Auditory learning: Uncorking performance bottlenecks

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Internal noise is ubiquitous to information processing systems in the brain. It can originate in low-level, sensory systems (e.g., stochastic neural firing) or high-level cognitive functions (e.g., fluctuations in attention). Added to inefficiencies associated with the decision making process, it compromises our ability to make perceptual judgements even under ideal conditions (i.e., in the absence of external noise). We present evidence herein that performance-limiting internal noise and inefficiency of various origins can be reduced through training, resulting in improved behavioural performance. We promote the view that reducing or even removing these limiting processes is what defines perceptual learning, and that transfer of learning to untrained tasks critically depends on those tasks having a limiting process in common with the trained task. We present implications of this view for our understanding of perceptual learning during development and in atypical populations, as well as to the more practical aspects of designing perceptual and cognitive training programmes that will demonstrate benefits beyond the training tasks themselves.

INTRODUCTION

In detecting, discriminating, and identifying sounds, the accuracy of perceptual judgements critically depends on the fidelity with which the information arriving at the ears is encoded and subsequently processed. To make the perceptual decisions required by a psychophysical task, listeners must implicitly (or explicitly) deduce the structure of, and be able to extract the task-relevant information from, the physical stimulus. However, the fidelity with which information is encoded by the nervous system is subject to degradation by random effects such as transmission

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through physiologically noisy pathways (e.g., stochastic neural encoding both peripherally and more centrally; Vogels *et al.*, 1989; Javel and Viemeister, 2000) and fluctuations in arousal and attention (Fox *et al.*, 2006; 2007), as well as deterministic effects such as erroneous assumptions about the structure and statistics of the task (e.g., Tanner *et al.*, 1967; Maddox and Bohil, 2001).

The purpose of this paper is to promote the view that perceptual learning – the improvement in performance due to experience and practice – results from lifting the processing limitations that act as bottlenecks to performance (coined "learning the limiting process" by Dosher and Lu, 2005). Because processing limitations can occur at multiple levels, perceptual learning is not confined to its traditional bottom-up description; changes occur at the level of the bottleneck, not restricted to low-level stimulus encoding or decoding. Although we are drawing upon evidence primarily from auditory learning, we conjecture that these are general principles that would apply equally in other modalities.

The concept of internal noise is central to psychophysics. According to signal detection theory (Green and Swets, 1966; Macmillan and Creelman, 2005), making a decision involves comparing a decision variable derived from the representation of the sensory input with a subjective decision criterion (see Fig. 1). Both internal representation and decision criterion are subject to variations that are intrinsic to the listener and limit the accuracy of the decision. We have recently shown that, even in the absence of differences in the physical stimuli, early variations in electrophysiological brain activity (event-related potentials occurring less than 100 ms after stimulus onset and associated with stimulus encoding) can predict discrimination decisions in a multiple-interval, forced-choice procedure (Amitay *et al.*, 2013). This study demonstrated that the magnitude of the variation in the internal representations of the stimulus engendered by the internal noise is comparable to the behaviourally just-noticeable physical differences introduced when measuring discrimination thresholds.

Here we present evidence that auditory training reduces internal noise originating at various levels of the perceptual processing hierarchy, as well as inefficiencies resulting from suboptimal placement of the decision criterion. We show that by varying aspects of the stimulus, training task and procedure, we vary what is being learned by creating limitations on performance at different levels of processing.

REDUCING INTERNAL NOISE THROUGH TRAINING

Jones *et al.* (2013) demonstrated that internal noise was reduced over several practice sessions on a pure-tone frequency discrimination task. By adding external noise along the task-relevant dimension (jittering the frequency difference), we were able to show a significant reduction in internal noise, although the methods used precluded pinpointing the source(s) of the noise. Simulations based on the behavioural data suggested noise reduction was achieved through reweighting of frequency-specific channels, i.e., change in $[\omega_1,\omega_2,\ldots\omega_n]$ (Fig. 1A).

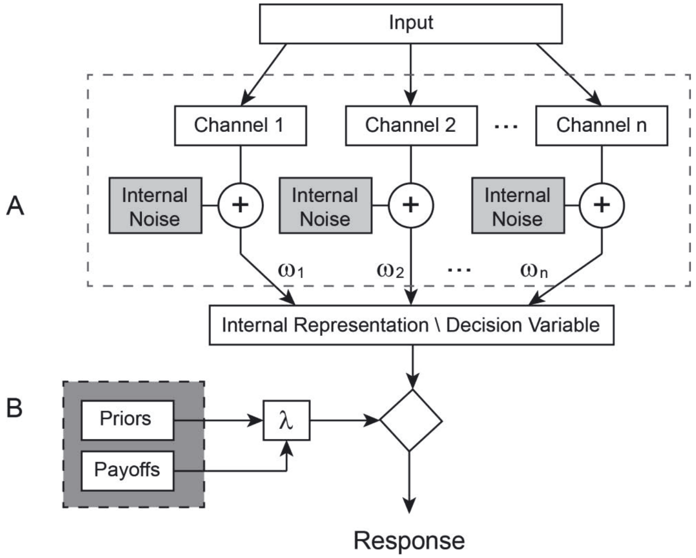

Fig. 1: A simple perceptual decision model. The incoming physical stimulus is transformed into an internal representation by summing over *n* independent information channels, each subject to internal noise (A). For simplicity we do not distinguish here between the internal representation and the decision variable computed from it, although this process may be subject to further internal noise (not specified in the text). A decision is made by comparing the decision variable to a criterion, λ, which may or may not be optimally placed (B).

Reducing low-level sensory noise

By varying tone duration in a frequency discrimination task, Amitay *et al.* (2012) observed that, while frequency discrimination thresholds improved on the trained task regardless of whether the tone was long (100 ms) or short (15 ms), training on short tones also improved discrimination of long tones, while training on long tones did not improve discrimination of short tones (Fig. 2). Our hypothesis, supported by simulations, was as follows: Frequency discrimination depends on the representations of each signal's frequency, and the accuracy of these representations is limited by phase locking noise due to the jitter in neural firing in the auditory nerve. One way of reducing this noise is increasing the integration time window (averaging over more cycles of the stimulus). We estimated the naïve (untrained) integration time for the 100-ms tones to be ~17 ms, while trained integration times are reportedly ~50 ms (Moore, 1973). Extending the integration window could not benefit the short tones, the duration of which was shorter than even the 17-ms naïve integration time window. Since extending the integration window was not possible for the short tones, we simulated the learning in this condition as reduced spike jitter in the auditory nerve. The simulation accurately predicted the transfer of learning from short to long tones (Fig. 2). The short tone duration imposed a limitation on which mechanism could support learning, resulting in a different limiting process being learned, but one which could benefit frequency discrimination regardless of tone duration.

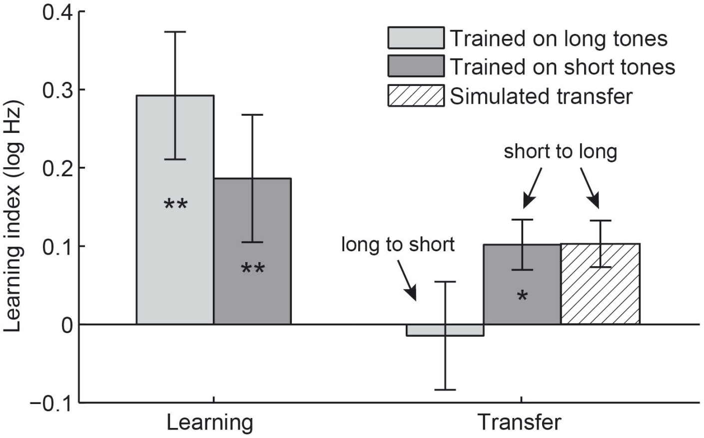

Fig. 2: Learning and transfer on a frequency discrimination task with long and short tones. The learning index is the difference between the pre-and post-training discrimination limens. Significant learning is marked by * $p < 0.05$; ** $p < 0.01$, corrected for multiple comparisons. Error bars denote s.e.m. Adapted from Amitay *et al.* (2012).

Reducing high-level cognitive limitations

Introducing uncertainty about the stimulus into a frequency discrimination task by roving the base value of the standard stimulus on a trial-by-trial basis impairs performance and slows learning down in good listeners (Amitay *et al.*, 2005). Since discrimination limens for a roving frequency exceed those observed when the individual frequencies are trained consecutively in a fixed frequency design, the limitation imposed on processing is unlikely to be due to bottom-up, sensory encoding of stimulus frequency. Despite the more protracted learning, training good listeners (those without exceedingly high naïve discrimination limens; see Amitay *et al.*, 2005) on a roving frequency discrimination task transferred fully to a fixed frequency discrimination task, while training on a fixed frequency resulted in naïve-like performance on the roving frequency task (Fig. 3).

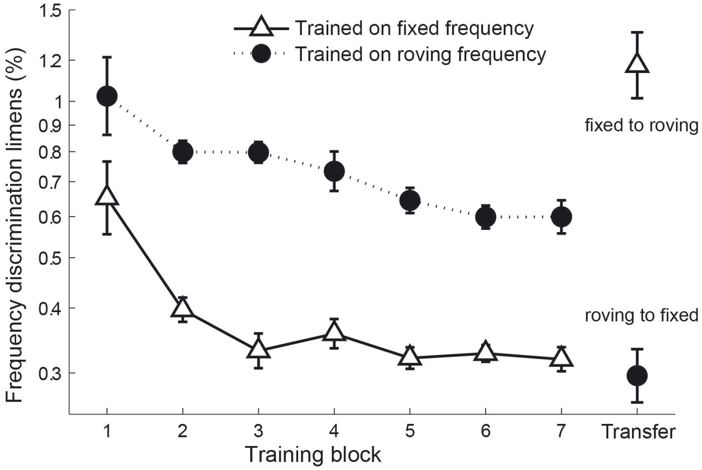

Fig. 3: Learning and transfer on a frequency discrimination task with a fixed- and roving frequency standard stimulus in good listeners (defined by thresholds on block 1). Discrimination limens (in percent of the standard frequency) are higher (poorer) and learning is slower in the roving frequency condition. However, training on roving frequency stimuli results in transfer to fixed frequency stimuli, but not *vice versa*. Each training block consisted of 500 trials. Limens are adjusted for initial (block 1) performance. Adapted from Amitay *et al.* (2005).

Two possible noise sources may affect processing under conditions of uncertainty. Firstly, uncertainty about the frequency of the incoming stimulus means that listeners cannot attend to a single frequency channel, but need instead to either shift their attention between channels in each trial or simultaneously monitor several different channels. However, learning to flexibly re-weight the channels (Fig. 1A) on every trial is an unnecessary skill when the frequency is not changing. Likewise, learning to weight them all equally should not benefit a discrimination that involves attending to just one channel. Therefore, learning a new weighting strategy does not explain the transfer results of Amitay *et al.* (2005).

A second alternative is that the constraint on processing is imposed by working memory. Unlike a fixed-stimulus discrimination for which a ‘perceptual anchor’ (Braida *et al.*, 1984) – a stable, long-term memory representation of the stimulus to which individual stimuli can be compared – can be formed, listeners trained with narrowly roving frequencies need to continually update working memory representations of the stimuli and compare them ‘online’ (see Banai and Amitay, 2012). Although reducing working memory limitations places greater processing demands on the system than forming perceptual anchors, this learning should benefit discrimination whether the stimulus is roved or not.

We have evidence that supports the suggestion that noise associated with working memory updating is at play in conditions involving stimulus uncertainty. Training on a roving frequency discrimination task differentially improved working memory capacity (compared to training on a fixed frequency discrimination) as measured using a tonal n-back task which required continual updating of tone representations but no fine discrimination of their frequencies (Zhang *et al.*, 2012). Moreover, training on the n-back task improved frequency discrimination for roving frequency stimuli. The learning was not specific to working memory for tones, and transferred to 3-back tasks with both visual shapes and auditory verbal stimuli (digits).

Taken together, these studies suggest that cognitive constraints such as working memory capacity may limit psychophysical performance, and that training on that psychophysical task, as well as training directed at the limiting process, serve to lift these constraints and improve performance on the trained task and other tasks constrained by the same limiting process (i.e., transfer). They also highlight the potential advantage of removing these types of processing limitations through training (i.e., transfer to very different tasks and between modalities). While perceptual learning is often very specific to the trained condition when the noise is of sensory origin, removing cognitive limitations appears to lead to transfer of learning to a much broader skill set (see also Green and Bavelier, 2003; Li *et al.*, 2009).

Reducing decision inefficiency due to response bias

Psychophysical thresholds are generally considered to measure perceptual sensitivity, but elevated thresholds can result from suboptimal placement of the criterion in decision making (Fig. 1B). Ideally, the decision criterion should be placed so as to maximise percent correct on the task. But an incorrect assessment of the utility (i.e., believing one response to be more beneficial; Maddox and Bohil, 2001), or erroneous *a priori* assumptions about the statistics of stimulus presentation (e.g., believing one response to be more likely to occur; Tanner *et al.*, 1967) that disregard the sensory evidence, can result in a systematic shift from the ideal criterion placement (bias), with an associated cost to performance.

Ratcliffe *et al.* (2012) have shown that bias in a yes/no amplitude-modulation detection task is reduced through training. Listeners were initially inclined to be liberal in their responses, responding ‘yes’ (‘signal present’) more often than ‘no’ (‘signal absent’). Training reduced this propensity. Even in multi-interval forced-choice procedures, considered to be bias-free, we have observed a response bias in naïve listeners that changed over the course of training (Halliday *et al.*, 2011).

Criterion placement can also be influenced by the responses to preceding trials. Jones *et al.* (2012) found this dynamic type of bias to be present in two-interval, forced-choice frequency discrimination tasks. Listeners were inclined to perseverate in their response choice after a correct response and alternate after an incorrect response. The bias was reduced, though not entirely eradicated, by training.

Simulations showed that this bias reduction could account for over one third of the shift in discrimination thresholds on psychoacoustic tasks.

Sources of decision inefficiency as well as sensory noise and cognitive constraints can therefore adversely affect performance, and play a part in perceptual learning.

AUDITORY LEARNING IN TYPICALLY DEVELOPING CHILDREN

In the previous section we have shown that perceptual learning can be described as a reduction in noise of sensory or cognitive origin, or inefficiencies associated with the decision. But learning in young adults, where both sensory and cognitive functions are largely mature, may be very different from learning in children. Children not only appear to have a greater degree of internal noise than adults (Buss *et al.*, 2006), but their perceptual performance may also be subject to constraints imposed by different sources of noise due to the different maturational trajectories of sensory and cognitive processes. While the ascending, sensory system is largely mature by 2 years of age (Moore, 2002), more central and cognitive functions continue to develop into adolescence and even adulthood (e.g., Bishop *et al.*, 2011; Moore and Linthicum, 2007). It is likely therefore that cognitive limitations will play a greater role than sensory limitations in children's difficulties in performing perceptual tasks (see Moore, 2012).

Indeed, Halliday *et al.* (2008) provided evidence in support of this suggestion by training 6-11 year old children on a frequency discrimination task with a fixed standard frequency. The children could be divided into subgroups based on their performance: Some were able to perform the task at the same level as naïve adults even without training ('adult-like'), some started with poorer performance but achieved adult-like performance levels with training ('trainable'), and some failed to achieve adult-like performance at any point ('non-adult-like'). Following training the children were tested on frequency discrimination with a roving standard frequency (Fig. 5 in Halliday *et al.*, 2008). Children in the non-adult-like and trainable subgroups had roving frequency difference limens that did not significantly differ from their pre-training fixed frequency difference limens. The adult-like subgroup, like adults (Fig. 3), had higher difference limens for roving- than fixed frequency discrimination. This transfer pattern suggests that the non-adult-like and trainable subgroups experience different limiting processes to the adult-like subgroup in their performance of the *fixed* frequency discrimination. It is possible these subgroups are unable to use the repetition in the stimuli to form perceptual anchors, resulting in similar discrimination limens for fixed and roving stimuli. This limiting process may have been learned by the trainable subgroup when training on fixed frequency discrimination, which would also explain why their learning failed to transfer to the roving condition.

The non-adult-like subgroup comprised of younger children (Table II in Halliday *et al.*, 2008) who had attentional lapses on 6.5% of trials (assessed as errors on trials in which the frequency difference was easily discriminable). In the two other subgroups the children were of a similar age and non-verbal IQ, but those who had adult-like performance from the start were distinguished by committing even fewer attentional lapses (1.1% in trainable, 0.1% in adult-like). Halliday *et al.* (2008) concluded that the inability to sustain attention was a limitation on frequency discrimination performance in the non-adult-like children. Until this bottleneck was removed, perceptual sensitivity could not increase through training.

Although inattention plays a large role in children's performance and ability to learn, in well motivated young adults it is unlikely to be an important factor in performance, or necessarily change significantly through training (see Jones *et al.*, 2013). This difference highlights the danger of applying learning rules derived from adults to children. Children need to overcome very different limitations to adults when training, so in effect they may be learning very different things. Moreover, it is likely that children will show a very different pattern of transfer to adults, because different tasks will be sharing the learned limiting process.

In addition to inattention, children may experience other performance bottlenecks different to those of adults. Although decisions and responses are identical in the model described in Fig. 1, this is not necessarily the case in every perceptual judgment task, and a distinction between these two processes may be more pronounced in children. For instance, motor errors may result in the response deviating from that intended, or the child may correctly identify the response but forget which key to press. Children may also be more susceptible to bias effects, though we are not aware of evidence in support of that.

A NOTE ON INDIVIDUAL VARIABILITY AND ATYPICAL LISTENERS

It is not only children who can be divided into subgroups with distinctly different learning and transfer patterns. Amitay *et al.* (2005) found a different learning and transfer pattern in 'good' and 'poor' listeners (distinguished by initially low or high discrimination limens, respectively). Unlike the good listeners described in Fig. 3, poor listeners had similar untrained thresholds for fixed- and roving frequency discrimination (Fig. 4). Surprisingly, it was the poor listeners in the group trained on fixed frequency that showed complete transfer to the roving frequency condition, while the poor listeners trained on roving showed only partial transfer to fixed-frequency (limens were lower than naïve, but higher than trained).

Although different sensory noise sources may contribute to the performance differences between good and poor listeners, it is more likely that the differences were rooted in cognitive limitations. Since both initial and transfer thresholds are similar for the fixed and roving conditions in the two groups of poor listeners, we could have concluded that the two training groups learned the same limiting process. However, the performance on the last training block is very different in the two groups, suggesting the learning is different. It is possible that both groups share learning of one limiting process but not another. For example, if the limitation imposed on poor listeners was of poor working memory affecting the forced-choice comparisons, both groups may have started by learning this process. If listeners in the fixed frequency training group then proceeded to improve thresholds through perceptual anchors in addition to working memory, this would explain transfer of learning to the roving condition. However, it is more difficult to reconcile the results for the poor listeners in the roving frequency training group with those from the good listeners, who showed full rather than partial transfer from roving- to the fixed frequency condition.

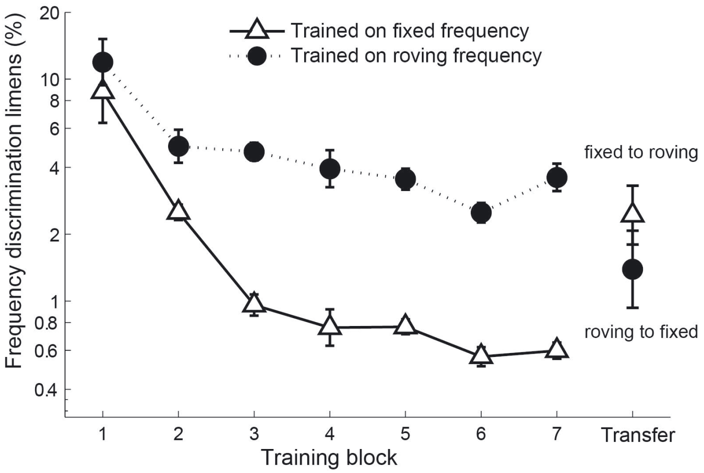

Fig. 4: Learning and transfer on a frequency discrimination task with a fixed- and roving frequency standard stimulus in poor listeners, defined based on naïve (block 1) limens. Initial discrimination limens (in percent of the standard frequency) are similar for the fixed- and roving frequency conditions both before and after training. Each training block consisted of 500 trials. Limens are adjusted for initial (block 1) performance. Adapted from Amitay *et al.* (2005).

Although we can only speculate on working memory as the performance-limiting noise that is removed through training in the Amitay *et al.* (2005) study, there is some evidence from other studies in atypical listeners that this may indeed be the case. For example, young adults with reading difficulties were shown to have similar limens for discrimination on fixed- and roving frequency tasks (Ahissar, 2007). This was interpreted as the inability to form perceptual anchors even when the task allowed for it. Training reading-disabled teenagers improved their ability in the fixed frequency condition, as well as showing transfer to an improvement in working memory function, suggesting cognitive-based constraints on performance are removed through training (Banai and Ahissar, 2009).

These results demonstrate that even within the adult population there is great variability in performance, some of which can be attributed to different limiting processes, or sources of noise, most likely of cognitive origin.

SUMMARY AND CONCLUSIONS

We have presented a view of perceptual learning as a process of removing performance-limiting constraints due to internal noise of both sensory (bottom-up) and cognitive (top-down) origin, as well as inefficiencies associated with the decision process. In this view, learning transfers from trained to untrained tasks when they share the limiting process that has been trained. We have shown that limiting processes may be different in adults and children (as well as other atypical populations), and that these differences affect not only what is learned but also how the learning transfers. Thus, the benefit of training a particular task may be specific to the trained population.

There are several implications to this view. First, from an applied perspective we cannot take a 'one-size fits all' approach to the learning process. Caution must be employed when applying results from young, motivated and well-rewarded adults to children, atypical learners or elderly populations (who may also suffer sensory and/or cognitive decline).

Second, from a more theoretical perspective, we should not assume that learning is a unitary and continuous process. The learning curve may actually result from a conglomeration of multiple effects, with different noise sources coming to the fore once the initially dominant noise source has been addressed. This also suggests that rather than just the length of practice (Jeter *et al.*, 2010), transfer of learning may depend on the cascade of limitations lifted through training. In support of this suggestion, Wright *et al.* (2010) have shown that transfer lags behind learning. Our interpretation of this would be that initial learning on the trained task addressed a limitation that was not shared by the transfer task, and that only once the shared limitation was learned did the learning transfer.

Finally, we offer a word of caution in interpreting the learning and transfer effects claimed for commercial training programs designed to address a variety of perceptual, cognitive and language difficulties through perceptual and/or cognitive training (e.g., Fast ForWord™: Tallal *et al.*, 1996). It is possible that the lack of conclusive evidence as to the efficacy of these programs lies in the choice of outcome measures, in terms of whether or not they share processing limitations with the trained tasks. In fact, these programs may be training something altogether different than the claims of their authors. For example, Fast ForWord™ may improve language by training the ability to selectively attend to sound (see Stevens *et al.*, 2008), or by lifting working memory constraints on updating rapidly presented stimuli rather than sensory-perceptual constraints on brief and rapidly presented stimuli, *per se*. A better understanding of the limiting processes in the target populations is imperative to help develop and optimise further training programs to address perceptual and cognitive processing limitations.

REFERENCES

Ahissar, M. (**2007**). “Dyslexia and the anchoring-deficit hypothesis,” Trends Cogn. Sci., **11**, 458-465.

Amitay, S., Hawkey, D.J.C., and Moore, D.R. (**2005**). “Auditory frequency discrimination learning is affected by stimulus variability,” Percept. Psychophys., **67**, 691-698.

Amitay, S., Zhang, Y.-X., and Moore, D.R. (**2012**). “Asymmetric transfer of auditory perceptual learning,” Front. Psychol., **3**, 508.

Amitay, S., Guiraud, J., Sohoglu, E., Zobay, O., Edmonds, B.A., Zhang, Y.X., and Moore, D.R. (**2013**). “Human decision making based on variations in internal noise: an EEG study,” PLoS ONE, **8**, e68928.

Banai, K., and Ahissar, M. (**2009**). “Perceptual learning as a tool for boosting working memory among individuals with reading and learning disability,” Learn. Percept., **1**, 115-134.

Banai, K., and Amitay, S. (**2012**). “Stimulus uncertainty in auditory perceptual learning,” Vision Res., **61**, 83-88.

Bishop, D.V.M., Anderson, M., Reid, C., and Fox, A.M. (**2011**). “Auditory development between 7 and 11 years: An event-related potential (ERP) study,” PLoS ONE, **6**, e18993.

Braida, L.D., Lim, J.S., Berliner, J.E., Durlach, N.I., Rabinowitz, W.M., and Purks, S.R. (**1984**). “Intensity perception. XIII. Perceptual anchor model of context-coding,” J. Acoust. Soc. Am., **76**, 722-731.

Buss, E., Hall, J.W., III, and Grose, J.H. (**2006**). “Development and the role of internal noise in detection and discrimination thresholds with narrow band stimuli,” J. Acoust. Soc. Am., **120**, 2777-2788.

Dosher, B.A., and Lu, Z.L. (**2005**). “Perceptual learning in clear displays optimizes perceptual expertise: Learning the limiting process,” Proc. Natl. Acad. Sci. USA, **102**, 5286-5290.

Fox, M.D., Snyder, A.Z., Zacks, J.M., and Raichle, M.E. (**2006**). “Coherent spontaneous activity accounts for trial-to-trial variability in human evoked brain responses,” Nat. Neurosci., **9**, 23-25.

Fox, M.D., Snyder, A.Z., Vincent, J.L., and Raichle, M.E. (**2007**). “Intrinsic fluctuations within cortical systems account for intertrial variability in human behavior,” Neuron, **56**, 171-184.

Green, C.S., and Bavelier, D. (**2003**). “Action video game modifies visual selective attention,” Nature, **423**, 534-537.

Green, D.M., and Swets, J.A. (**1966**). *Signal Detection Theory and Psychophysics* (John Wiley & Sons, New York).

Halliday, L.F., Taylor, J.L., Edmondson-Jones, A.M., and Moore, D.R. (**2008**). “Frequency discrimination learning in children,” J. Acoust. Soc. Am., **123**, 4393-4402.

Halliday, L.F., Moore, D.R., Taylor, J.L., and Amitay, S. (**2011**). “Dimension-specific attention directs learning and listening on auditory training tasks,” Atten. Percept. Psycho., **73**, 1329-1335.

Javel, E., and Viemeister, N.F. (**2000**). "Stochastic properties of cat auditory nerve responses to electric and acoustic stimuli and application to intensity discrimination," J. Acoust. Soc. Am., **107**, 908-921.

Jeter, P.E., Dosher, B.A., Liu, S.H., and Lu, Z.L. (**2010**). "Specificity of perceptual learning increases with increased training," Vision Res., **50**, 1928-1940.

Jones, P.R., Moore, D.R., and Amitay, S. (**2012**). "The role of response bias when learning a forced-choice task," Proceedings of the British Society of Audiology (BSA) Annual Conference, Nottingham, United Kingdom.

Jones, P.R., Shub, D.E., Moore, D.R., and Amitay, S. (**2013**). "Reduction of internal noise in auditory perceptual learning," J. Acoust. Soc. Am., **133**, 970-981.

Li, R., Polat, U., Makous, W., and Bavelier, D. (**2009**). "Enhancing the contrast sensitivity function through action video game training," Nat. Neurosci., **12**, 549-551.

Macmillan, N.A., and Creelman, C.D. (**2005**). *Detection Theory: A User's Guide* (Lawrence Erlbaum Associates Inc., Mahwah, New Jersey).

Maddox, W.T., and Bohil, C.J. (**2001**). "Feedback effects on cost-benefit learning in perceptual categorization," Mem. Cognit., **29**, 598-615.

Moore, B.C.J. (**1973**). "Frequency difference limens for short-duration tones," J. Acoust. Soc. Am., **54**, 610-619.

Moore, D.R. (**2002**). "Auditory development and the role of experience," Br. Med. Bull., **63**, 171-181.

Moore, D.R. (**2012**). "Listening difficulties in children: Bottom-up and top-down contributions," J. Comm. Disord., **45**, 411-418.

Moore, J.K., and Linthicum, F.H., Jr. (**2007**). "The human auditory system: A timeline of development," Int. J. Audiol., **46**, 460-478.

Ratcliffe, N., Jones, P.R., Moore, D.R., and Amitay, S. (**2012**). "The role of response bias when learning a yes/no task," Proceedings of the British Society of Audiology (BSA) Annual Conference, Nottingham, United Kingdom.

Stevens, C., Fanning, J., Coch, D., Sanders, L., and Neville, H. (**2008**). "Neural mechanisms of selective auditory attention are enhanced by computerized training: Electrophysiological evidence from language-impaired and typically developing children," Brain Res., **1205**, 55-69.

Tallal, P., Miller, S.L., Bedi, G., Byma, G., Wang, X., Nagarajan, S.S., Schreiner, C., Jenkins, W.M., and Merzenich, M.M. (**1996**). "Language comprehension in language-learning impaired children improved with acoustically modified speech," Science, **271**, 81-84.

Tanner, T.A., Haller, R.W., and Atkinson, R.C. (**1967**). "Signal recognition as influenced by presentation schedules," Percept. Psychophys., **2**, 349-358.

Vogels, R., Spileers, W., and Orban, G.A. (**1989**). "The response variability of striate cortical neurons in the behaving monkey," Exp. Brain. Res., **77**, 432-436.

Wright, B.A., Wilson, R.M., and Sabin, A.T. (**2010**). "Generalization lags behind learning on an auditory perceptual task," J. Neurosci., **30**, 11635-11639.

Zhang, Y.-X., Moore, D.R., Molloy, K., and Amitay, S. (**2012**). "Bidirectional transfer of working memory and perceptual learning," Proceedings of the British Association for Cognitive Neuroscience (BACN), Newcastle, United Kingdom.