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PERSPECTIVE

Improving comparability across cognitive training trials for brain aging: A focus on interoperability

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Abstract

Cognitive training may promote healthy brain aging and prevent dementia, but results from individual studies are inconsistent. There are disagreements on how to evaluate cognitive training interventions between clinical and basic scientists. Individual labs typically create their own assessment and training materials, leading to difficulties reproducing methods. Here, we advocate for improved **interoperability**: the exchange and cooperative development of a consensus for cognitive training design, analysis, and result interpretation. We outline five guiding principles for improving interoperability: (i) design interoperability, developing standard design and analysis models; (ii) material interoperability, promoting sharing of materials; (iii) interoperability incentives; (iv) privacy and security norms, ensuring adherence to accepted ethical standards; and (v) interpretability prioritization, encouraging a shared focus on neurobiological mechanisms to improve clinical relevance. Improving interoperability will allow us to develop scientifically optimized, clinically useful cognitive training programs to slow/prevent brain aging.

KEYWORDS
cognitive training, dementia, interoperability

HIGHLIGHTS

- Interoperability facilitates progress via resource sharing and comparability.
- Better interoperability is needed in cognitive training for brain aging research.
- We adapt an interoperability framework to cognitive training research.
- We suggest five guiding principles for improved interoperability.
- We propose an open-source pipeline to facilitate interoperability.

1 | INTRODUCTION

Alzheimer's disease and Alzheimer's disease related dementias (AD/ADRD) are a major public concern. Non-pharmacological interventions are an important frontline intervention for preventing or slowing cognitive decline and brain aging seen in AD/ADRD. Cognitive training in the context of brain aging refers to a broad set of interventions aimed at enhancing global or specific cognitive functions to slow or prevent age-related cognitive decline by training specific cognitive abilities or processes.[1] According to a recent Alzheimer's Association taskforce review, cognitive training is the most studied, but most contentious type of non-pharmacological intervention for preventing brain aging.[2] The National Academies, in collaboration with the National Institutes of Health (NIH), recently highlighted the promise of cognitive training in preventing, slowing, or delaying the onset of preclinical and clinical stages of AD/ADRD and cognitive aging.[3] Recently, a large (N=2802) clinical trial showed that a specific type of cognitive training focused on speed of processing significantly reduced the risk

of dementia over 10 years,[4] increasing optimism for this approach. Meta-analyses have shown positive results across multiple domains in older adults at risk for dementia,[5,6] as well as cognitively healthy older adults,[7] although with significant heterogeneity in findings[7] and mixed quality in studies.[8] Given both the promise and limitations of cognitive training in AD/ADRD research, there is broad agreement that an improved understanding of mechanisms of action, better identification of predictors of gain, and more widespread implementation of best practice standards are needed in the field.[2] However, many studies fall short of best practices and there are inconsistencies, particularly between the basic and clinical sciences, in standards and practices in cognitive training research. It is important to note that, when talking about this disconnect in this paper, we do not aim to stereotype clinical and basic scientists, but instead to highlight the differences in how the fundings and publishing systems of these different fields evaluate research. This may broadly align with differences in the priorities of the scientists themselves, but this is certainly not always the case at the individual level. In this paper, we will first introduce five major problems in the field of cognitive training and AD/ADRD research, and then propose that a focus on improved interoperability: the exchange and cooperative development of a consensus for cognitive training design, analysis, and result interpretation, will help to advance scientific progress in the field (see Figure 1).

RESEARCH IN CONTEXT

1. **Systemic review**: The authors reviewed the literature on cognitive training in the context of brain aging using traditional (e.g., PubMed and Google Scholar) sources. The literature was used to support both the need for improved interoperability in the field, as well as to provide examples that suggest a willingness and ability to engage in practices that improve interoperability. The relevant citations are appropriately cited.
2. **Interpretation**: Our literature review suggested that improved interoperability would be beneficial and possible to achieve in the field. This led us to propose a framework for improving interoperability based on five elements: (i) design interoperability, (ii), material interoperability, (iii) interoperability incentives, (iv) privacy and security norms, and (v) interpretability prioritization.
3. **Future directions**: In addition to this framework, we suggested that an open-source pipeline may facilitate improved interoperability, and hope that both the framework and pipeline will be used in future to improve interoperability in the field.

2 | EXISTING PROBLEMS RELATED TO THE COMPARABILITY OF COGNITIVE TRAINING RESEARCH

Problem 1. The lack of agreement over what constitutes successful cognitive training.[9] Cognitive training outcomes include the trained effect, or "proximal training outcomes" (i.e., improvements measured specifically using the practiced cognitive training program), near transfer effect (i.e., improvements in the targeted cognitive domain, assessed using a similar but non-trained task), far transfer effect (i.e., improvements in cognitive domains that are not practiced directly in the training), and broad training effect (i.e., improvements across

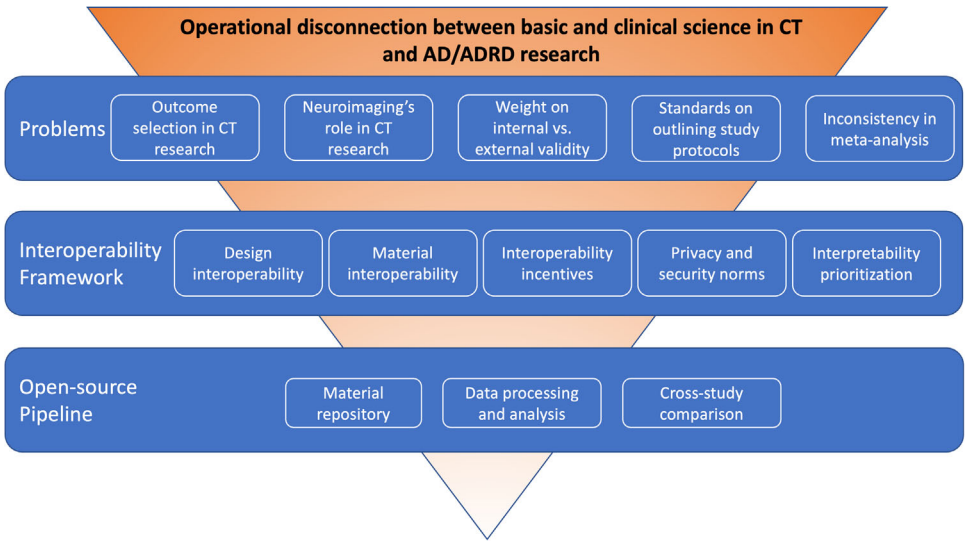

FIGURE 1 Proposed interoperability framework to improve comparability and collaboration across basic and clinical research into cognitive training for brain aging. We propose that a focus on five elements of interoperability will help clinical and basic scientists share their expertise to create a more coherent cognitive training for brain aging field, and suggest that an open-source pipeline with the capacity to store materials, analyze data, and compare across studies will incentivize and enable interoperability.

several cognitive domains, often including global cognitive measures, that are both practiced and not practiced directly in the training, alongside improvements in clinically relevant real-world outcomes). Basic science typically considers cognitive trainings that demonstrate any transfer effects, including both near and far transfer,[10] as scientifically significant, whereas clinical science often emphasizes the clinical importance of improving clinically established measures (e.g., clinically validated measures of executive function[11] or episodic memory,[12] instrumental activities of daily living,[13] which include managing finances, shopping, transportation, preparing and cooking food, or AD/ADRD incidence or progress[14]). In addition to this disconnect between basic and clinical sciences, differences in the prioritization of certain outcomes when evaluating cognitive training results are also driven by variation in the goals of cognitive training: some scientists believe that broad training effects are necessary for significant clinical impact,[15,16] while others believe that training specific cognitive domains can still lead to important clinical and quality of life improvements.[9] Additionally, meta-analyses often emphasize effects on global cognitive measures,[6,8] even if individuals studies are not primarily targeted at these outcomes, and these global cognitive measures (e.g., Montreal Cognitive Assessment) that were designed as broad screening tools may not be as sensitive to cognitive change as domain-specific tasks.

Problem 2: Variability in the use of neuroimaging in cognitive training research. Studying mechanisms of action using brain imaging is challenging due to the non-specific, indirect nature of available human brain imaging techniques, and the complexity of neuroimaging analysis allows for significant researcher choice. Basic science often focuses on identifying novel brain plasticity mechanisms, using advanced analysis methods (e.g., modularity,[17] the extent to which the brain can be divided into distinct modules, derived from graph theory analysis), that may explain training effects, while clinical science targets established brain profiles that can be extracted more simply (e.g., mean connectivity within the default mode network) as part of clinical outcomes reflecting brain integrity, or as part of treatment response-related post-hoc analyses. This difference reflects the different priorities of the basic and clinical sciences, with the former often judged on scientific novelty while the latter focuses on further establishing easily-interpretable measures to enable their use in clinical practice. Of note, both of these examples of brain profiles are based on the analysis of brain connectomes that are generated by measuring the connections between brain regions in terms of either their function (usually correlated BOLD signal) or structure (various approaches to identifying white matter tracts). While other approaches exist (e.g., using brain responses to a specific task), analysis of connectomes is becoming increasingly popular (e.g.,[18]), with significant potential for increased interoperability.

Problem 3: The different weight placed on internal versus external validity. Basic science studies rarely explicitly state the phase of cognitive training research being performed, and different subfields focus on either establishing sufficient internal validity (i.e., knowing the precise causal relationships involved), using well-controlled environments (corresponding to stage 0–2 of a clinical trial[19]), or demonstrating external validity (i.e., whether results will generalize) using large, relatively diverse samples with little attention paid to biological mechanisms.[20] Both internal and external validity are necessary in clinical science if results of cognitive training are to be translated to clinical practice (i.e., stage 3 or later[19]), in which environments and samples are less tightly controlled.[21] Issues in balancing internal and external validity are not absent from clinical science, but at least in principle the importance of both aspects is highlighted to a greater extent by the use of established stage models.

Problem 4: Different standards for developing and describing study protocols.[22] Clinical science usually uses clinically established measures as outcomes and established intervention designs/paradigms, and records/registers designs in public clinical trial repositories. Recently, sharing of raw data has also been increasingly required by funders of clinical science, such as the NIH. In contrast, there are fewer enforced reporting requirements for studies in humans conducted in basic science. This leads to increased variability in methods and reporting. While some research groups register and share their study protocols, and share data in online repositories (sometimes with greater rigor than would be required by clinical research standards), others do not register designs, provide clear protocols, or share data. Due to the nature of understanding, designing, and revising cognitive training paradigms, a lack of clear and consistent reporting of study protocols, data, and analysis methods can make it difficult to re-create the methods used by other groups. Improving protocol standards is also critical for facilitating an improved understanding of how cognitive training elements, including dosage, timing, maintenance (booster sessions), etc., affect outcomes. These elements are underappreciated in cognitive training research when compared to traditional clinical trials, and their importance could be emphasized in future design standards. For example, it is currently unclear the extent to which treatment effects increase with dosage of cognitive training (both when considering the length of each training session and the overall length of the training program), and whether this relationship is linear; if there is an "ideal" dosage for cognitive training, whether this varies across paradigms, etc. There are many reasons to think there may not be a simple linear dose-response relationship: simply doing more cognitive training is unlikely to be more beneficial: it may depend on maintaining a prolonged "mismatch" between cognitive resources and demands of the paradigm,[23] but even increasing the length of mismatch may not increase treatment effects, as long sessions may increase fatigue which could interfere with plasticity. Improved interoperability is necessary to answer these sorts of critical practical questions in cognitive training research, to provide increased power to detect moderators of outcomes.

Problem 5: Inconsistency in meta-analysis. Researchers in the field of cognitive training appreciate the importance of meta-analysis to provide clarity given the heterogenous findings in the literature. However, meta-analyses also show inconsistent findings.[5,6,16,24–26] This is partly due to the inconsistent reporting mentioned above, leading to a large number of studies not being included in meta-analyses (it is worth noting that several meta-analyses have reported a lack of publication bias,[6,25] while others have seen changes in the significance of findings when accounting for publication bias[26]). Some meta-analyses[27] also

TABLE 1 Research guidelines for designing models of cognitive training for brain aging that incorporates brain profiles.

Purpose	Behavioral trial stage (NIH stage model)	Brain profile as a mediator (Science of Behavioral Change Framework)	Brain profile as a moderator (Precision medicine approach)
Explore potential brain mechanism's relationship with a behavior.	Stage 0: mechanistic study (including mechanistic intervention study).	A brain profile mediates the relationship between variable *A* (a potential intervention target in later stage intervention) and variable *B* (a potential intervention outcome in later stage intervention).	The relationship between variable *A* and variable *B* differs in participants with selected brain profile.
Intervention is feasible on changing primary outcomes.	Stage 1: feasibility.	N/A	Intervention is feasible in participants with selected brain profile.
Intervention has efficacy on changing outcomes and selected mechanisms.	Stage 2–3: efficacy.	Intervention changes a brain profile, and the change of brain profile relates to the change of primary outcome.	Intervention is efficacious in participants with selected brain profile.
Intervention is effective in real-world setting and can be disseminated.	Stage 4-5: effectiveness and dissemination.	N/A	Intervention is effective in participants with selected brain profile.

include a range of cognition-oriented treatments that go beyond cognitive training, including rehabilitation, cognitive stimulation, and general engagement, which are difficult to compare and unlikely to affect AD/ADRD via the same mechanisms. Further, with the lack of standardizing of methods, and lack of clarity in how to compare different methods, meta-analyses often combine rhetorical apples and oranges that can violate the assumptions of employed statistics.[22] Additionally, meta-analyses are often led by clinical scientists that prioritize randomized controlled trials by clinical researchers, and can miss basic science findings. These findings might be particularly important in understanding moderators of cognitive training outcomes, which show the least consistency in meta-analysis results due to a lack of power compared to analyses of main effects. Encouragingly, a recently developed platform (CogTale) for evaluating, synthesizing, and disseminating evidence from cognitive interventions allows clinicians/researchers to perform customizable meta-analyses with information on effect sizes and research quality, and also provides briefings to the general public.[28] Although meta-analyses results are only as good as the studies that comprise then, this platform shows an ability and willingness for cognitive intervention researchers to collaborate and engage in collective research, providing confidence that improved interoperability would have a significant impact.

3 | POTENTIAL SOLUTION: INTEROPERABILITY

We propose that translating a framework from healthcare interoperability to cognitive intervention science could be a practical solution to advance comparability of clinical and basic science in the field of cognitive training. The interoperability framework emphasizes five key elements: adoption and optimization, standards, interoperability incentives, privacy and security, and rules of engagement.[29] Here, we will explain how these five elements can be translated to advance standards in cognitive training studies, while also improving methodologically rigor and allowing for research in more diverse populations.[3] This framework comes from a 2013 government report aimed at improving interoperability in healthcare, and since its publication this industry has seen significant advances in interoperability.[30–32] This conceptual framework laid the foundation for more ambitious practical changes, including the Trusted Exchange Framework and Common Agreement,[33] providing a roadmap toward improved interoperability in other fields. We hope that applying this framework to the field of cognitive training will be similarly beneficial, and aim to increase the speed of improvements compared to the considerably larger and more complex field of healthcare by combining it with a practical next step involving the development of an open-source pipeline.

Principle 1. Design interoperability: A fundamental element of cognitive training research is study design. We suggest that a key to improving comparability is the adoption and optimization of consistent trial design across basic and clinical research. There are three major study designs employed in the context of cognitive training for brain aging (see Table 1). In many cases, the same trial might allow one or more of these models to be tested: **(a)** interventions that aim at directly modifying brain or cognitive aging, defined using a specific behavioral or neural marker with clinical relevance, For example, Montreal Cognitive Assessment score (cognitive aging) or AD-associated neurodegeneration (brain aging) levels **(intervention effect/outcome model)**. For example, in our Computer-Based Cognitive Training for Older Adults with Mild Cognitive Impairment (CogTE) study, relative to an active control, cognitive training on speed of processing was hypothesized to improve attention and processing speed and increase brain functional activation in prefrontal subregions associated with these cognitive domains in older adults with mild cognitive impairment (MCI).[34] In the behavior domain, working memory training has been predicted to lead to changes in fluid intelligence.[35] Relatedly, we need to pay attention to several interrelated study design aspects that would influence the evaluation of the intervention effect, including the choice of usual care control versus attention control versus active control

depending on the stage and purpose of intervention testing, the difference between absolute versus relative efficacy (i.e., within-group vs. between-group changes after intervention), and the decision on hypothesis testing on noninferiority versus equivalence versus superiority effects when comparing a newly developed cognitive training with a control condition. These issues have been emphasized in pharmacological or other non-pharmacological clinical trial design for new intervention development[36,37] **(b)** studies that target forms of brain plasticity believed to give rise to cognitive outcomes of interest **(mediation model)**. For example, in the CogTE study, improved whole-brain integration (indexed by participation coefficient) explained how speed of processing training improved working memory (a cognitive domain that was not directly practiced in training).[38] Or in the case of working memory training, it has recently been shown that near transfer (e.g., transfer to an untrained working memory task) mediates far transfer to fluid intelligence[10]; **(c)** studies that aim at understanding heterogeneity in the intervention response, e.g., who is most responsive to treatment, or which mechanism helps buffer against the adverse effect of brain pathophysiologies on functional outcomes **(moderation model)**. For example, in CogTE study, we revealed that, compared to others in the intervention group or in the control group, a subgroup of participants in the intervention group with clinically meaningful improvement across episodic memory and executive function had significantly better regional segregation (indexed by clustering coefficient) at baseline and improved segregation after intervention.[39] Or in the case of working memory training, our ongoing study is currently enrolling 30,000 people to try to better understand how individual differences moderate working memory training effects.[40] As demonstrated in these examples, some trials can be used to address all three model frameworks. Clarifying these models prior to conducting trials, and then reporting them clearly in publications, is not only fundamental to increasing the rigor and reproducibility of the field, it is also essential to reduce the disconnect between basic and clinical sciences. Currently, clinical science emphasizes the paramount importance of primary effects (i.e., what, if anything, does the intervention causally affect): funding and primary report papers usually rest on these effects, with mechanistic models (i.e., mediation or moderation) relegated to post-hoc analyses that are often less rigorous or likely to have been registered in advance. On the other hand, basic scientists are often primarily interested in mechanisms, and analyze any datasets that can provide power to either an investigation of biological mechanisms or an individual difference analysis (i.e., attempting to understand for whom, and why, interventions show effects). To allow for improved causal and mechanistic inference simultaneously, all levels of analysis should be considered during trial design, hopefully encouraging collaboration between clinical and basic scientists with complementary expertise in establishing clinical relevance/causal inference and mechanistic precision, respectively.

Element 2. Material interoperability: The original interoperability framework emphasizes the importance of consistent implementation standards (e.g., shared workable solutions) across systems. Here we emphasize the importance of a consensus on sharing intervention and assessment protocols, including a full understanding of both the behavioral and brain imaging protocols for acquiring and preprocessing data; and the advanced analytical methods for examining mediation, moderation, and intervention effects. We emphasize three essential operational elements for supporting comparability across different interventions: (i) sharing operational details on intervention protocols and key variable assessments, and encouraging the exchange and cross-trial comparisons of intervention and assessment protocols and instruments; (ii) systematically processing and extracting features of key variables and conducting main analyses aligned with the objective of an intervention; and (iii) supporting systematic comparisons across different cognitive training trials. For example, at the Brain Game Center for Mental Fitness and Well-being,[41] both intervention tools and outcome measures are shared freely with other research groups. In particular, validating outcome measures[42–44] and sharing with other groups can both facilitate faithful replication across studies as well as apples-to-apples comparisons of outcomes. This will benefit both basic scientists, who are often more up-to-date with the most recent advances in preprocessing and analysis, and clinical scientists, who are more aware of the standards required for interventions to have clinical relevance. Connecting the data generators (often clinical scientists running large-scale clinical trials) with the software generators (often basic scientists focused on a specific scientific task) will increase collaboration, as well as both the speed and reproducibility of science in the field. The success of CogTale[28] suggests that both basic and clinical scientists are eager to share resources to reduce the burden on individual labs. Material interoperability, if done well, also serves a second purpose: incentivizing interoperability by making it beneficial for researchers to engage in resource/material sharing.

Element 3. Interoperability incentives: One of the most important aspects of a practical framework is ensuring that it is adopted within the field. To try and ensure the adoption of interoperability, it is necessary to produce incentives for researchers to engage in these practices. One incentive involves making interoperability the "easy" choice, by allowing researchers to use shared stores and pipelines to streamline their own work, both by providing a clear "cookbook" to follow and by making open-source pipelines easier to use than the competing bespoke methods that are currently available. Additionally, interoperability can be encouraged by funding agencies, in a similar manner as data-sharing requirements have grown over the last couple decades. Federal agencies are already encouraging tool sharing and other open science practices that are consistent with interoperability.

Element 4. Privacy and security norms: Consistent with the original definition, database security is essential, requiring certification and close monitoring before and during the use of open-source resources. This will require careful consideration of the balance between guaranteeing privacy/security and ease-of-use for researchers. Currently many HIPAA compliant systems are cumbersome, expensive, and inaccessible to basic research groups (as they are often intended for clinical studies involving PHI data rather than basic research studies in which data are typically all de-identified). Thus, it is important to create shared servers that can support both data collection and data sharing that are appropriate and appreciative of the different needs and constraints of basic and clinical research in this space (e.g., the need to de-face imaging data to make it unidentifiable).

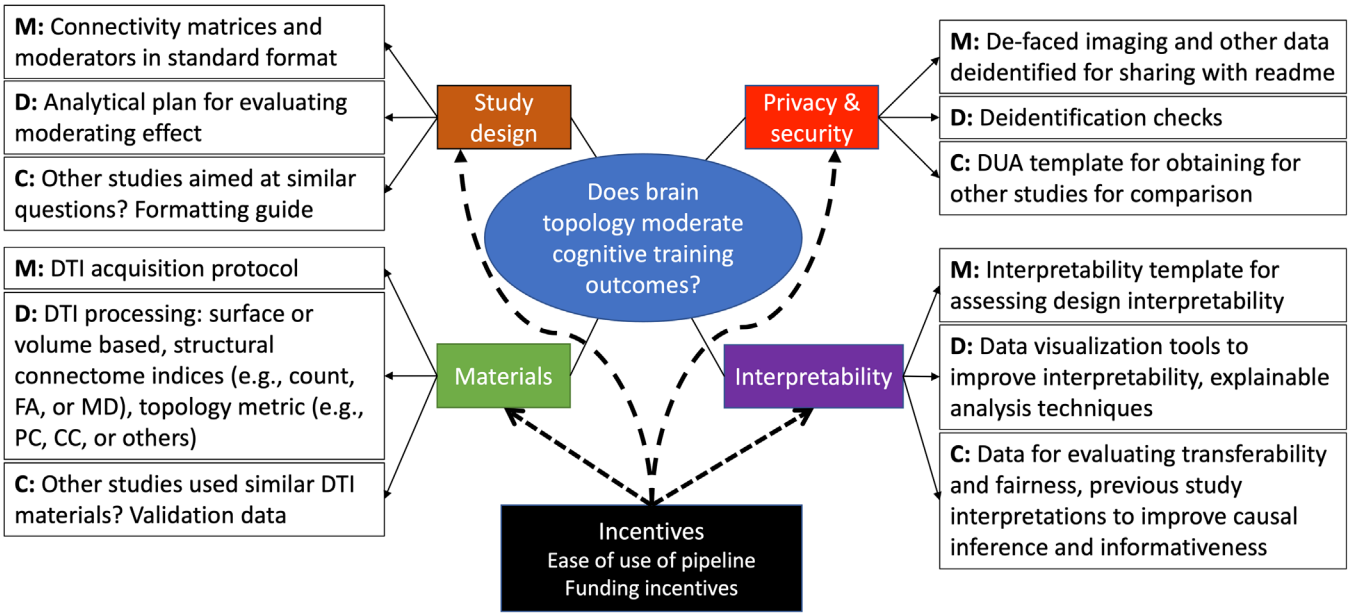

FIGURE 2 An example of how a cognitive training for brain aging trial would benefit from an open-source pipeline. This specific trial aims to understand the moderating role of brain topology on cognitive training outcomes. Across four elements of interoperability, this trial could use the material repository (M), data processing and analysis (D), and cross-study comparison (C) capabilities of the pipeline to ease their own research process while also contributing to improved comparability, collaboration, rigor, and reproducibility in the field at large. Interoperability incentives, including the ease-of-use of the pipeline itself, will increase interoperability across the other four elements.

Element 5. Interpretability prioritization: To ensure a shared focus on interpretability, we will adopt this as the principle governing the "rules of engagement". The original definition of "rules of engagement" emphasizes a good governing practice to ensure a trusted exchange. Here, we emphasize developing evaluation criteria for the interpretability of intervention findings in cognitive training studies. Interpretability is a multi-dimensional construct, and different aspects are prioritized by different stakeholders, including clinical and basic scientists.[45,46] For example, while both clinical and basic scientists appreciate the importance of an identified mechanism being neurobiologically plausible (one level of interpretation), clinical scientists may prioritize a causal mechanism that fits into an established disease model (e.g., effect on AD pathology[47]), while basic scientists may prioritize links between the mechanism and novel approaches in their field (e.g., network science[18] in cognitive neuroscience) that are cross-diagnostic. These different priorities cause disconnects, seen in brain aging research in general, and in cognitive training research more specifically. Our previous paper outlines how four desiderata from Lipton[48] – causality, informativeness, transferability, and fairness—are critical for understanding these tensions,[49] and we here re-emphasize their importance for guiding and evaluating cognitive training research, to bridge the gap in priorities between basic and clinical scientists. Interoperability may also improve interpretability across these desiderata in the field as a whole: for example, by allowing researchers to more easily compare their findings with those in unrepresented groups, they can assess whether their research is likely to widen healthcare disparities (i.e., ensure " fairness").

4 | PRACTICAL NEXT STEPS: AN OPEN-SOURCE PIPELINE FOR COGNITIVE TRAINING RESEARCH

While this interoperability framework provides guidance for cognitive training researchers, the primary means by which interoperability can be improved is via the development of open-source, easy-to-use pipelines. These would make engaging in interoperability the norm for researchers by establishing how it can benefit them, particularly smaller labs with interesting ideas but limited resources. NIH-funded clinical trial registration and data sharing websites are available but difficult to use to search for relevant interventions or conduct comparisons across trials. Therefore, we propose several essential functions of an **open-source pipeline** (see Figure 2) for supporting interoperability:

Material repository: Currently, NIH-funded intervention studies are required to register on *clinicaltrials.gov* and make the data available on open-access platforms (e.g., NDA, OSF). However, by encouraging users to share the following materials prior to data collection: protocol description, cognitive assessments and training scripts, and imaging data acquisition protocols, in a repository tailored to cognitive training data (i.e., with knowledge of designs and outcomes measures) we can enhance design and material interoperability simultaneously, while also ensuring consistent privacy and security norms. This same repository could then be used throughout the intervention to easily upload data in a standard format (e.g., using Brain Imaging Data Structure [BIDS] with de-facing for MRI data[50]). We note that funding that supports sharing of materials, especially assessment materials, could be transformative in advancing interoperability.

Data processing and analysis: To be maximally useful, a pipeline would need to provide a standard, up-to-date means of preprocessing and analyzing both behavioral and brain imaging data, while allowing for researcher choice at important decision points that are still debated in the field (e.g., volume-based vs. surface-based, structural and/or functional connectome, task-based vs. resting state, global signal regression or not). The pipeline should be able to conduct multiverse analyses to understand whether findings are robust to specific preprocessing choices.[51] The pipeline should also be able to extract the most commonly used brain imaging features (e.g., graph-based indices, large-scale network connectivity, task-related activation patterns), and conduct behavior-brain analyses (e.g., generalized estimating equations and mixed-effects modeling of the intervention effect on the outcome, mediator, and moderator, for time-dependent assessments; structural equation modeling on the mediator and moderator, for time-independent assessments or complex latent variables). Analysis and visualization would need to be implemented in a manner that prioritizes interpretability of mechanism action, avoiding black-box approaches that may improve predictions but not be interpretable.

Cross-study comparison: There is a need to promote comparison of intervention effects based on key research questions (e.g., do similar intervention protocols result in similar outcome effects? Have other mediators or moderators been explored under similar intervention protocols?). Existing meta-analyses mostly use effect size data, generated from different preprocessing procedures and analyses by different groups. With access to individual interventions' protocol, raw data, preprocessing and analysis, this pipeline could be used to conduct more reliable comparisons across clinical trials to understand both similarities and discrepancies that occur between trial results using mega-analysis.[52]

5 | CONCLUSION

In this paper, we urge the need for investing research and funding efforts toward improving interoperability to help guide investigators in asking and answering the right research questions related to cognitive training for brain aging,[53] and facilitating comparability and collaboration in the design and analysis of these intervention studies. This will be particularly beneficial in reducing the gap between clinical (often data generators) and basic (often software and theory generators) scientists with complementary expertise. We propose that an open-source pipeline tailored to cognitive training studies with the capacity to both store and analyze data using standardized approaches that allow sufficient space for researcher choice is the most practical approach to improving interoperability in a way that is likely to engage researchers.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest. Author disclosures are available in the supporting information.

CONSENT STATEMENT

There were no humans subjects used in this research.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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