Article

Policy Insights from the Behavioral and Brain Sciences
2023, Vol. 10(2) 324–332

DOI: 10.1177/23727322231195268
journals.sagepub.com/home/bbs
Sage

Perceptual Learning: Policy Insights From Basic Research to Real-World Applications

Aaron R. Seitz[1], Allison Sekuler[2], Barbara Dosher[3], Beverly A. Wright[4], Chang-Bing Huang[5], C. Shawn Green[6], Christopher C. Pack[7], Dov Sagi[8], Dennis Levi[9], Duje Tadin[10], Elizabeth Quinlan[11], Fang Jiang[12], Gabriel J. Diaz[13], Geoffrey Ghose[14], Jozsef Fiser[15], Karen Banai[16], Kristina Visscher[17], Krystel Huxlin[18], Ladan Shams[19], Lorella Battelli[20], Marisa Carrasco[21], Michael Herzog[22], Michael Webster[23], Miguel Eckstein[24], Nicholas B. Turk-Browne[25], Nitzan Censor[26], Peter De Weerd[27], Rufin Vogels[28], Shaul Hochstein[29], Takeo Watanabe[30], Yuka Sasaki[31], Uri Polat[32], Zhong-Lin Lu[33], and Zoe Kourtzi[34]

Abstract

Perceptual learning is the process by which experience alters how incoming sensory information is processed by the brain to give rise to behavior—it is critical for how humans educate children, train experts, treat diseases, and promote health and well-being throughout the lifespan. Knowledge of perceptual learning requires basic and applied research in humans and non-human animal models, which informs strategic targets for advancing applications. Commercial products to induce perceptual learning are proliferating rapidly with limited regulation (e.g., for rehabilitation), while at the same time basic science is increasingly restricted by changing regulations (such as new granting-agency definitions of clinical trials). Realizing the full potential of perceptual learning requires balancing basic and translational science to advance new knowledge, while serving and protecting consumers. Reforms can promote open, accessible, and representative research, and the translation of this research to applications across different sectors of society.

Keywords

perceptual learning, brain plasticity, clinical trials, clinical applications, consumer applications

[1]Northeastern University, Boston
[2]McMaster University, Hamilton
[3]University of California, Irvine
[4]Northwestern University, Evanston
[5]Institute of Psychology, Beijing
[6]University of Wisconsin-Madison, Madison
[7]McGill University, Montreal
[8]Weizmann Institute of Science, Rehovot
[9]University of California, Berkeley
[10]University of Rochester, Rochester
[11]University of Maryland, College Park
[12]University of Nevada Reno, Reno
[13]Rochester Institute of Technology, Rochester
[14]University of Minnesota, Minneapolis
[15]Central European University, Vienna
[16]University of Haifa, Haifa
[17]University of Alabama, Birmingham
[18]University of Rochester, Rochester
[19]University of California, Los Angeles
[20]Harvard Medical School, Boston
[21]New York University, New York
[22]École Polytechnique Fédérale de Lausanne
[23]University of Nevada Reno, Reno
[24]University of California, Santa Barbara
[25]Yale University, New Haven
[26]Tel Aviv University, Tel Aviv
[27]Maastricht University, Maastricht
[28]KU Leuven, Leuven
[29]Hebrew University, Jerusalem
[30]Brown University, Providence
[31]Brown University, Providence
[32]Bar-Ilan University, Ramat Gan
[33]New York University Shanghai, Shanghai and New York University, New York
[34]University of Cambridge, Cambridge, UK

Corresponding Author:
Aaron R. Seitz, Northeastern University, VSS member.
Email: a.seitz@northeastern.edu

Social Media

Perceptual learning fine-tunes how humans process sensory information and informs how we learn to do tasks and enjoy the world around us. This article addresses balancing basic and translational science of perceptual learning to better serve society.

Key Points

- Perceptual systems change across the lifespan in response to how we interact with the world around us. This has broad implications for education, medicine, technology, and society.
- Basic research of perceptual learning in human and animal models is essential for informing constraints on this learning, and methods to augment it.
- Applications of perceptual learning hold great potential to help people by addressing perceptual needs ranging from sensory loss and developmental perceptual disorders, to augmenting perceptual skills needed for everyday activities.
- Regulation should aim to promote discovery and applications, to advance new knowledge, balancing goals to both serve and protect consumers.
- Effective policies necessitate close interactions among funding agencies, regulatory agencies, scientists, clinicians, companies, and consumers.

Perceptual systems in the brain constantly change to optimize how people process incoming sensory information needed to understand and act in the world. This process, called perceptual learning (PL), is fundamental to almost everything people do (Seitz, 2017). From early in life, experience with the world establishes basic perceptual functions needed to recognize faces, develop language, and perform complex tasks. Moreover, when perceptual systems are damaged by disease, injury, or aging, they show amazing abilities to learn (e.g., ability to read braille or understand speech from a cochlear implant). PL research has applications across the lifespan, from helping children to overcome developmental disorders to assisting older adults to compensate for sensory losses. PL benefits the workplace, for example, enabling radiologists to diagnose cancer or for air traffic controllers to simultaneously monitor multiple aircraft. Artificial intelligence (AI) systems also rely on PL for effective sensing, such as speech and face recognition on phones and computers, self-driving cars, automation in factories, computer-assisted diagnostics, etc. Furthermore, PL helps humans adapt to these new technologies. Even entertainment, sports, and hobbies rely on PL—for example, training baseball players to hit fastballs, chefs to create interesting dishes, sommeliers to provide wine recommendations, and for everyone to appreciate these experiences. PL is fundamental across lifespan and has implications for virtually every human endeavor.

This article overviews key areas of PL research, opportunities for application, and its bidirectional relationship with public policy. Research informs how PL can be shaped through numerous methods, and how it differs across the lifespan and diverse individuals. Policies influencing research can either advance or stifle knowledge. Funding mechanisms and regulatory structures are needed to promote rigorous, reliable science representing and serving diverse people. Likewise, with opportunities for translation of PL to education, medicine, and technology sectors, policies are needed to promote beneficial products and services while restricting those that are harmful. Effective policy can promote education of consumers and providers, inspire diverse individuals to engage with research and applications, and ultimately help society to benefit from knowledge and applications of PL.

PL as a Window Into Brain and Behavior

The term PL was originally coined by Eleanor Gibson in her foundational research on human development (Gibson, 1969), whom introduced PL in the context of how visual systems learn through experience. For example, observing that human babies appreciate falling hazards only after learning to crawl was key to understanding the development of stereovision. Following this research, Held and Hein (1963) used animal models to demonstrate the importance of active vision in development by having one kitten actively walk around a circular arena while passively moving a second kitten through the same environment via a rig. Although both kittens viewed the same environment, the kitten only passively experiencing the environment failed to develop normal behaviors such as avoiding visual cliffs or moving toward visual objects of interest, while the kitten that actively walked around the arena developed normally (Held & Hein, 1963).

A breakthrough in understanding how brain changes underlie experience-driven sensory refinements came from pioneering work of Hubel and Wiesel, whom showed alignment of signals from the two eyes, called stereopsis, which is critical for depth perception, depends on early postnatal experience (Hubel & Wiesel, 1970). Their experiments showed that, if vision is temporarily blocked in one eye during early infancy, a permanent change in the visual pathways ensues, substantially reducing input from that eye to visual cortical neurons responsible for stereopsis. Curiously, similar manipulations in adulthood had minimal consequences. This fundamental work led to significant changes in treatments of humans with amblyopia, where interventions balancing interocular signals are now known to be most effective when applied during early infancy. This limited time window of learning and plasticity was termed a "critical period." Subsequent investigations discovered similar developmental windows in the context of auditory processing, and integration of visual and auditory information. Although these early results seemed to suggest strong, immutable, biological limits for PL in adulthood, more recent studies demonstrate PL occurs across the lifespan. For example, children with late-onset vision, following bilateral cataract removal, show significant, though partial, recovery of vision (McKyton et al., 2015).

PL Helps Explain the Generalizability of Training

A hallmark of PL has been how exquisitely specific outcomes can be to the trained task. A case example is vernier acuity—the ability to detect subtle misalignments of two vertical lines as subtle as 10x smaller than our visual acuity. With training, performance quickly improves but training gains with vertical lines fail to carry over to the same task using horizontal lines (Poggio et al., 1992). Furthermore, when vernier training is done with one eye, it may not transfer to the untrained eye (Karni & Sagi, 1991), which is interesting given information from the two eyes is integrated in primary visual cortex, after which most visual brain processes are binocular. The specificity of PL has been explored for numerous stimulus dimensions (e.g., orientation, motion properties, depth, color, tone frequency, locations on the skin, etc.) and provide clues to where learning may be occurring in the brain (Sagi, 2011). These findings have important implications for visual rehabilitation as they inform how to target brain processes necessary to achieve desired patient outcomes (Das & Huxlin, 2010).

However, these early findings also provided a foundation for contemporary research into how and when PL generalizes. Numerous studies now show PL can generalize to visual acuity, reading (Polat, 2009), or even playing baseball (Deveau et al., 2014). These improvements occur without changing the optical characteristics of the eye (Polat et al., 2012) and are thought to be related to brain plasticity. A key observation is that whereas training with simple, unvaried stimuli and very precise judgments leads to specificity, training with more complex, naturalistic, and/or varied stimuli leads to broader generalization (Ahissar et al., 2009; Maniglia & Seitz, 2018). For example, radiologists learn to detect medically relevant stimuli at different locations and orientations on the screen, perhaps because their professional experience involves viewing a diversity of stimuli across different contexts. Interestingly, action video games provide another source of complex and variable training, and playing video games can improve a range of visual skills and transfer broadly even to tasks such as laparoscopic surgery (Hogle et al., 2008). Specificity found in early PL research may have resulted from targeting single features, for which there is not a computational need or benefit to generalizing; this is also true of artificial neural networks trained on PL tasks (Wenliang & Seitz, 2018). In contrast, training on either a variety of stimuli (Xiao et al., 2008) or easier task levels (Ahissar & Hochstein, 1997) induces generalization.

Animal Models Provide Foundational, Mechanistic Knowledge

While research in humans informs understanding of PL, additional foundational knowledge has come from research in nonhuman animal models. Recording from individual neurons in nonhuman primates shows PL changes response properties of neurons at different stages of visual processing, including primary visual cortex (V1, Schoups et al., 2001), extrastriate visual cortex (medial superior temporal area (MST), Gu et al., 2011; V4, Yang & Maunsell, 2004), and even prefrontal cortex (Jing et al., 2021). Thus, PL helps explain how multiple regions across the brain learn together as a network (Maniglia & Seitz, 2018).

In animal models, neural networks can be perturbed in ways not possible in humans. For example, the seminal studies controlling experiences during animal development revealing critical periods and more recent research showing potential to restore critical period-like plasticity through drugs or even light deprivation (Duffy & Mitchell, 2013), which could revolutionize treatment of human sensory disorders. Furthermore, ability to alter neural activity directly in animals, through inactivation or stimulation, allows researchers to determine whether learning alters causal relationships between brain regions and behavior (Chowdhury & DeAngelis, 2008; Liu & Pack, 2017). From a broader perspective, practically all animal and much human research includes an aspect of PL, whether intentional or not. Thus, understanding PL may help to understand results of any study that involves extensive training.

PL as a Model System to Study Brain Plasticity

PL is distinctive in its combination of stimuli that can be well characterized mathematically and tasks in which performance evolves on both fast (seconds) and slow timescales (months). This has allowed for highly detailed characterization of the functional forms of learning, and development of computational models that capture complex properties of learning. This renders PL an excellent test-bed for investigating how factors such as attention, reward, sleep, brain stimulation and more, augment and shape learning (Online Box 1), while providing a window into how diverse individuals learn (Bejjanki et al., 2014; Karvelis et al., 2018).

Computational models of PL provide critical glue that linking basic and applied human research with mechanistic findings from animals. These frameworks help explain how different learning rules and architectures interact to produce learning outcomes (Dosher & Lu, 2020). For example, models suggested that feedback during training changes the rate of learning rather than simply serving as a "supervisor" of what should be learned (Herzog & Fahle, 1999). Other models suggest why training with multiple stimuli in some cases overwrites earlier learning and in others adds to learning (Sotiropoulos et al., 2011). Newer models provide insight regarding how multiple stages of processing (increasingly used in artificial neural networks adopted in modern AI systems) shape learning, how dimensions of learning are distributed across network layers (Liu et al., 2015; Shibata et al., 2014), and how specificity or transfer occurs (Dosher et al., 2013). Together, human, animal, and computational model systems of PL inform mechanistic understanding of learning and plasticity (Tadin et al., 2019).

Clinical Applications of PL

PL as a strategy to improve human functioning could theoretically help to compensate for many common forms of sensory loss. PL research serves double duty in this context. First, it helps characterize impact of various diseases on aspects of sensory processing and performance. Second, PL is increasingly used as a therapeutic agent to improve perception in the context of disease, injury, or prosthetic implants. For instance, consider cochlear implants—currently the most successful, sensory prosthetic. As these implants provide impoverished representation of sound frequencies, patients need training to gain useful auditory function. PL will likely be necessary for any sensory prosthetic, helping the brain optimize processing of inputs that differ significantly from those prior to injury. Similar PL may be required for the clinical use of virtual and augmented reality systems (Shin et al., 2023).

Applications to Vision Loss

With so much of the human brain devoted to visual processing, it comes as no surprise that visual impairment devastates quality of life. Pathology can originate within the visual system or be secondary to more generalized neurological or mental conditions such as multiple sclerosis, major depression, schizophrenia, dementia, and autism, or to systemic processes such as abnormalities of metabolism, genetics, immune function, and even normal aging. Historically, some of the most prominent clinical targets for PL include amblyopia (Levi & Li, 2009), cortical visual impairments (Pollock et al., 2019; Saionz et al., 2021), refractive errors (Polat et al., 2012), low vision in youths (Nyquist et al., 2016) or older adults (DeLoss et al., 2014), and restoration of vision following removal of juvenile cataracts (Kalia et al., 2017). New challenges emerge as treatments for vision loss increasingly involve prosthetics—whether electronic versions applied to the retina (e.g., Argus II, Palanker, 2023) or cortex (cortical prostheses, Fine & Boynton, 2023), or through optogenetics (Provansal et al., 2022), gene therapies (Moraru et al., 2022), or stem cell transplantation (Öner, 2018). For instance, it is increasingly clear that new criteria and methods are needed to assess, and improve through training, the "ultra-low vision" created by these approaches (Ayton et al., 2020).

Applications to Hearing Loss

More than 5% of the world's population and more than 25% of individuals over the age of 65 have disabling hearing loss. Untreated hearing loss is associated with substantially increased risk of dementia (Jiang et al., 2023). The mainstream intervention for children, adults, and older adults with hearing loss is amplification in the form of hearing aids or cochlear implants. However, while amplification is beneficial, speech outcomes, which are a main target, remain suboptimal because amplification does not restore all aspects of auditory function (Humes & Coughlin, 2009). Auditory training is an obvious candidate to improve speech outcomes. Indeed, PL has been observed for speech in all ages of listeners with and without amplification devices (de Larrea-Mancera et al., 2022; Whitton et al., 2017). Some cochlear implant centers in the United States even recommend self-training (using commercially available programs online), although the evidence base is lacking. In adult cochlear implant users, specific types of auditory training can improve certain auditory outcomes, and benefits can be sustained for months (Cambridge et al., 2022). For adults with hearing aids, the situation is similar, but skepticism is higher because in some cases, learning seems fairly specific to the trained conditions (Humes et al., 2019).

Bidirectional Relationship of PL With Public Policy

Policies facilitating PL research can promote improved understanding of mechanisms of learning and opportunities to translate this understanding for human benefit. Likewise, policies informed by research can promote safe and effective applications. The following sections discuss some areas where policy makers can engage with scientists to realize the benefits of PL research for society.

Opportunities and Barriers to Basic Research

Widespread adoption of PL for clinical and nonclinical purposes relies on research to determine which capacities to train, how best to train them, and broader understanding of individual differences. Although there exists substantial understanding of when PL is specific or generalizes, and what methodologies may boost learning, major challenges remain for understanding how PL manifests across diverse populations, and how multiple approaches to training compare and interact. Although existing grant funding mechanisms that support individual investigators or small groups of investigators are important and needed, these mechanisms do not adequately support comparison across approaches developed in different labs, or the large-scale, representative research needed to understand diverse populations.

To achieve the most rigorous, reliable, representative, and valid research results, mechanisms are needed to support large-scale, multisite collaborations that recruit diverse and historically underrepresented peoples. This research should include a mixture of human, animal, and computational models to best derive integrative knowledge. Equally important is to understand how moderating factors lead to individualized outcomes—how medications, environmental toxins, genetic and disease factors, cultural and socioeconomic factors differentially, and in some cases negatively, impact PL. Engaging in more representative research requires both resources to coordinate scientific teams, as well as to reach diverse peoples and to build the trust necessary to engage them in the research process.

A barrier to basic research has been the National Institutes of Health (NIH)'s recent changes in policies on "clinical trials." Whereas historically, the clinical trial framework applied to research on diagnostics and treatments for medical conditions, the new policy defines a clinical trial as "a research study in which one or more human subjects are prospectively assigned to one or more interventions (which may include placebo or other control) to evaluate the effects of those interventions on health-related biomedical or behavioral outcomes." This change in definition has been interpreted to include all PL research in humans. The merit of this policy change is an increase in stewardship of research to promote transparency and accountability. Moreover, BESH (basic experimental studies involving humans; NOT-OD-18-212, scheduled to expire in 2024) provides some flexibility to basic research studies that meet the NIH definition of a clinical trial (e.g., those that have no "specific application toward processes or products in mind"). However, many questions remain: Why is not all human research included in this increased stewardship? Shouldn't all research be transparent and accountable? How does one draw the line between different types of research? If BESH is the solution then why can't it be retrospectively applied to studies that preceded, or did not know about, the framework? Does regulation of basic research as clinical trials create barriers to entry to PL and other research domains? What support to researchers and institutions is needed to ensure research facing greater regulation and administrative burdens can still flourish?

Given these concerns, many scientists oppose the designation of PL research as clinical trials. Arguments against this designation are motivated by concerns of increased obstacles to basic science and that application of clinical trial regulations to basic research can be arbitrary and inconsistent. Take for example a situation where a researcher shows a series of pictures of x-rays and asks participants to report whether there is a tumor in each image. This is not a clinical trial. What if the researcher then examined whether seeing these images improved one's ability to detect tumors in a new set of x-rays? Is that a clinical trial? It depends: If the researcher's intent was to train people to better recognize tumors in radiological images, then "yes." If examination of training effects were asked post hoc, then "no." This gives rise to unequal treatment of researchers whose studies are designed to understand mechanisms of PL and incentives researchers to avoid the clinical trial designation. Broadening the definition of clinical trials also had consequences beyond the impact on scientists, as it became harder for the public to distinguish between clinical trials whose primary goals are to develop therapeutic interventions, and those whose primary goals are to expand basic knowledge.

The long-term impact of these policies are still emerging and it remains to be determined whether the shift from basic research studies to clinical trials has transformed PL research sufficiently to increase its clinical application. On the one hand, blinding investigators, research staff, and participants to which interventions were implemented and to whom, as is required in clinical trials, should result in less biased data and analyses, increasing the rigor of results. Larger sample sizes required by power calculations in these studies should increase reproducibility. On the other hand, the clinical-trial designation requires all procedures to be in place before research can commence and data analyses are delayed until the entire cohort has progressed through the intervention and results can be unmasked. Thus, researchers must often wait for 3–4 years to fully analyze the data, slowing scientific progress. This not only delays publication (threatening progress report expectations on grants, future funding, and job security within academic institutions) but also prevents the dynamic, creative process of science, which happens continuously as data are acquired across a study. As early results in a study trickle in, they sometimes yield discoveries and realizations that prompt small or large changes in the course of the research, theories, interpretations, etc. To truly advance science, policies should strive to promote the rapid, creative process of science in complement to solid, reproducible, predictable science.

Breakthroughs require both structures that promote discovery, and those that can weed out which discoveries are reliable and which may not be. The clinical-trial framework is just one of a number of strategies to promote rigorous research. For example, the open-science movement provides numerous tools such as preregistration, data sharing, and tool sharing that increase scientific rigor without the burden and poor fit for basic research of ClinicalTrials.gov. Importantly, these systems can be nimble, allowing for statistically valid changes along the route of basic science, without sacrificing the transparency of process that ultimately is the goal of clinical trial structures. Embracing open-science frameworks would put PL research on an equal footing with other research approaches that seek to understand basic behavioral and brain processes, while providing greater consistency for how basic research studies are regulated. Furthermore, if a central goal of the clinical trial framework is to share results of research with the public, in addition to other researchers, then shouldn't all research that is publicly funded have the same mandate to provide publicly available reports of their research findings? It is important to consider more flexible ways to obtain the goals of transparency and accountability and to create structures that are most appropriate to the different stages of research, ranging from basic science to clinical applications. Importantly, the argument for an appropriate regulatory context for *basic research* is complementary to the need for properly regulated clinical trials to address prospective *treatments* that could be used in medical settings, candidate applications that emerge from creative fundamental research should then be tested rigorously in clinical trials.

Opportunities and Barriers to Clinical Translation

When applied to patient populations, PL tasks have the distinct advantage of being minimal-risk, low-cost, and biologically noninvasive to the participant. However, very few PL approaches developed in the lab ever make it to the clinic. As such, structural factors that limit widespread adoption of PL should be examined. For example, in contrast to the broad insurance coverage for physical therapy, there is little to no coverage in the United States for PL therapies. Without an ability to recover costs, it will be difficult for clinicians to adopt PL-based therapies.

The development of PL as a clinically implemented therapy faces barriers at multiple levels. For example, clinical practitioners rely on the U.S. Food and Drug Administration (FDA)'s approval (for both safety and efficacy) and on insurance codes before applying treatments to patients. Unlike psychological treatments administered by a therapist, PL approaches that could benefit patients with vision or hearing disorders are classified as "devices" by the FDA, because they usually employ a physical system (cochlear implant, hearing aid for hearing loss; computer/computerized system for delivery of visual training for vision loss). Devices are only approved by the FDA if they demonstrate safety and efficacy through masked, randomized clinical trials. It is too early to tell if the large bolus of "clinical-trial-like" basic science studies created by the NIH change in policy detailed above will generate more rapid FDA approvals for PL research. If yes, perhaps this policy experiment should be considered a success in overcoming at least some of the barriers facing clinical translation of research. If not, we should think more carefully about top-down policy implications of changes at the level of one of the major, indirect employers of basic scientists in the United States—the federal government. Key questions that emerge include: How can scientists have a more effective voice in such policy changes, and how can the delay decrease between voicing concerns and implementation of strategies to mitigate them?

Opportunities and Barriers to Other Applications Related to PL

Given the profound technological shifts society is now experiencing, there is a great need to better understand how humans learn to interact with evolving technology, as well as how technological learning systems optimize their processes to address human needs. The development of prosthetic devices, computer-assisted diagnostics, or better, personalized assistants on our smartphones and computers all rely upon understanding how our perceptual systems learn and adapt to these novel systems. The emergence of various augmented and virtual reality technologies offers a unique opportunity to deliver PL interventions to large numbers of users while still maintaining the high degree of empirical control that is the cornerstone of lab-based PL research. Research is also needed to understand mechanisms of harmful effects of technology in relationship to how they interact with and shape our perceptual systems, as well as to develop technologies that better interact with how humans perceive and learn, to provide positive outcomes.

One concern is that the regulatory environment addressing digital technologies in health care has not caught up with the current state of the field. For example, outside of an FDA-approved treatment for a specific diagnosis, health interventions are often regulated by the Federal Trade Commission (FTC). Unlike the FDA, the FTC does not employ staff scientists and relies upon outside experts to determine evidentiary standards and to evaluate if interventions meet these standards. Perhaps as a result, the FTC has been inconsistent in the scientific standards required of various "brain training companies," including those focused on PL—applying the standard of "double-blind" controlled trials in some cases and "blinded to the maximum extent practical" in others. Although this difference seems subtle, the reality is that, unlike drug studies where two pills can be identical, in behavioral interventions, participants are aware of their activities, rendering complete blinding often infeasible and sometimes unnecessary. Thus, inconsistent regulations and gaps between regulatory agencies and the cognizant scientific community are challenges that continue to threaten the balance between protecting and serving consumers.

Closing Thoughts

PL research has profound impacts on society (see Online Box 2 for example). Everything humans do relies upon perceptual abilities and their plasticity. Whether through explicit practice or happenstance, human perceptual systems are constantly learning and adapting to the surrounding environment.

Research provides scientific understanding, creates new opportunities to optimize skills and recover from injuries, and helps identify factors harmful to human perceptual processes. Furthermore, PL, due to its well-characterized properties, is a valuable platform for understanding other aspects of learning and brain plasticity, and for exploring ways to rehabilitate or optimize brain processes. Beyond this, PL is an important component of modern machine learning and continues to inform artificial intelligence systems as well as human–computer interactions.

Policy implications of PL are manifold. Basic knowledge of PL can inform best practices in education, the workplace, healthcare, and even in entertainment industries. Funding policies that promote rigorous, representative, collaborative, and creative research are necessary to ensure the creation of new knowledge. Forums where scientists can interact with policy makers to discuss how PL can impact these many sectors of society would elevate practices and reduce harms. In addition, clinical applications of PL can help diverse patient populations. However, work is needed to balance regulatory systems to promote applications that can benefit patients, getting these into the hands of those who need them most. Commercial applications of PL could benefit many people seeking to optimize their perceptual abilities and again, regulations for this need to find appropriate balance between protecting and serving consumers. Research suggests that PL is of fundamental importance across the lifespan. Realizing its potential benefits to society, while minimizing possible harms, will necessitate close interactions between regulators and scientists, together with clinicians, companies, and consumers, in a process where there is opportunity for both strengths and limitations of the science to be considered, as policy is discussed and made.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Supplemental Material

Supplemental material for this article is available online.

References

Ahissar, M., & Hochstein, S. (1997). Task difficulty and the specificity of perceptual learning. *Nature*, *387*(6631), 401–406. https://doi.org/10.1038/387401a0

Ahissar, M., Nahum, M., Nelken, I., & Hochstein, S. (2009). Reverse hierarchies and sensory learning. *Philosophical Transactions of the Royal Society London B Biological Sciences*, *364*(1515), 285–299. https://doi.org/10.1098/rstb.2008.0253

Ayton, L. N., Rizzo, J. F., Bailey, I. L., Colenbrander, A., Dagnelie, G., Geruschat, D. R., Hessburg, P. C., McCarthy, C. D., Petoe, M. A., Rubin, G. S., & Troyk, P. R., & HOVER International Taskforce. (2020). Harmonization of outcomes and vision endpoints in vision restoration trials: Recommendations from the international HOVER taskforce. *Translational Vision Science & Technology*, *9*(8), 1–64. https://doi.org/10.1167/tvst.9.8.25

Bejjanki, V. R., Zhang, R., Li, R., Pouget, A., Green, C. S., Lu, Z.-L., & Bavelier, D. (2014). Action video game play facilitates the development of better perceptual templates. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(47), 16961–16966. https://doi.org/10.1073/pnas.1417056111

Cambridge, G., Taylor, T., Arnott, W., & Wilson, W. J. (2022). Auditory training for adults with cochlear implants: A systematic review. *International Journal of Audiology*, *61*(11), 896–904. https://doi.org/10.1080/14992027.2021.2014075

Chowdhury, S. A., & DeAngelis, G. C. (2008). Fine discrimination training alters the causal contribution of macaque area MT to depth perception. *Neuron*, *60*(2), 367–377. https://doi.org/10.1016/j.neuron.2008.08.023

Das, A., & Huxlin, K. R. (2010). New approaches to visual rehabilitation for cortical blindness: Outcomes and putative mechanisms. *The Neuroscientist*, *16*(4), 374–387. https://doi.org/10.1177/1073858409356112

de Larrea-Mancera, E. S. L., Philipp, M. A., Stavropoulos, T., Carrillo, A. A., Cheung, S., Koerner, T. K., Molis, M. R., Gallun, F. J., & Seitz, A. R. (2022). Training with an auditory perceptual learning game transfers to speech in competition. *Journal of Cognitive Enhancement*, *6*(1), 47–66. https://doi.org/10.1007/s41465-021-00224-5

DeLoss, D. J., Watanabe, T., & Andersen, G. J. (2014). Optimization of perceptual learning: Effects of task difficulty and external noise in older adults. *Vision Research*, *99*, 37–45. https://doi.org/10.1016/j.visres.2013.11.003

Deveau, J., Ozer, D. J., & Seitz, A. R. (2014). Improved vision and on-field performance in baseball through perceptual learning. *Current Biology*, *24*(4), R146–R147. https://doi.org/10.1016/j.cub.2014.01.004

Dosher, B. A., Jeter, P., Liu, J., & Lu, Z.-L. (2013). An integrated reweighting theory of perceptual learning. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(33), 13678–13683. https://doi.org/10.1073/pnas.1312552110

Dosher, B., & Lu, Z.-L. (2020). *Perceptual learning; How experience shapes visual perception*. MIT Press.

Duffy, K. R., & Mitchell, D. E. (2013). Darkness alters maturation of visual cortex and promotes fast recovery from monocular deprivation. *Current Biology*, *23*(5), 382–386. https://doi.org/10.1016/j.cub.2013.01.017

Fine, I., & Boynton, G. M. (2023). *Pulse trains to percepts: A virtual patient describing the perceptual effects of human visual cortical stimulation*. BioRxiv. https://doi.org/10.1101/2023.03.18.532424

Gibson, E. J. (1969). *Principles of perceptual learning and development*. Appleton-Century Crofts.

Gu, Y., Liu, S., Fetsch, C. R., Yang, Y., Fok, S., Sunkara, A., DeAngelis, G. C., & Angelaki, D. E. (2011). Perceptual learning reduces interneuronal correlations in macaque visual cortex. *Neuron*, *71*(4), 750–761. https://doi.org/10.1016/j.neuron.2011.06.015

Held, R., & Hein, A. (1963). Movement-produced stimulation in the development of visually guided behavior. *Journal of Comparative and Physiological Psychology*, *56*(5), 872–876. https://doi.org/10.1037/h0040546

Herzog, M. H., & Fahle, M. (1999). Effects of biased feedback on learning and deciding in a vernier discrimination task. *Vision Research*, *39*(25), 4232–4243. https://doi.org/10.1016/S0042-6989(99)00138-8

Hogle, N. J., Widmann, W. D., Ude, A. O., Hardy, M. A., & Fowler, D. L. (2008). Does training novices to criteria and does rapid acquisition of skills on laparoscopic simulators have predictive validity or are we just playing video games? *Journal of Surgical Education*, *65*(6), 431–435. https://doi.org/10.1016/j.jsurg.2008.05.008

Hubel, D. H., & Wiesel, T. N. (1970). The period of susceptibility to the physiological effects of unilateral eye closure in kittens. *The Journal of Physiology*, *206*(2), 419–436. https://doi.org/10.1113/jphysiol.1970.sp009022

Humes, L. E., & Coughlin, M. (2009). Aided speech-identification performance in single-talker competition by older adults with impaired hearing. *Scandinavian Journal of Psychology*, *50*(5), 485–494. https://doi.org/10.1111/j.1467-9450.2009.00740.x

Humes, L. E., Skinner, K. G., Kinney, D. L., Rogers, S. E., Main, A. K., & Quigley, T. M. (2019). Clinical effectiveness of an at-home auditory training program: A randomized controlled trial. *Ear and Hearing*, *40*(5), 1043–1060. https://doi.org/10.1097/AUD.0000000000000688

Jiang, F., Mishra, S. R., Shrestha, N., Ozaki, A., Virani, S. S., Bright, T., Kuper, H., Zhou, C., & Zhu, D. (2023). Association between hearing aid use and all-cause and cause-specific dementia: An analysis of the UK Biobank cohort. *The Lancet Public Health*, *8*(5), e329–e338. https://doi.org/10.1016/S2468-2667(23)00048-8

Jing, R., Yang, C., Huang, X., & Li, W. (2021). Perceptual learning as a result of concerted changes in prefrontal and visual cortex. *Current Biology*, *31*(20), 4521–4533.e3. https://doi.org/10.1016/j.cub.2021.08.007

Kalia, A., Gandhi, T., Chatterjee, G., Swami, P., Dhillon, H., Bi, S., Chauhan, N., Gupta, S. D., Sharma, P., Sood, S., Ganesh, S., Mathur, U., & Sinha, P. (2017). Assessing the impact of a program for late surgical intervention in early-blind children. *Public Health*, *146*, 15–23. https://doi.org/10.1016/j.puhe.2016.12.036

Karni, A., & Sagi, D. (1991). Where practice makes perfect in texture discrimination: Evidence for primary visual cortex plasticity. *Proceedings of the National Academy of Sciences of the United States of America*, *88*(11), 4966–4970. https://doi.org/10.1073/pnas.88.11.4966

Karvelis, P., Seitz, A. R., Lawrie, S. M., & Seriès, P. (2018). Autistic traits, but not schizotypy, predict increased weighting of sensory information in Bayesian visual integration. *ELife*, *7*, 1–29. https://doi.org/10.7554/eLife.34115

Levi, D. M., & Li, R. W. (2009). Perceptual learning as a potential treatment for amblyopia: A mini-review. *Vision Research*, *49*(21), 2535–2549. https://doi.org/10.1016/j.visres.2009.02.010

Liu, J., Dosher, B. A., & Lu, Z.-L. (2015). Augmented Hebbian reweighting accounts for accuracy and induced bias in perceptual learning with reverse feedback. *Journal of Vision*, *15*(10), 10. https://doi.org/10.1167/15.10.10

Liu, L. D., & Pack, C. C. (2017). The contribution of area MT to visual motion perception depends on training. *Neuron*, *95*(2), 436–446.e3. https://doi.org/10.1016/j.neuron.2017.06.024

Maniglia, M., & Seitz, A. R. (2018). Towards a whole brain model of perceptual learning. *Current Opinion in Behavioral Sciences*, *20*, 47–55. https://doi.org/10.1016/j.cobeha.2017.10.004

McKyton, A., Ben-Zion, I., Doron, R., & Zohary, E. (2015). The limits of shape recognition following late emergence from blindness. *Current Biology*, *25*(18), 2373–2378. https://doi.org/10.1016/j.cub.2015.06.040

Moraru, A. D., Costin, D., Iorga, R. E., Munteanu, M., Moraru, R. L., & Branisteanu, D. C. (2022). Current trends in gene therapy for retinal diseases (review). *Experimental and Therapeutic Medicine*, *23*(1), 26. https://doi.org/10.3892/etm.2021.10948

Nyquist, J. B., Lappin, J. S., Zhang, R., & Tadin, D. (2016). Perceptual training yields rapid improvements in visually impaired youth. *Scientific Reports*, *6*, 37431. https://doi.org/10.1038/srep37431

Öner, A. (2018). Stem cell treatment in retinal diseases: Recent developments. *Turkish Journal of Ophthalmology*, *48*(1), 33–38. https://doi.org/10.4274/tjo.89972

Palanker, D. (2023). *Electronic retinal prostheses*. Cold Spring Harbor Perspectives in Medicine. https://doi.org/10.1101/cshperspect.a041525

Poggio, T., Fahle, M., & Edelman, S. (1992). Fast perceptual learning in visual hyperacuity. *Science*, *256*(5059), 1018–1021. https://doi.org/10.1126/science.1589770

Polat, U. (2009). Making perceptual learning practical to improve visual functions. *Vision Research*, *49*(21), 2566–2573. https://doi.org/10.1016/j.visres.2009.06.005

Polat, U., Schor, C., Tong, J.-L., Zomet, A., Lev, M., Yehezkel, O., Sterkin, A., & Levi, D. M. (2012). Training the brain to overcome the effect of aging on the human eye. *Scientific Reports*, *2*, 278. https://doi.org/10.1038/srep00278

Pollock, A., Hazelton, C., Rowe, F. J., Jonuscheit, S., Kernohan, A., Angilley, J., Henderson, C. A., Langhorne, P., & Campbell, P. (2019). Interventions for visual field defects in people with stroke. *Cochrane Database of Systematic Reviews*, *5*(5), CD008388. https://doi.org/10.1002/14651858.CD008388.pub3

Provansal, M., Marazova, K., Sahel, J. A., & Picaud, S. (2022). Vision restoration by optogenetic therapy and developments toward sonogenetic therapy. *Translational Vision Science & Technology*, *11*(1), 18. https://doi.org/10.1167/tvst.11.1.18

Sagi, D. (2011). Perceptual learning in vision research. *Vision Research*, *51*(13), 1552–1566. https://doi.org/10.1016/j.visres.2010.10.019

Saionz, E. L., Feldon, S. E., & Huxlin, K. R. (2021). Rehabilitation of cortically induced visual field loss. *Current Opinion in Neurology*, *34*(1), 67–74. https://doi.org/10.1097/WCO.0000000000000884

Schoups, A., Vogels, R., Qian, N., & Orban, G. (2001). Practising orientation identification improves orientation coding in V1 neurons. *Nature*, *412*(6846), 549–553. https://doi.org/10.1038/35087601

Seitz, A. R. (2017). Perceptual learning. *Current Biology*, *27*(13), R631–R636. https://doi.org/10.1016/j.cub.2017.05.053

Shibata, K., Sagi, D., & Watanabe, T. (2014). Two-stage model in perceptual learning: Toward a unified theory. *Annals of the*

New York Academy of Sciences, *1316*(1), 18–28. https://doi.org/10.1111/nyas.12419

Shin, J.-H., Kim, M., Lee, J.-Y., Kim, M.-Y., Jeon, Y.-J., & Kim, K. (2023). Feasibility of hemispatial neglect rehabilitation with virtual reality-based visual exploration therapy among patients with stroke: Randomised controlled trial. *Frontiers in Neuroscience*, *17*, 1142663. https://doi.org/10.3389/fnins.2023.1142663

Sotiropoulos, G., Seitz, A. R., & Seriès, P. (2011). Perceptual learning in visual hyperacuity: A reweighting model. *Vision Research*, *51*(6), 585–599. https://doi.org/10.1016/j.visres.2011.02.004

Tadin, D., Park, W. J., Dieter, K. C., Melnick, M. D., Lappin, J. S., & Blake, R. (2019). Spatial suppression promotes rapid figure-ground segmentation of moving objects. *Nature Communications*, *10*(1), 2732. https://doi.org/10.1038/s41467-019-10653-8

Wenliang, L. K., & Seitz, A. R. (2018). Deep neural networks for modeling visual perceptual learning. *The Journal of Neuroscience*, *38*(27), 6028–6044. https://doi.org/10.1523/JNEUROSCI.1620-17.2018

Whitton, J. P., Hancock, K. E., Shannon, J. M., & Polley, D. B. (2017). Audiomotor perceptual training enhances speech intelligibility in background noise. *Current Biology*, *27*(21), 3237–3247.e6. https://doi.org/10.1016/j.cub.2017.09.014

Xiao, L.-Q., Zhang, J.-Y., Wang, R., Klein, S. A., Levi, D. M., & Yu, C. (2008). Complete transfer of perceptual learning across retinal locations enabled by double training. *Current Biology*, *18*(24), 1922–1926. https://doi.org/10.1016/j.cub.2008.10.030

Yang, T., & Maunsell, J. H. R. (2004). The effect of perceptual learning on neuronal responses in monkey visual area V4. *The Journal of Neuroscience*, *24*(7), 1617–1626. https://doi.org/10.1523/JNEUROSCI.4442-03.2004