

Original Research Article

The registered footprint of health-professions education studies across the WHO International Clinical Trials Registry Platform: a cross-registry meta-research study

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ABSTRACT

Background: Trial and study registries are an underused meta-research lens on health-professions education (HPE), but keyword retrieval cannot reliably isolate learner-focused studies because education and training terms are dominated by patient-education and clinical-trial vocabulary. We mapped the registered HPE footprint across the WHO International Clinical Trials Registry Platform (ICTRP), testing whether classification rather than filtering recovers the learner-focused signal.

Methods: From a frozen ICTRP cross-registry export (10 June 2026), 16 narrow plus four broad education terms yielded 1,390 records after three-tier de-duplication. Because keyword precision was low (narrow-term interventional positive predictive value 0.182, 95% CI 0.130-0.248) and no term subset reached 0.85, we applied a four-value blind protocol to all 1,383 classifiable records, double-coding a random 200-record reliability sample.

Results: Classification identified 109 registered HPE studies (7.9%, 95% CI 6.6-9.4%): 60 interventional and 49 observational (HPE-versus-rest Cohen κ 0.906). The footprint was small and pandemic-concentrated: 97 of 109 (89%) were registered in 2020-2023, peaking in 2021, and 99 of 109 (90.8%) were COVID-themed, across 11 registries and 29 countries (India most represented). Of 60 trials, 36 (60%) were randomized (median planned enrolment 100). Prospective registration was documented for 51 of 108 (47.2%) and a results record for only 18 of 109 (16.5%).

Conclusions: Registries reveal a small, pandemic-era-concentrated HPE footprint that keyword search misses; recovering it requires manual, double-coded classification of the candidate net. Low retrievability and sparse registry-visible results signal opportunities to strengthen prospective registration and results posting. Because this is a retrieved rather than exhaustive footprint, the counts carry a recall caveat.

Keywords: Clinical trials registries, Health professions education, International Clinical Trials Registry Platform, Meta-research, Reproducibility of results, Research transparency

INTRODUCTION

Prospective trial registration is one of the central safeguards clinical research projects has built against selective reporting and avoidable waste. After the International Committee of Medical Journal Editors made registration before first-participant enrolment a precondition for publication in 2004-2005, explicitly to deter the selective publication and outcome-switching

that earlier reporting scandals had exposed, the 2007 update widened the registrable definition to any prospectively assigned health-related intervention, broad enough to encompass behavioural and educational interventions, and the 2008 revision of the Declaration of Helsinki made registration and results dissemination an ethical duty.¹⁻³ The WHO International Clinical Trials Registry Platform (ICTRP) federates national and regional primary registers under a shared minimum

dataset, turning a patchwork of registries into a single searchable window onto the global research pipeline.⁴

Registration does not guarantee publication: a substantial share of registered studies never reach print, so the published literature is a survivorship-biased subset of what was planned and conducted, and non-registration and non-reporting are core mechanisms of research waste.^{5,6} Registries have therefore become an established meta-research lens for profiling a field's portfolio and exposing its methodological weaknesses- most famously across the roughly 96,000 ClinicalTrials.gov studies shown to be dominated by small, single-centre designs.⁷ Health-professions education (HPE) research is a fit candidate for this lens: it has grown rapidly and increasingly adopted experimental and simulation-based designs, yet has rarely been viewed through the registration machinery it has only begun to use.⁸

The work closest to this question stops short of it. Pino and colleagues conducted the first registry-based audit of educational-intervention entries but studied patient, family, and caregiver education, not health-professions learners.⁹ Tolsgaard and colleagues profiled randomized medical-education studies from the published literature rather than registrations, and so could see neither prospectively registered nor unpublished or discontinued registered work.¹⁰ Al-Durra and colleagues benchmarked prospective-registration compliance across all clinical disciplines at once, with education never isolated and the registry treated as a transparency yardstick rather than a landscape to enumerate.¹¹ Because HPE interventions fall outside the product-based mandates that govern drugs and devices, their registration rests on inconsistently enforced editorial policy- a gap pronounced enough to have prompted proposals for a dedicated medical-education registry.¹²

This footprint is hard to see, for two reasons. First, registry “education” and “training” vocabulary maps overwhelmingly onto patient self-management education and non-pedagogic clinician-facing uses, so keyword filtering returns a corpus in which genuine learner-focused content is only a minority signal; isolating it requires classifying records rather than filtering them.⁹ Second, the period in which any footprint would have grown was unusual: COVID-19 forced a pivot to remote teaching, distance learning, and simulation, and a surge-then deceleration- in medical-education output.¹³⁻¹⁵ These modalities were, however, already rising before 2020, and pandemic-era changes in registration enforcement independently inflated the count of registered studies; any concentration of registered HPE studies in these years is therefore better read as pandemic-era co-timing than as evidence that the pandemic drove the field into the registries.^{16,17}

We therefore mapped the registered HPE footprint directly, at the level of the registries themselves. From a frozen cross-registry ICTRP export we assembled the

education and training candidate net and- rather than trusting any keyword filter- manually and blindly classified every candidate record to separate learner-focused HPE studies from patient education and other non-HPE uses of the same vocabulary, establishing reproducibility by independently double-coding a random reliability sample. We then described the resulting cohort across the dimensions a registry makes visible: which registers and countries they came from, when they were registered and how far they concentrated in the pandemic years, their designs and planned sample sizes, and their transparency, including prospective registration and the presence of a registry-visible results record. To our knowledge this is the first ICTRP-wide, cross-registry landscape of registered health-professions-education studies, interventional and observational, built by manual, blinded, single-pass adjudication of the entire retrieved candidate net, with reproducibility established by independent double-coding of a random reliability sample rather than of every record. Because the retrieval vocabulary cannot capture HPE records that carry no education or training terminology, this cohort should be read as the retrieved registered HPE footprint rather than an exhaustive ICTRP census. Our aim was deliberately descriptive: to make visible a footprint that publication-anchored evidence cannot show, and to establish how it must be retrieved.

METHODS

Study design and data source

This was a cross-sectional, cross-registry landscape analysis (registry meta-research) of records held in the World Health Organization International Clinical Trials Registry Platform (ICTRP), which aggregates the WHO network of primary registries together with ClinicalTrials.gov in a single cross-registry search interface. Records were obtained through the official ICTRP Search Portal export function as comma-separated files containing the platform's 58 standard fields, and were frozen to a single snapshot dated 10 June 2026; all subsequent analyses were performed offline on the cached export, with no further network queries, so that every reported figure derives from one fixed, reproducible data state. The study was reported in line with the STROBE statement, extended by RECORD for routinely-collected health data.

Search, de-duplication, and the candidate net

The portal was queried with 20 search terms: 16 narrow health-professions-education (HPE) terms (medical education, health professions education, nursing education, nurse education, continuing medical education, interprofessional education, medical student, medical students, nursing students, resident training, residency training, clinical teaching, clinical clerkship, simulation training, faculty development, objective structured clinical examination) and four broad education terms

(education, training, teaching, curriculum); two narrow terms returned no records. The narrow-term union- the precision-critical cohort anchor- was de-duplicated across registries with a three-tier fuzzy procedure on the normalized trial identifier: Tier 1 linked records sharing a secondary registry identifier across different registries; tier 2 linked cross-registry pairs with a high fuzzy title match (token-set ratio ≥ 90 , or 85–90 supported by concordant country and a registration-date difference ≤ 90 days); and tier 3 flagged residual near-matches for manual review without automatic merging. Same-registry high-similarity pairs were not merged, because cross-registry duplication (one trial registered in two registries) was the de-duplication target. The broad-term union and the final candidate net were then consolidated by exact de-duplication; a within-cohort audit found no residual cross-registry duplicate among the analysed studies (Figure 1). Because this audit was applied to the 109 analysed HPE studies rather than to the full 1,390-record candidate net, residual duplication within the candidate denominator cannot be entirely excluded, though it would affect net-level yield estimates more than the HPE count. Study type was taken from the platform field (values containing “intervent” as interventional, “observ” as observational); the seven records with residual study-type values were excluded from this partition but were nonetheless screened under the same four-value protocol, and none met the HPE criterion.

Cohort construction by classification, not term-filtering

Because registry “education” and “training” vocabulary is applied predominantly to patient self-care education and to clinician-wellbeing or clinical-treatment studies, keyword retrieval is an imprecise filter for HPE content. We confirmed this with a positive predictive value (PPV) purity audit: a full census of the narrow-term interventional queue, together with a broad-excluded random sample and a sample drawn from the high-volume registers (IRCT, CTRI, ChiCTR), was independently classified, and each PPV was estimated with Wilson score 95% confidence intervals. The audit was evaluated against a pre-specified release rule- a point PPV of at least 0.85 with a Wilson lower bound of at least 0.80, set a priori so that any term-filtered cohort would be predominantly true HPE. Because no term subset met this rule at any usable sample size (results), the cohort was assembled by classifying every record in the candidate net rather than by term filtering; this bounds precision, not recall, which is addressed by the term-set robustness analysis below.

Classification followed a four-value blind protocol fixed in a written codebook before adjudication. For each record only the public title, scientific title, condition, and intervention text were shown; the trial identifier, source register, and retrieving search term were withheld. Each record was labelled HPE, patient education, other non-HPE, or unclear, where HPE denotes a study whose learners or intended recipients are health professionals or

trainees (for example medical, nursing, pharmacy or allied-health students, residents, or qualified clinicians acquiring professional competencies). Pre-specified boundary rules turned on the study’s primary intent: a study whose principal aim was a clinician’s own health or psychological state- a wellbeing, mindfulness, or burnout intervention in which clinicians were recipients rather than learners- was labelled other non-HPE, whereas a study aimed at acquiring teaching, communication, clinical, or other professional competencies was labelled HPE; patient or lay self-management education and physical rehabilitation or exercise “training” were labelled patient education or other non-HPE; and records with insufficient text were labelled unclear and never defaulted to HPE. Because only these four fields were shown and ambiguity was resolved against HPE, the resulting count is a conservative lower bound. Each record was coded once under this protocol by the primary classification panel; reproducibility was then estimated by independent re-coding of a random 200-record sample, not by double-coding every record. Records labelled HPE constituted the analysed cohort.

Inter-rater reliability

A random sample of 200 records (seed 42) was drawn from the full classified pool and re-coded by a second, independent panel blinded under the same written codebook. Disagreements within the reliability sample were used only to estimate agreement and were not fed back to revise the main-pool labels, which therefore rest on a single classification pass. Agreement was summarized with Cohen’s κ for the four-value labels and for the binary HPE-versus-rest decision, alongside raw percentage agreement, and interpreted against the Landis and Koch benchmarks ($\kappa > 0.80$ indicating “almost perfect” agreement).

Variables and analysis

We extracted the source register; recruitment country or countries; registration date and derived calendar year; recruitment status; study design; planned target sample size; primary outcome; trial phase; minimum inclusion age; ethics status; and the results field. Allocation was classified as randomized controlled trial, non-randomized, or unclear from the free-text study-design field using a rule set robust to registry-specific phrasing- for example, the Iranian register’s “randomization:” label (which contains “random” even when the value is “not randomized”) and single-arm designs labelled with a randomization-sequence method were not miscounted as randomized. Planned target sample size was parsed as the first integer in the target-enrolment field, and a record was flagged COVID-19/pandemic-themed when a case-insensitive expression (COVID, SARS-COV, coronavirus, or pandemic) matched its combined title, condition, and intervention text. Two framings are deliberate: prospective-versus-retrospective registration was taken from the ICTRP portal field as supplied (a

portal-classified measure, not reconstructed from dates, whose formats vary across registers), and a “registry-visible results record” was defined as the presence of a results record in the export (a register-dependent visibility measure, not a direct measure of investigator results-reporting). Country names were normalized to a consistent set of reporting units before tabulation; target learner profession and education modality (interventional trials only) were sub-coded by a single coder, separately from and not part of the reliability-validated HPE adjudication. Structured-field completeness was computed overall and by source register, and robustness to the discretionary vocabulary by a leave-one-term-out analysis over the 20 terms. The export was frozen with a SHA-256 manifest of every raw and derived artefact; analyses used Python 3.13 (pandas; standard-library statistics), with proportions accompanied by Wilson score 95% confidence intervals and Cohen’s κ computed from the agreement matrix.

Ethics

The study analysed publicly available, de-identified records from international trial registries and involved no human participants, intervention, or identifiable personal data. Institutional ethics-committee approval was therefore not required.

RESULTS

A low-precision candidate net resolved by classification

On the frozen 10 June 2026 ICTRP snapshot, 16 narrow health-professions-education (HPE) terms plus four broad education terms (education, training, teaching, curriculum) returned, after three-tier cross-registry de-duplication, 1,390 unique candidate studies (Figure 1): 1,052 interventional, 331 observational, and 7 residual-type records (other, prevention, treatment study, screening) excluded from classification. Keyword retrieval was a poor filter for HPE content (Table 1A): in the full census of 165 narrow-term interventional records only 30 were HPE— a positive predictive value (PPV) of 0.182 (Wilson 95% CI 0.130-0.248)— and precision was

lower still in a broad-excluded random sample (8/100; 0.080, 95% CI 0.041-0.150) and the high-volume registers IRCT/CTRI/ChiCTR (2/45; 0.044, 95% CI 0.012-0.148). No term subset reached a PPV of 0.85 with a Wilson lower bound of 0.80 at any usable sample size, so the cohort was assembled by classifying every record under the four-value blind protocol rather than by term filtering (Table 1B): among the 1,052 interventional records, 60 were HPE, 214 patient education, 776 other non-HPE, and 2 unclear; among the 331 observational records, 49 were HPE, 6 patient education, 271 other non-HPE, and 5 unclear.

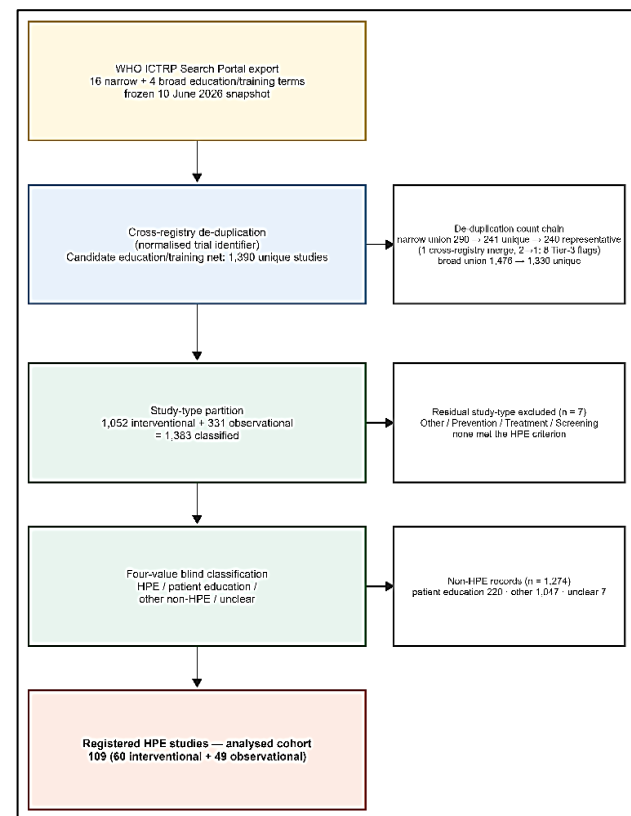


Figure 1: Assembly and classification of the cross-registry HPE cohort.

Table 1: Construction of the registered-HPE cohort from the cross-registry candidate net.

(A) Positive predictive value (PPV) of keyword-retrieved candidate subsets (purity audit; four-value blind protocol, independent judges).						
Sample	N	HPE	PPV	Wilson 95% CI		
Narrow-term interventional census	165	30	0.182	0.130-0.248		
Broad-excluded random sample	100	8	0.080	0.041-0.150		
High-volume registers (IRCT/CTRI/ChiCTR)	45	2	0.044	0.012-0.148		
(B) Four-value classification of the full candidate net.						
Study type	Candidate net	HPE	Patient education	Other non-HPE	Unclear	HPE yield
Interventional	1,052	60	214	776	2	5.7%
Observational	331	49	6	271	5	14.8%
Total classified	1,383	109	220	1,047	7	7.9%

A small, reproducibly identified HPE footprint

Across the 1,383 classified records, 109 were registered HPE studies- 60 interventional trials and 49 observational studies- accounting for 7.9% (Wilson 95% CI 6.6-9.4%) of the classified education/training net; HPE was rarer among interventional (60/1,052; 5.7%) than observational (49/331; 14.8%) records. The classification was highly reproducible: on a random 200-record sample (seed 42) re-coded by a second blind panel, four-value Cohen's κ was 0.850 (raw agreement 94.5%) and the cohort-defining HPE-versus-rest κ was 0.906 (98.5%). Because HPE is a rare class, we also report decision-specific agreement: positive specific agreement 0.914, negative 0.992, and prevalence-and-bias-adjusted κ (PABAK) 0.970, confirming the minority class was identified reproducibly (the two panels found 17 and 18 HPE records and agreed on 16).

Registries, countries, and pandemic-era timing

The 109 studies spanned 11 primary registries and 29 countries (Table 2; Figure 3). ClinicalTrials.gov contributed the most records (41), followed by the Clinical Trials Registry-India (CTRI, 29), the German Clinical Trials Register (8), and the Iranian, Japanese, and ISRCTN registries (6 each); the remainder came from CRIS, ChiCTR, and TCTR (3 each) and REBEC and ANZCTR (2 each). India was the country most frequently represented (30 country mentions, predominantly via CTRI), followed by Germany and Turkey (8 each), Iran, the United States, and the United Kingdom (6 each), and Egypt (5). Registrations concentrated in the pandemic period (Figure 2): 97 of 109 (89.0%) fell in 2020-2023,

rising from 34 in 2020 to a peak of 39 in 2021 then declining (15 in 2022, 9 in 2023, 6 in 2024, 4 in 2025, and 1 in the partial 2026 snapshot), with a single pre-2020 registration (2018). Over the cohort, 99 of 109 (90.8%, 95% CI 83.9-94.9%) were COVID-19- or pandemic-themed, more so among observational (46/49; 93.9%) than interventional (53/60; 88.3%) records- a calendar co-timing, not an attribution of cause.

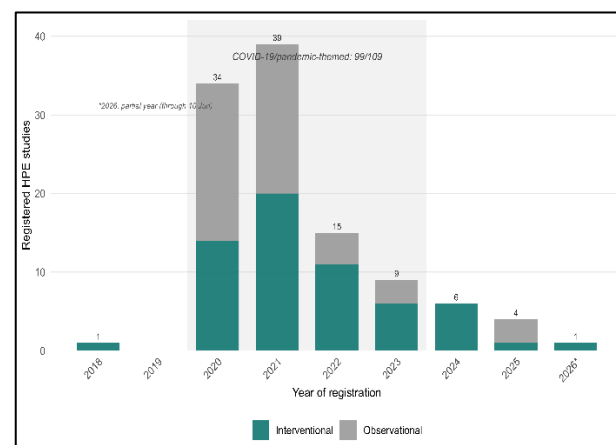


Figure 2: Annual registrations of HPE studies by study type, 2018–2026.

Stacked bars show registered HPE studies per calendar year of registration, partitioned into interventional and observational types; the shaded interval marks the 2020-2023 pandemic period to indicate calendar co-timing only, not causal attribution, and the COVID-19/pandemic-themed proportion (99/109) is annotated. Registrations peak in 2021; the 2026 bar is a partial year through 10 June 2026.

Table 2: Characteristics of the 109 registered HPE studies, overall and by study type.

Characteristics	Overall (n=109)	Interventional (n=60)	Observational (n=49)
Source registries, N distinct	11	10	9
Countries represented, N distinct	29	21	18
Registered 2020–2023, N (%)	97 (89.0)	51 (85.0)	46 (93.9)
COVID-19/pandemic-themed, N (%; 95% CI)	99 (90.8; 83.9-94.9)	53 (88.3; 77.8-94.2)	46 (93.9; 83.5-97.9)
Randomised allocation, M (%)	—	36 (60.0%)	n/a
Planned sample size, median (IQR) †	100 (45-300)	60 (41.5-182)	215 (55-450)
Prospective registration, N/n (%; 95% CI) ‡	51/108 (47.2; 38.1-56.6)	28/60 (46.7; 34.6-59.1)	23/48 (47.9; 34.5-61.7)
Registry-visible results record, N/n (%; 95% CI)	18/109 (16.5; 10.7-24.6)	14/60 (23.3; 14.4-35.4)	4/49 (8.2; 3.2-19.2)
Not recruiting/closed, N (%)	93 (85.3)	51 (85.0)	42 (85.7)

† Planned sample size over the 107/109 records with a parsable target enrolment (58 interventional, 49 observational; range 5-9,209), values being the first integer of the free-text target-enrolment field. ‡ Prospective-versus-retrospective registration assessable for 108/109 records. “Registry-visible results record” denotes a results record present in the ICTRP export and is register-dependent (Table 3), not a direct measure of investigator results-reporting.

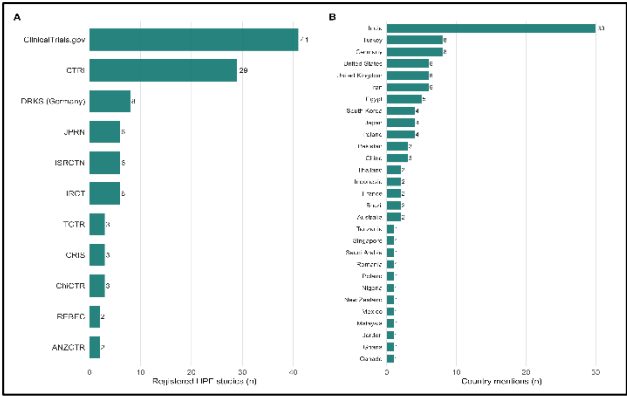


Figure 3: Distribution of the 109 registered HPE studies across registries and countries.

(A) Studies per source registry (11 registries). (B) Country mentions across the cohort (29 countries; multi-country studies counted once per represented country, so values are non-mutually-exclusive country mentions, not lead-country counts). Bars are ordered most to least frequent.

Designs, learners, and modalities

Of the 60 interventional trials, 36 (60.0%) were randomized, 22 non-randomized, and 2 unclear. Planned samples were modest: across the 107 of 109 records with a parsable target the median was 100 (IQR 45-300; range 5-9,209), interventional trials being smaller than observational studies [median 60 (IQR 41.5-182) versus 215 (IQR 55-450)]. Target learner populations- single-coder sub-categorizations, separate from the reliability-validated adjudication- were most often the general health workforce (42 studies; including unspecified health-care workers and care-home, mental-health, public-health, dentistry, veterinary, laboratory-technologist, and paramedic trainees), followed by medical (30), nursing (21), interprofessional (6), pharmacy (5), midwifery (3), and allied-health (2) learners. Among the 60 interventional trials, the delivered education modality was a course, seminar, or workshop in 18, simulation in 17, and online, distance, or e-learning in 17, with smaller numbers of skills/procedural (6), gamified (1), and blended (1) interventions.

Transparency markers were limited and register-dependent

Where assessable (108 of 109), 51 studies (47.2%, 95% CI 38.1-56.6%) were registered prospectively, and a registry-visible results record was present for only 18 of 109 (16.5%, 95% CI 10.7-24.6%); most were not recruiting or closed (93/109; 85.3%). Observational studies carried a results record less often than interventional trials [4/49 (8.2%) versus 14/60 (23.3%)], with near-identical prospective-registration proportions (47.9% versus 46.7%; Table 2). Structured-field completeness was high for core fields (date of registration and recruitment status 109/109, primary outcome 108, target size 107, countries 104) but lower for study design (89), phase (85), minimum age (72), ethics status (59),

and a results field (18) (Table 3); these gaps were register-dependent rather than random- the ethics-status field was absent from ClinicalTrials.gov exports (0/41) and minimum-age bounds from CTRI and ISRCTN (0/29, 0/6), while a results record appeared almost only for ISRCTN (6/6), JPRN (4/6), and the German register (3/8), with isolated records in CRIS, ClinicalTrials.gov, and REBEC and none in CTRI, IRCT, ChiCTR, ANZCTR, or TCTR (Figure 4).

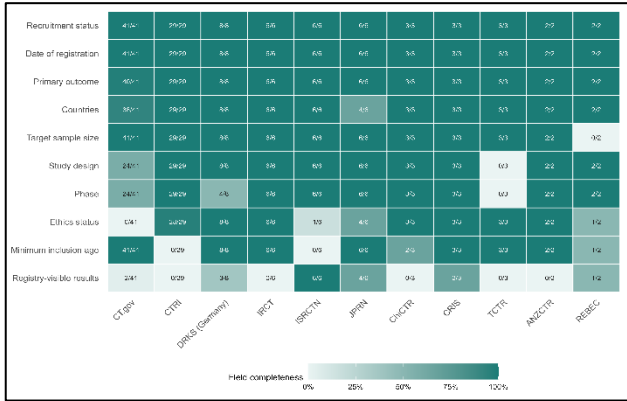


Figure 4: Registry-visible field completeness across the 11 source registries.

Heatmap of structured-field completeness- the proportion of non-empty values (annotated N/total)- for each of the 10 extracted data fields across the 11 primary registries contributing the 109 studies; registries are ordered by cohort size and fields by mean completeness. Cell shading runs low (pale) to high (teal). The registry-visible results record field indexes whether a results record was present in the ICTRP export, a register-dependent visibility signal rather than a measure of investigator results-reporting.

Table 3: Structured-field completeness across the 109 registered HPE studies.

Data field	Complete, (n=109)
Date of registration	109
Recruitment status	109
Primary outcome	108
Target sample size	107
Countries	104
Study design	89
Phase	85
Minimum inclusion age	72
Ethics status	59
Registry-visible results record §	18

§ This row indexes whether a results record was present in the ICTRP export, which depends on whether the contributing register exposes a results field; it is a measure of register-dependent visibility, not of investigator results-reporting. Completeness varied systematically by source register (Figure 4).

The cohort did not depend on any single search term

A leave-one-term-out analysis over the 20 terms showed the interventional subset did not depend on any single

term: removing all 16 narrow terms retained 56 of 60 trials (93.3%), the narrow terms uniquely contributing only 4 trials, and the broad terms being load-bearing by design (training retrieved 41 trials, education 23; removing training lost 19). Every identified interventional HPE trial was retrieved by at least one of the 20 terms. This gauges within-net dependence on the recorded terms, not recall, and cannot quantify HPE studies that no education or training term retrieved.

DISCUSSION

We mapped the footprint of registered health-professions-education (HPE) studies across the WHO International Clinical Trials Registry Platform (ICTRP) and found it small, recent, geographically uneven, modest in scale, and weakly transparent (Results). To our knowledge this is the first ICTRP-wide, cross-registry landscape of registered health-professions-education studies, interventional and observational, built by manual, blinded, single-pass adjudication of the entire retrieved candidate net, with reproducibility established by independent double-coding of a random reliability sample rather than of every record. Prior work comes close without addressing this directly- Pino and colleagues audited educational-intervention entries but in patient rather than learner populations, Tolsgaard and colleagues profiled published education RCTs rather than registrations, and Al-Durra and colleagues benchmarked registration transparency across all disciplines without isolating education.⁹⁻¹¹ We discuss below why these studies were so hard to find, what their pandemic-era concentration does and does not mean, and how their transparency profile should be read.

The cohort had to be classified, not filtered

The central methodological lesson is that registered HPE studies cannot be identified with acceptable precision by keyword filtering: narrow-term retrieval was markedly imprecise (positive predictive value 0.182, 95% CI 0.130-0.248), falling to 0.080 and 0.044 in broader and high-volume-register samples, and no term subset reached an acceptable threshold, so we classified every record under a blind four-value protocol. This matches systematic-review guidance to search registries broadly and screen a large, low-precision net by hand; the imprecision is registry architecture- interfaces lack a deeply indexed controlled vocabulary and vary across the network- not a fixable search string.^{18,19} It arises because registry “education” and “training” vocabulary maps overwhelmingly onto patient-directed intervention: patient-education studies (214) outnumbered learner-focused HPE studies (60) among interventional records by more than three to one, and records seldom mark the recipient in primary fields, so manual adjudication is the reference standard when unstructured text defeats algorithmic sorting.^{9,20} Mining registries for HPE therefore requires classification, not filtering, with realized precision and reliability reported.²¹

Pandemic-era concentration, not pandemic causation

Registrations peaked in 2021, the majority registered during the pandemic years and COVID-themed, more so among observational (94%) than interventional (88%) records. We read this as pandemic-era clustering, not evidence that the pandemic caused HPE registration to rise; co-timing is correlation, and several confounders sever any causal chain. The dominant modalities- e-learning, blended learning, simulation- were already rising before 2020, compatible with acceleration rather than origination; prospective-registration enforcement and journal mandates tightened over the same period, so a rise in registered studies overstates any rise in conducted ones; expedited review and disproportionate attention to COVID-labelled work encouraged pandemic framing of ongoing research; and fast, inexpensive cross-sectional surveys bypass the patient-facing approvals interventional work requires, proliferating wherever disruption created something to measure.^{14,16,17,22,23} Each mechanism would produce a pandemic-era registration peak without the pandemic having “driven” HPE science.

A transparency profile partly constrained by registry architecture

The transparency findings are easy to misread as a verdict on investigators. Fewer than half the studies were prospectively registered (47.2%), and a registry-visible results record was present for only 16.5%, lower for observational (8.2%) than interventional (23.3%) studies. Our prospective-registration rate is comparable to the cross-field benchmark: Al-Durra and colleagues found only 41.7% of RCTs published in 2018 prospectively registered despite most reporting a registration number.¹¹ This is an ecosystem-wide gap, not an HPE-specific failing, unsurprising given HPE interventions fall outside product-based mandates. The results figure needs the firmest framing: a registry-visible results record means only that a results record was present in the ICTRP export, which depends on whether the contributing register exposes a results field at all; our completeness audit shows such fields essentially absent from some major registers, so a missing record is a composite of investigator non-posting, study non-completion, weakly enforced results modules, or no exposed field, and we read it as register-dependent visibility rather than investigator non-compliance, though it remains a transparency failure from the registry user’s perspective.²⁴ Our 16.5% sits within the low 8-27% band reported for registry-visible results across clinical research, rising where posting is mandated and enforced, and the lower observational visibility likely reflects that observational registration remains weakly codified and contested, rather than investigator behaviour- hence our separate analysis of the two study types.²⁵⁻²⁸ These registry-level deficits sit atop documented design and reporting fragility in HPE, and the registry is where the absence of the central safeguards against research waste- prospective

registration and complete reporting- first becomes visible.^{6,10,29}

Several limitations bound these findings, each stated with its mitigation. First, our HPE definition was deliberately conservative, excluding clinician wellbeing and mindfulness studies as well as patient and lay education by protocol; the count of 109 is therefore a lower bound that a more permissive boundary would likely enlarge. Second, the analysis rests on a single 10 June 2026 snapshot with register-dependent field coverage, so absolute completeness counts- especially the results-field signal- are register-conditioned rather than direct measures, and prospective registration is read from the ICTRP portal field as supplied rather than reconstructed from dates. Third, the learner-profession and education-modality sub-categorizations were single-coder and descriptive; the cohort-defining HPE adjudication, by contrast, was validated by independent double-coding of a random reliability sample (four-value Cohen's κ 0.850; HPE-versus-rest κ 0.906; PABAK 0.970), though the main-pool labels rest on a single classification pass. Fourth, we worked from registry text alone, without protocols or quality assessment, so we cannot adjudicate study conduct. Fifth, because HPE registration is largely voluntary and falls outside product-based mandates, the cohort is a self-selected, non-representative slice of what enters the registries rather than the field as a whole; its geography, scale, pandemic theme, and transparency describe the registered footprint, not the epidemiology of HPE research. Sixth, the cohort is bounded by the discretionary search vocabulary: the leave-one-term-out analysis shows the interventional subset is not an artefact of any single term, but the vocabulary omitted some HPE synonyms- for example trainee, intern, fellowship, competency-based, or assessment used without an accompanying education or training word- so a record carrying only such terminology would fall outside the net. Our figures therefore describe the retrieved registered HPE footprint rather than an exhaustive ICTRP census. Within these bounds the principal findings- rarity, pandemic-era concentration, geographic skew, small planned size, and weak registry-visible transparency- are robust.

CONCLUSION

Trial registries are an underused but informative lens on health-professions-education research, revealing- within the terminology retrievable from ICTRP- a registered footprint that is small, pandemic-era-concentrated, geographically uneven, modest in scale, and only intermittently visible in its results, a profile the publication-filtered literature cannot show. Two implications follow: the field needs more consistent prospective registration and results posting, so the planned, the ongoing, and the abandoned become as visible as the published; and anyone studying HPE through registries must recover the learner-focused signal by manual, reproducible adjudication of the retrieved

candidate net, because keyword filtering returns a corpus dominated by patient education. Making this sparse footprint a more useful transparency infrastructure would hold a growing, increasingly experimental field to the standards the rest of clinical research has spent two decades building.

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