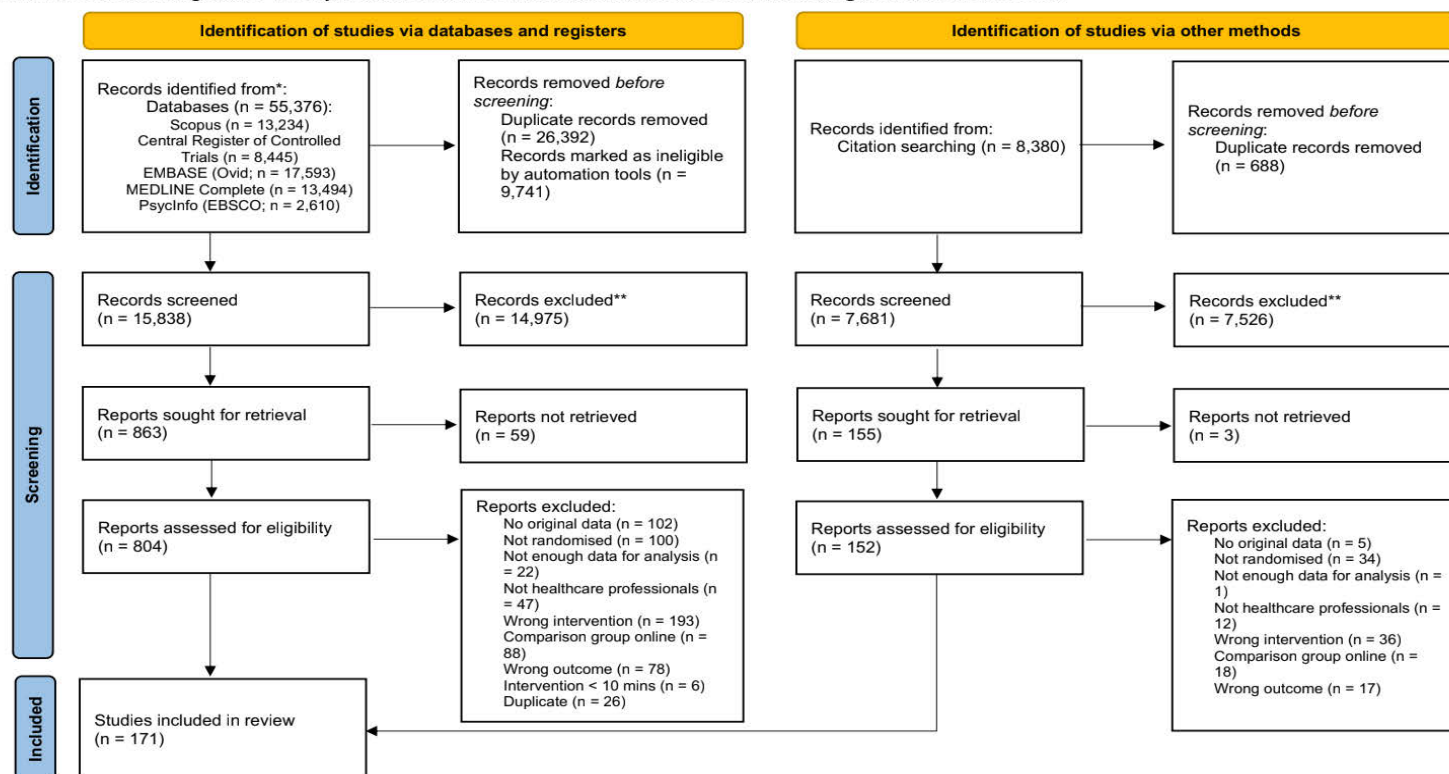
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Figure 1

PRISMA flow diagram for inclusion in this systematic review

PRISMA 2020 flow diagram for new systematic reviews which included searches of databases, registers and other sources



From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 2021;372:n71. doi: 10.1136/bmj.n71. For more information, visit: <http://www.prisma-statement.org/>

Figure 2

2

Forest plot of pooled result for online learning compared against static controls

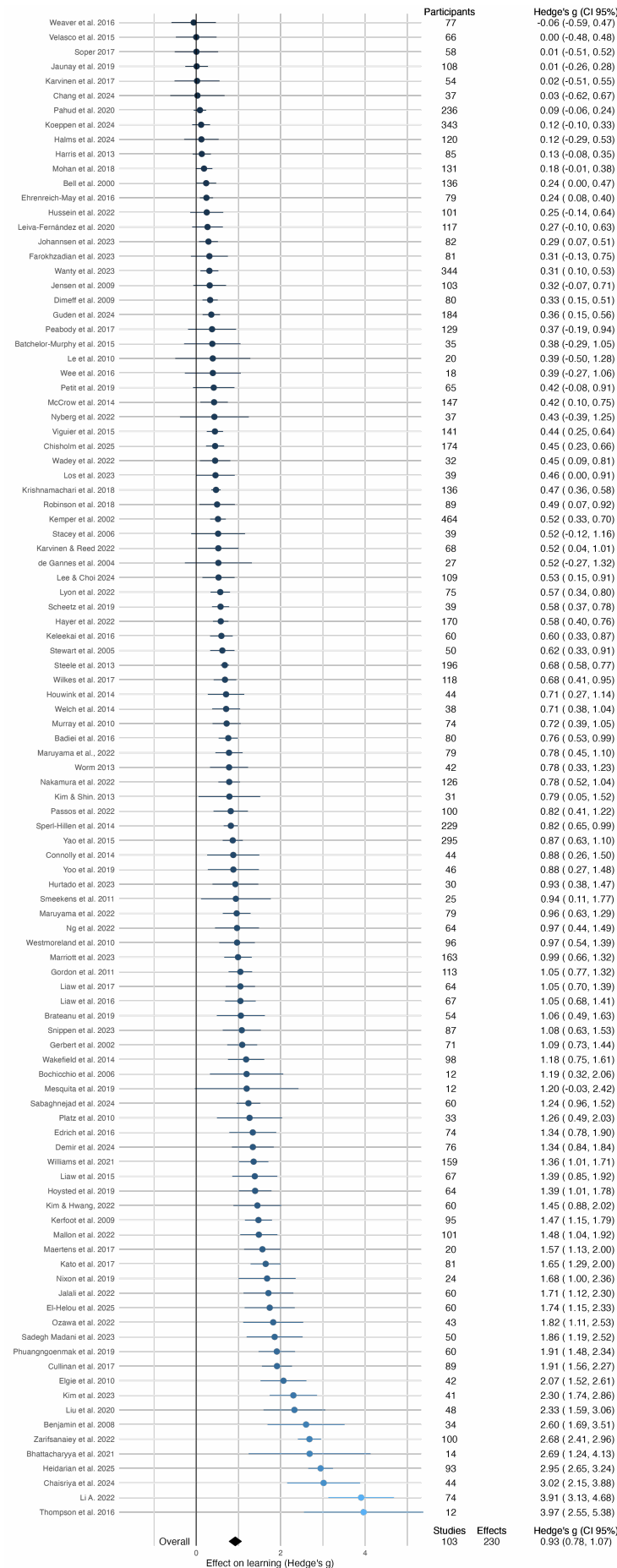


Figure 3

Summary of moderation analyses for online learning versus static controls by outcomes, participant, intervention, and comparison.

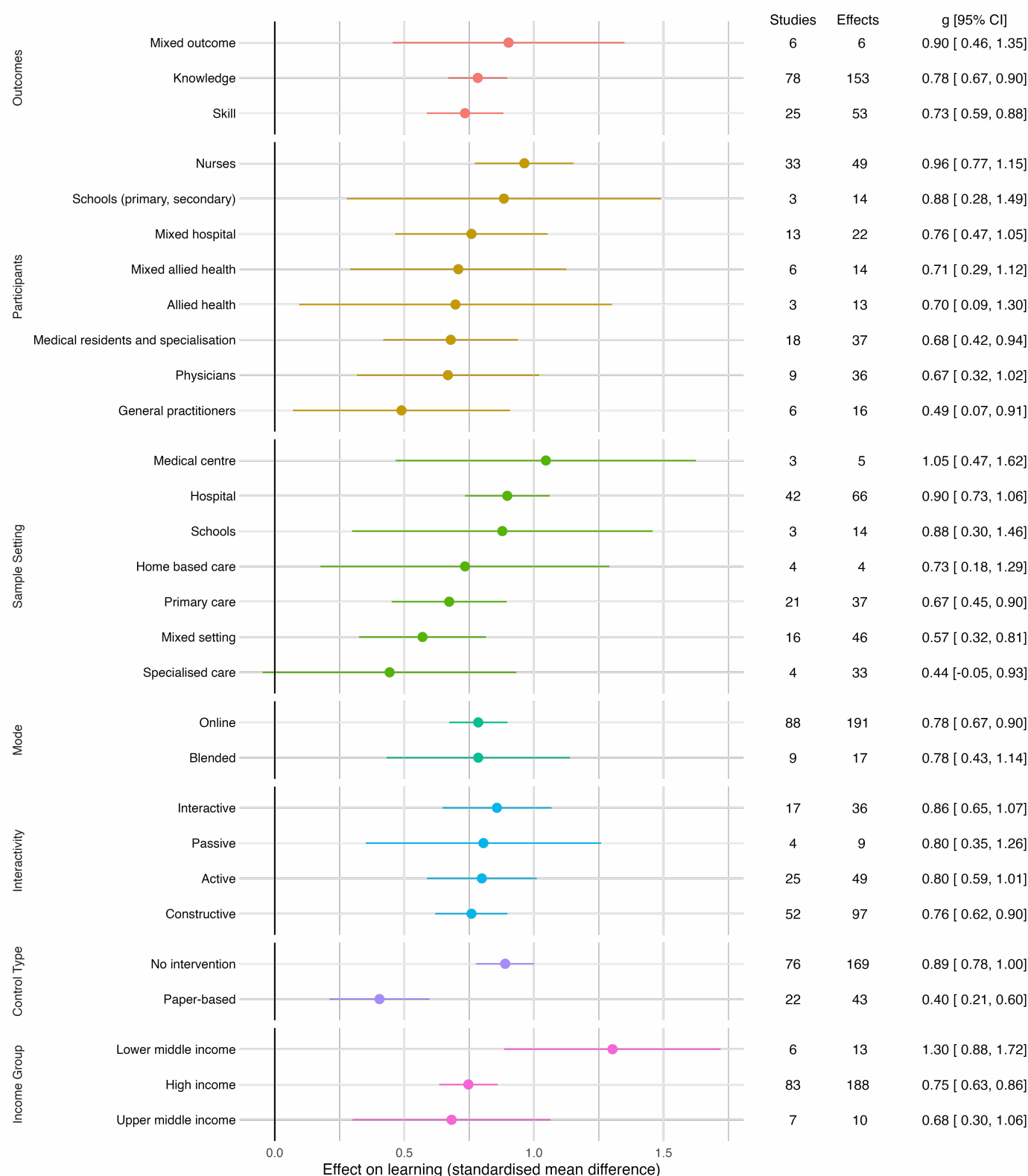


Figure 4

4

Forest plot of pooled result for online learning compared against face-to-face controls

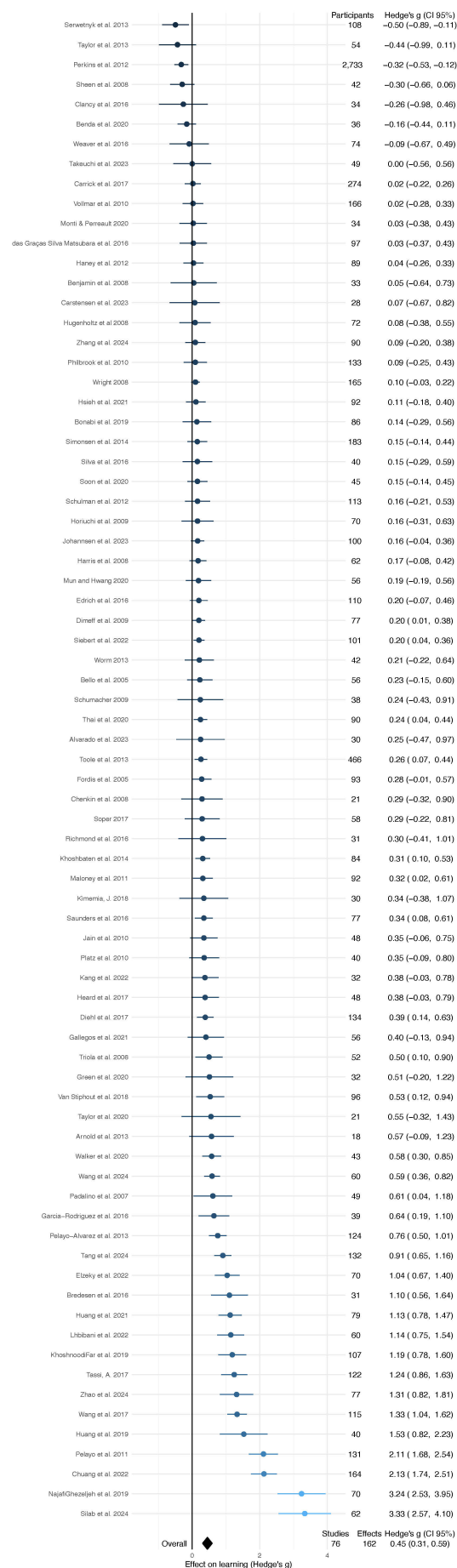


Figure 5

5

Summary of moderation analyses for online learning versus face-to-face by outcomes, participant, intervention, and comparison

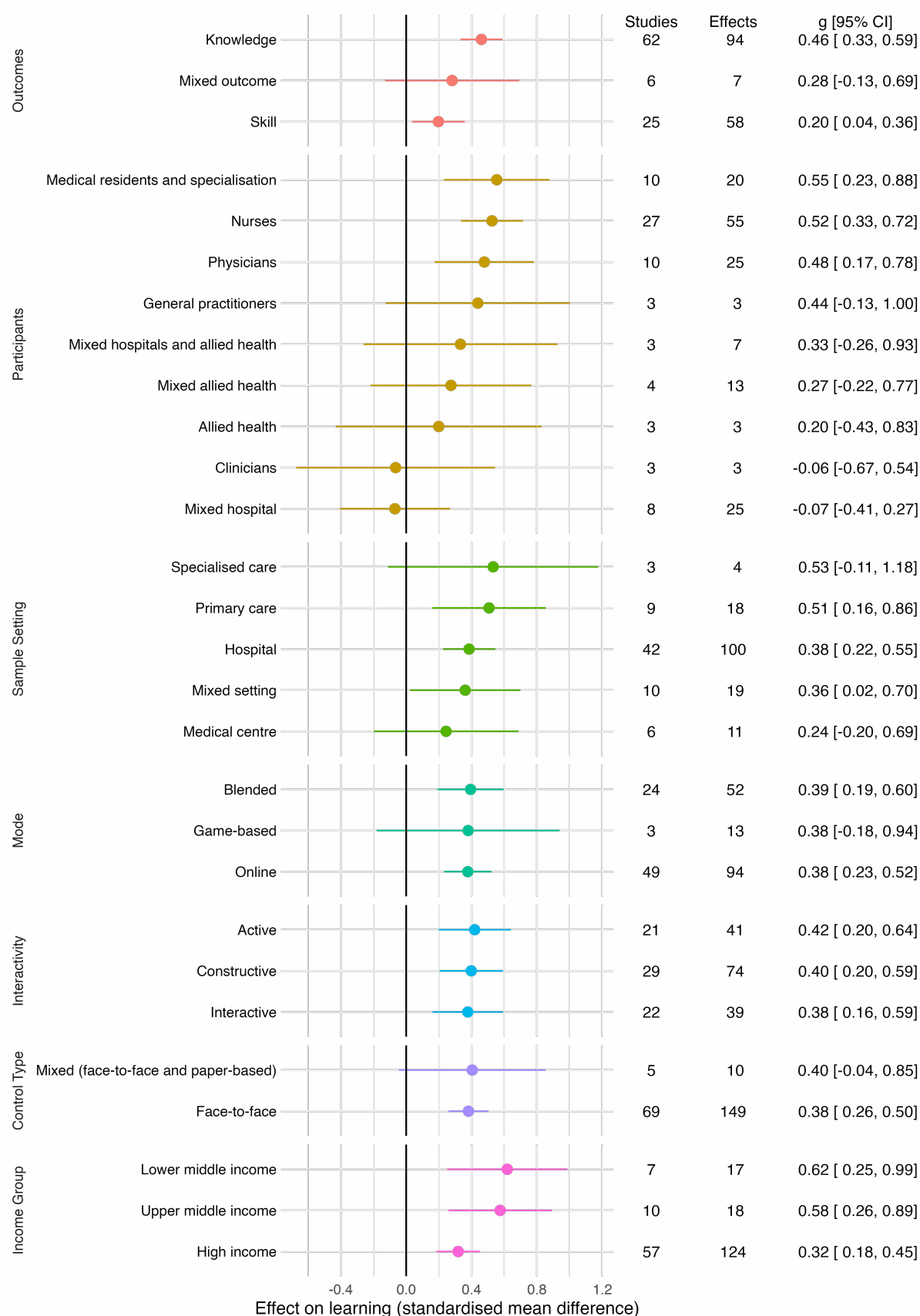


Figure 6

6

Risk of bias summary plot

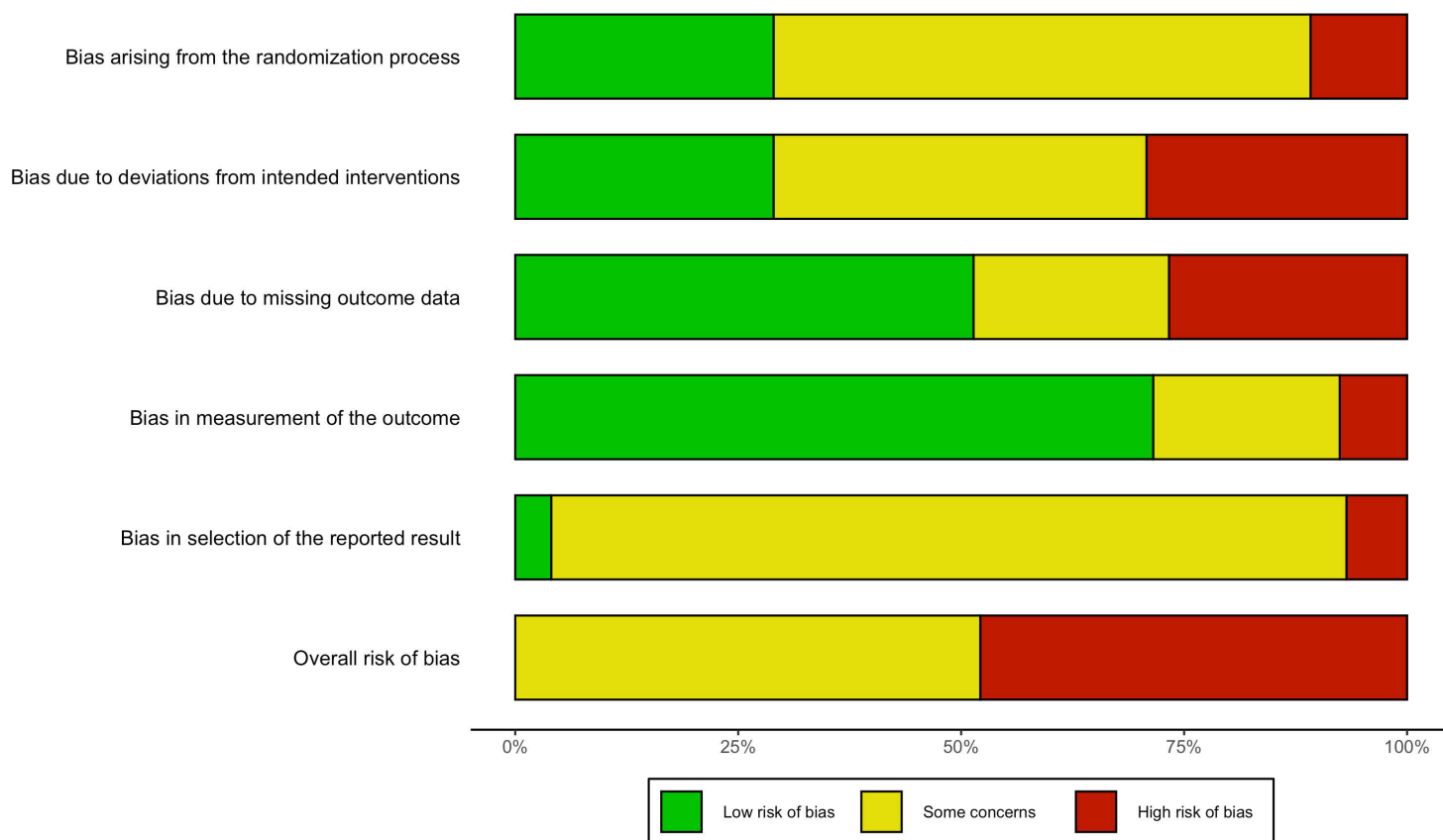


Figure 7

7

Sensitivity analysis for static comparison studies with low risk of bias vs main analysis

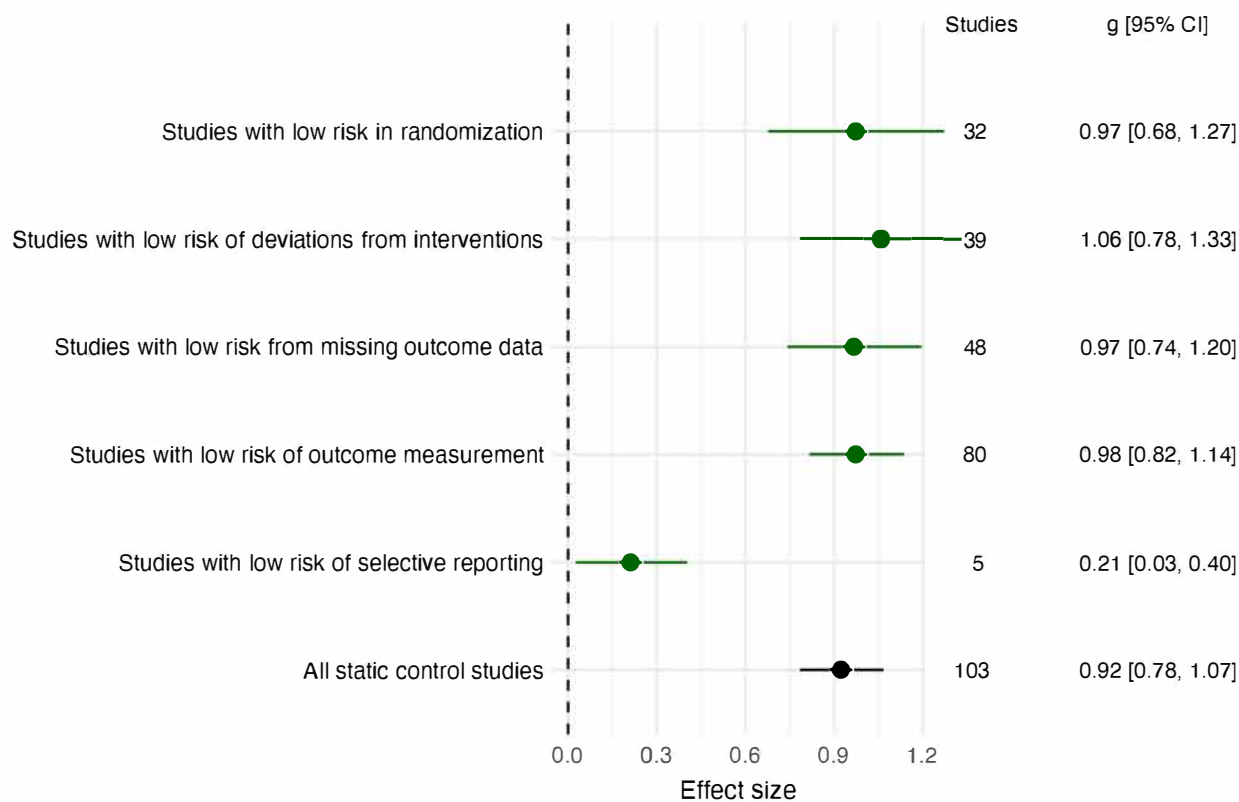


Figure 8

8

Sensitivity analysis for face-to-face comparison studies with low risk of bias vs main analysis

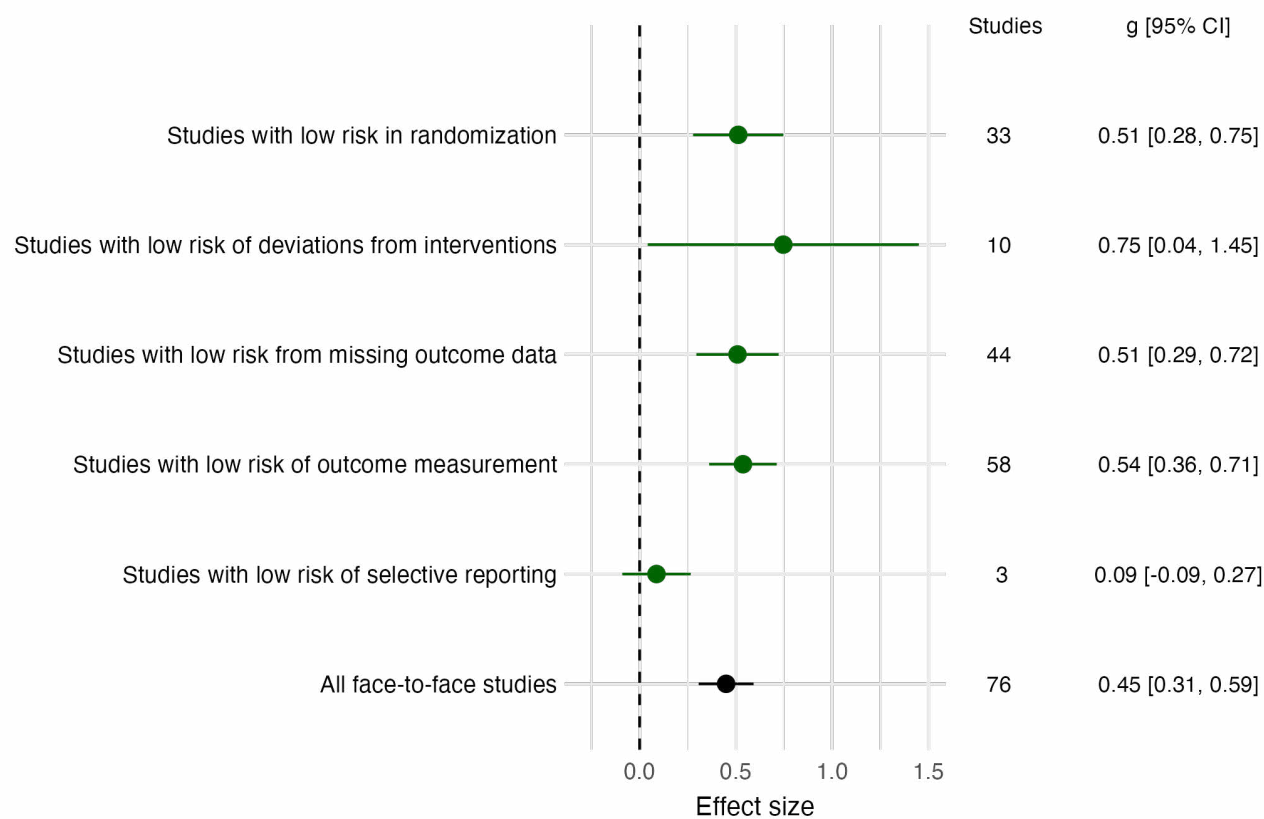


Figure 9

Funnel plots moderated by main effects analyses

Funnel Plots by Main Comparisons

