Available online at www.sciencedirect.com

ScienceDirect

Current Opinion in Behavioral Sciences

Review

The prediction illusion: perceptual control mechanisms that fool the observer

Warren Mansell, Tauseef Gulrez and Michael Landman

A key claim in the philosophy of science is the inseparable relationship between theory and observation. Whilst measurement of an organism's actions is fundamental to building and testing accurate theoretical models, the interpretation of the activity is itself subject to the perspective of the researcher, which can be manifested as biases and illusions. We introduce four types of illusion (environmental, self-caused, self-affected, perceptual) that appear to require prediction and have supported the development of probabilistic predictive processing models. Yet, in each case, we review recent evidence in which a nonpredicting system leads to the same observations. In each case, the alternative architecture is a system that implements the dynamic control of ongoing, currently perceived variables through varying its actions to counteract disturbances — a perceptual control system. We propose that predictive processing is probably limited to a smaller class of observations, such as long-term planning.

Address
Curtin enAble Institute, School of Population Health, Curtin University, Perth, Australia

Corresponding author: Mansell, Warren (warren.mansell@curtin.edu.au)
Mansell, Warren (𝕏 @warrenmansell),
Landman, Michael (𝕏 @mikelandman_au)

Current Opinion in Behavioral Sciences 2025, **62**:101488

This review comes from a themed issue on **Control Theory**

Edited by: **Dr. Henry Yin** and **Dr. Warren Mansell**

For complete overview of the section, please refer to the article collection, "Control Theory and Closed-Loop Behavior in Humans, Other Animals, and AI/Robots (2025)"

Available online 20 February 2025

Received: 5 November 2024; Revised: 9 January 2025; Accepted: 28 January 2025

https://doi.org/10.1016/j.cobeha.2025.101488

It is self-evident that the human mind *can* predict. Our conscious experiences indicate that we can imagine a future event and estimate its likelihood, and collectively, humans use maths and science to predict future outcomes. There is also evidence that the nervous system can predict the consequences of its actions during planning and decision-making [25]. Maybe owing to this accumulating evidence, a view of the whole nervous system as a 'prediction machine' prevails in contemporary neuroscience (e.g. [28]); this view claims that the brain is *fundamentally* engaged in prediction during every behavioural and mental activity. Yet, just because a system appears to be predicting *from the outside* does not mean that prediction is explicitly being implemented *within the system* itself. Indeed, science is replete with examples where the folk understanding that is based on observation is revealed to be an illusion and gives way to shift in perspective that clarifies what is going on: the Earth appears flat, but it is spherical; the Sun appears to rise over a stationary Earth, but the Earth is known to orbit the Sun, for example. Within the behavioural sciences, there are clear demonstrations that the brain can use simple heuristics for tasks such as object interception and decision-making in the absence of formal, statistical prediction [12,31,8]. In this article, we review examples of activities that appear *as if* the brain is predicting, yet they can be explained through a process known as perceptual control. Also, the article will not contrast the evidence for opposing theories. Instead, the aim is to illustrate that many examples of the activities and abilities of humans and other animals that are typically described as instances of prediction can be explained and simulated by a system that does not predict.

In order to reach our conclusion, it is necessary to first define prediction — in the varieties of ways it has been used — and then to define perceptual control, for which we utilise perceptual control theory (PCT; [24,22,23]). PCT control systems *specify* the states of perceptual variables that are controlled through counteracting potentially unpredictable disturbances in the environment. By default, PCT control systems do not predict these states because they do not need to, as explained later.

Definitions of prediction

Prediction can be regarded as a hypothesis held by an agent, such as an observing person, with regard to what will happen within a specific system, in the future. For example, a meteorologist predicts a thunderstorm in Kansas in three days time. Typically, the term 'prediction' is used in a way that excludes the predicting agent from the causality of the system being observed. In the previous example, the meteorologist has no control over the weather. Indeed, the whole field of prediction — such as within the stockmarket and popular betting — depends upon methods, such as preventing insider trading and match fixing, to exclude the predicting agent from having any control over the future prospects of the system. In the absence of control over the future outcome, therefore, prediction involves identifying patterns in current and historical data to infer future, novel data.

When implemented in machine learning, specific forms of statistical analysis are used to model prediction, on the assumption that what appears to be prediction is in fact implemented as prediction within the agent itself. In turn, the field of predictive coding in neuroscience adopts a statistical model for how the brain computes its outputs, expressing its predictions as probability distributions [30]. Bayesian statistics is a contemporary mathematical approach to this. Because there is an assumed level of uncertainty about the future, it is typically expressed as an axiomatically real function that assigns values in an interval of 0 and 1 to events known as a 'probability'. In essence, Bayes' law is as follows:

$$\Pr(X \mid Obs) = \frac{\Pr(Obs \mid X) \times \Pr(X)}{\Pr(Obs)}$$

In the above equation, Pr(X) is the initial belief or prior probability assigned to a hypothesis based on our existing knowledge, assumptions, or intuition, whereas Pr (Obs|X) is the probability of observing the evidence given the hypothesis. The product of these two variables gives an updated belief or probability assigned to the hypothesis after considering the evidence. Bayes' theorem also provides a closed-loop mechanism for updating beliefs based on new evidence. As a system gathers more information, it can refine its prior probabilities (Pr(X)) to obtain more accurate posterior probabilities (Pr(X|Obs)). Relatedly, active inference is the process of utilising immediate action to reduce prediction error, and it has been described and simulated as a closed-loop system [29]. Thus, active inference has the capacity to correct predictions 'on the fly'; an ability that has its precursors within classic control theory in engineering and biology, which was also the inspiration for PCT.

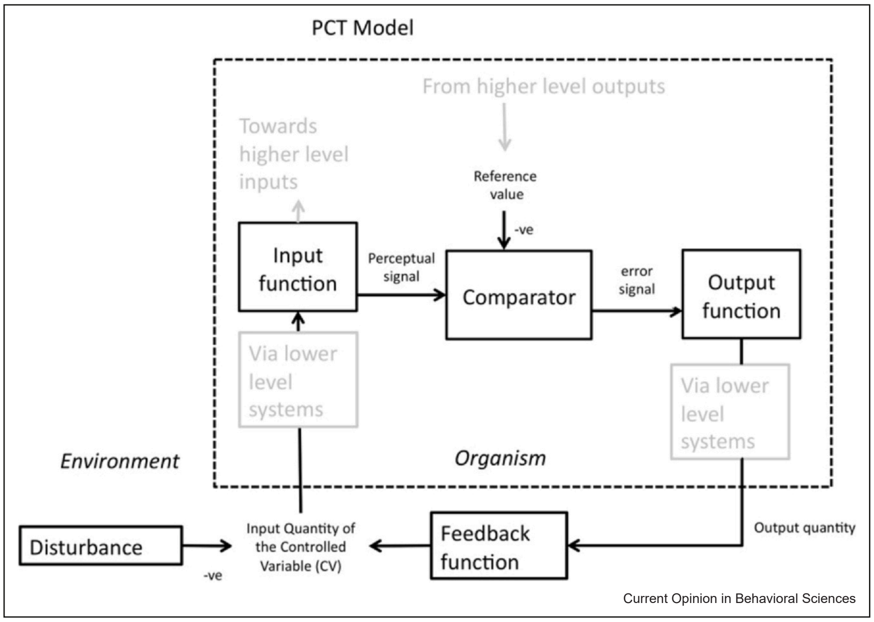
Definition of perceptual control

The notion that the brain is a control system has a strong tradition. However, the term 'control' has many uses, so it requires a distinct definition. According to Powers [24], control is the achievement and maintenance of an internally specified value of a variable (the controlled variable or CV) despite the effects of disturbances. This architecture, now known as PCT, does not require probabilistic prediction. According to PCT, action and perception are linked in a continuous, closed loop via the body and environment. Within this arrangement, the simple discrepancy between the currently perceived value of a variable and its internally specified value (the reference value) drives actions that counteract disturbances to reduce the discrepancy (see Figure 1). This is *negative feedback control*. Thus, rather than calculating cause-and-effect predictions of future variables regarding the self, others, and the environment, a control unit within a PCT architecture continuously varies its output to bring its inputs in line with their reference values. The output of a control unit (see Figure 1) sets the reference values for control units at a lower level in a hierarchy, and this process occurs iteratively, branching reference signals for 'desired inputs' to successively lower levels until the interface between the nervous system and the rest of the body. At this point of the closed loop, the features of the body and environment within the loop are known as the *feedback function*. Thus, PCT also utilises morphological computation [31]. A PCT system is characterised by *variability* in its behaviour — and this variability is functionally required in order to control internally specified variables. Therefore, the PCT model directly contrasts with models based on probability theory in which small variations in input or output are typically regarded as noise; the focus is predicting the occurrence of categorical 'events' rather than continuous variables, which typically propose that an adaptive response is predicted and planned in advance (although, see 'active inference' earlier). For a similar argument within the philosophy of science, see Arocha [1].

The analogy of the Watts Governor

To start our case, we first introduce an example of a *de facto* closed-loop control system that appears to predict — Watt's steam engine governor [2]. The governor is a mechanical system that was critical to the industrial development of steam power in the 19th century [10]. It varies the valve aperture from a steam inlet to counteract both variations in the pressure supplied from the boiler and variations in the load on the engine, ensuring that the engine turns at a consistent, controllable rate (see Figure 2). The governor does not predict or make probabilistic estimations. Yet, it looks like it has the capacity to anticipate and pre-empt disruptive surges in the steam pressure supplied and to any changes in its load. Furthermore, its operation can be reproduced accurately using a probabilistic model that *predicts* its input [2]. Thus, the appearance of prediction can be validated by a predictive model *whilst being a knowingly false account* [15]. It appears as though scientists assume a linear temporal pathway from cause to effect, such that a predictive account is appealing even when the system to be explained is purposive and has a known circular causality that does not utilise prediction. The culmination of this assumption is a pervasive view that prediction is

Figure 1



A single PCT control unit, which illustrates how a variable is kept at an internally specified reference value through outputs that counteract disturbances in the environment. The rectangular blocks indicate specific functional components of a control unit, and the greyed-out sections indicate how this unit sits within a branching hierarchy of similar units. Note that in PCT, there are potentially eleven levels in the hierarchy, each of which is an increasingly abstract perception of the level below.

fundamental to the nervous system (e.g. [5]). The visible closed-loop mechanism of the Watts Governor exposes the prediction illusion, but the following examples from human performance require experimentation or computational modelling to reveal the illusion at work.

A typology of observations of prediction

For the purposes of this article, we have divided up the experimental observations that are typically described as instances of prediction into four categories that are each elaborated in their own, following section:

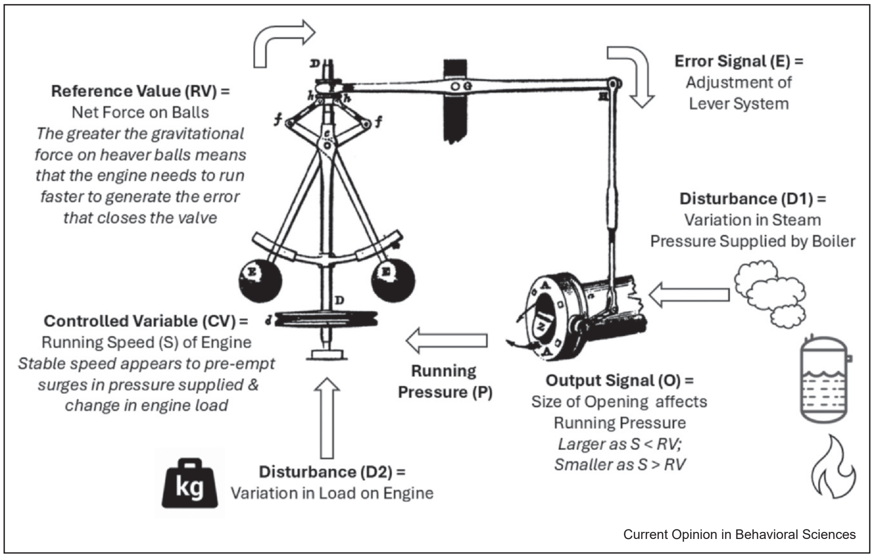
1) *Environmental:* the system's prediction of the value of an environmental variable, for example, the future location of a projectile.
2) *Self-caused:* the prediction of the effects of the system's own actions on an environmental variable; for example, the future location of a lever being pulled.
3) *Self-affected:* the system's prediction of the effects of external variables on the system itself, that is, the future deviation of the body from vertical when the walking surface changes angle.
4) *Perceptual:* the prediction of future sensory input to the system itself, for example, the future sound of a syllable, or a visual pattern.

Each of these categories will be described in turn, alongside contemporary studies that demonstrate that the apparent prediction is achieved by a nonpredicting PCT system.

Environmental prediction illusions

Several studies of object interception generate this illusion. When one agent intercepts a moving object, such as a fielder catching a ball, it can appear as though the agent had predicted the physical location of the object at the time it was intercepted. However, detailed research indicates this is not the case. For example, in the case of catching a flyball, the fielder runs whilst catching the ball, altering their path whilst running, and has minimal ability to explicitly predict the landing location, all of which is inconsistent with a predictive model [8]. The properties of real-world ball catching have been simulated by a perceptual control system in a range of studies where the variables controlled are horizontal and vertical optical velocity [16]. For example, within the video games Breakout and Pong, a software agent controlled the horizontal distance between the paddle and ball to achieve human-like performance that appears as though the agent had predicted the horizontal location of the ball as it reached the paddle at the bottom of the screen [9]. Across multiple studies of manual tracking of a one-dimensional target, the impression of predicting the location of the target is achieved when the CV is simply to keep the distance between the cursor and target at zero [20]. Even when the target moves in a predictable sinusoidal pattern, a close match with human performance

Figure 2



A diagram of a Watt's Governor that maps its components onto a PCT closed-loop model and explains how it appears to 'predict' how to respond to variations in load and pressure supplied without any capacity for prediction [15].

is achieved by a control system that does not predict but rather biases the perception of the current position by a function of the current velocity of the target [19].

Self-caused prediction illusions

When an agent completes a task effectively, it can appear as though the agent is predicting the effects of its own actions. Indeed, this predictive capacity makes intuitive sense for effective decision-making and is the basis for a number of theories, including contemporary versions of the *efference copy hypothesis* [26]. Yet, in the presence of dynamic disturbances, the capacity to, and the worth of, predicting one's own contribution to any specific movement variable is questionable. For example, think of the example of slalom skiing down a slope; is it even possible or adaptive to differentiate the contribution of gravity, terrain, slope angle from one's own muscle movements, to predict one's speed and direction? Within PCT, the various disturbances are not identified. Instead, the incoming perceptual signals are continuously subtracted from the downward signals that are received from the level above and that specify the reference value of the controlled perceptual variable. This subtraction leads to a dynamically varying error signal. The present-time variations in this error signal circumvent the need to predict which effects are 'self-caused', and which are not.

The role of a dynamic disturbance has been made explicit within a manual tracking task to reveal the prediction illusion; a study of tracking in two dimensions required a participant (the actor) to keep a cursor at the bottom of the computer screen on a fixed target by counteracting a disturbance pattern (generated by the computer) with movements of a computer mouse [14]. The mouse movements themselves were displayed at the top of the same screen at the same time. An uninformed observer viewed the whole screen and was asked to describe the effects of the actor's movements. Unknown to both participants, the computer-generated disturbance to the cursor was an upside down, mirror image of the word 'hello'. Whilst the *actors* were unaware of writing 'hello', the *observers* concluded that the participant had planned to write the word 'hello' on the screen, which implies that the actor had already predicted that the word 'hello' would be the result of their own actions. Yet the experiences of both the actors and observers were a result of perceptual control, taken from two different perspectives. Moreover, the effects of the mouse movements on writing a fully legible word were instantaneously reactive and therefore could not be the result of a predictive process.

In addition, a simulation study has illustrated that closed-loop models of this kind provide the most parsimonious solution to a variety of scenarios presumed to rely on an agent predicting the results of its actions [7]. The researchers constructed a variety of phototaxis scenarios (moving towards a light), in which the self-caused movements had an impact on the environment. Genetic algorithms were used to create a variety of architectures to solve the phototaxis problems. The most parsimonious and effective solutions did not require the agent to predict the results of its actions; instead they formed simple, closed-loop, control systems.

Self-affected prediction illusions

When an agent experiences a disturbance, it needs to counteract its effects in order to maintain control. For example, the inverted pendulum is a weight that is balanced on a pole and which can be kept near vertical by movements to the base. It appears as though the agent is measuring disturbances and predicting the effects of these on its displacement from vertical, and applying the predicted force necessary to return to vertical. Indeed, some software controllers for inverted pendulums use this method. Yet a recent study has shown that greater stability is achieved by movements at the base that are formally less predictable, as indexed by high entropy [4]. More critically, within a robotic inverted pendulum device, a closed loop agent was readily able to keep balance despite disturbances, performing at least as well as an agent that did depend on predictive processing [13]. Several other robotic devices give the impression that they are predicting the forces necessary to counteract disturbances and yet use a closed-loop PCT architecture with no prediction involved, including a quadruped robot [3], and a robotic arm [17].

Perceptual prediction illusions

A final type of prediction is arguably more fundamental than those above to predict future sensory input. In line with this, it appears to be occurring whenever an agent assumes or identifies a feature of their environment based on incomplete information or the presence of ambiguity or noise and that assumption turns out, over time, to be correct. Perhaps the most elegant study to reveal this prediction illusion comes from research on the pattern completion properties of neural systems [6]. If a system can specify a specific pattern, does it predict that pattern? Or is it simply a good or bad fit? Does a jigsaw puzzle with a missing piece 'predict' the shape of the missing piece?

The brain recognises familiar images, such as faces, within 100 ms, even when the presented image is heavily degraded. When this process of pattern completion is used in computer vision, it is not typically described as prediction. Yet when one considers 'time' as simply an additional dimension, then pattern completion can extend over time and be observed as prediction. Critically, researchers on pattern completion produced a closed-loop homeostatic system of a network of 100 nodes that adjusted their connections in order to maintain their activation at a target value, despite disturbances from the environment [6]. The system received 1000 disturbances that were each simple sentences with a different word allocated to each node. The system was able to 'fill in' the missing words of possible sentences when one word was presented owing to its strength of connections with the presented words, without any formal use of prediction or encoding of probabilities. Furthermore, in another strand of research, perceptual control models can utilise temporal pattern matching, for example, entrainment to a rhythm [18], such that agents in synchrony can appear to be predicting one another's responses, yet they are simply entrained through negative feedback control to the same rhythmic pattern.

Even 'true' prediction may not be probabilistic

Prediction does seem to occur when a living organism mentally simulates a potential future outcome that is tested against future data, *in the absence of overt action*. Yet, even this process does not necessarily require the computation of probabilities and can be carried out by a nonprobabilistic perceptual control system. The details are beyond this article, but they involve recirculating reference values as inputs to the system, and allowing a trial-and-error learning process known as reorganisation to alter the properties of the control system until the desired perceptual input is produced [11]. This imaginal process is particularly evident in speech production, which appears to use imagined feedback to a perceptual goal in order to correct for potential errors downstream through variations in muscle action [21,27].

Conclusion

Whilst advances in behavioural sciences require the accurate and objective *measurement* of behaviour, the scientists' *interpretation* of that behaviour, for example as an instance of prediction, or control, or both, must remain open to scientific enquiry. The current article described a typology of instances in which prediction is inferred to be occurring, often leading to theories and models *assuming* this to be the case. Yet, each of these observations can be explained and reproduced accurately by systems that control currently sensed variables through acting dynamically against disturbances to those variables, that is, perceptual control systems. The PCT system is parsimonious and often accounts for results that are inconsistent with predictive processing. Moreover, at higher levels of perception, such as sequence control, and through mental simulation and reorganisation, PCT has the propensity to model instances of 'nonillusive' or 'true' prediction.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements
Thank you to Henry Yin, Tony Fitzgerald and Tom Cochrane for their comments and suggestions.

References and recommended reading
Papers of particular interest, published within the period of review, have been highlighted as:

- • of special interest
- •• of outstanding interest

1. Arocha JF: **Scientific realism and the issue of variability in behavior**. *Theory Psychol* 2021, **31**:375-398.
• A critique of scientific approaches that draw upon probability theory to account for variability in behaviour, in contrast to those that treat the variability as functional, such as perceptual control theory.

2. Baltieri M, Buckley CL, Bruineberg J: **Predictions in the eye of the beholder: an active inference account of Watt governors**. *Artif Life Conf Proc* 2020, **32**:121-129.

3. Barter JW, Yin HH: **Achieving natural behavior in a robot using neurally inspired hierarchical perceptual control**. *Iscience* 2021, **24**:102948.

4. Catenacci Volpi N, Greaves M, Trendafilov D, Salge C, Pezzulo G, Polani D: **Skilled motor control of an inverted pendulum implies low entropy of states but high entropy of actions**. *PLoS Computational Biology* 2023, **19**:e1010810.

5. Clark A: **Beyond desire? Agency, choice, and the predictive mind**. *Australas J Philos* 2020, **98**:1-15.

6. Falandays JB, Nguyen B, Spivey MJ: **Is prediction nothing more than multi-scale pattern completion of the future?** *Brain Research* 2021, **1768**:147578.
•• This study shows how systems, including visual perception, language models, and unsupervised neural networks, can exhibit predictive behaviors as an emergent property of dynamic, homeostatic processes rather than through formal probabilistic calculations.

7. Garner J, Egbert MD: **Embodiment enables non-predictive ways of coping with self-caused sensory stimuli**. *Front Comput Sci* 2022, **4**:896465.
•• This study generated a range of agents whose actions affected their own sensory inputs such that it appeared as though the agent was predicting the effects of its actions. The study set them a task requirement to head towards a light and the most successful agents did not require the capacity for prediction.

8. Gigerenzer G: **Embodied heuristics**. *Front Psychol* 2021, **12**:711289.

9. Gulrez T, Mansell W: **High performance on Atari games using perceptual control architecture without training**. *J Intell Robot Syst* 2022, **106**:45.

10. Head J: **On a simple construction of steam engine governor having a close approximation to perfect action**. *Proc Inst Mech Eng* 1871, **22**:213-228.

11. Huddy V, Mansell W: **Loss and restoration of control: A perceptual control theory perspective on the role of mental simulation**. The Interdisciplinary Handbook of Perceptual Control Theory. Academic Press; 2023:59-74.

12. Jaeger J, Riedl A, Djedovic A, Vervaeke J, Walsh D: **Naturalizing relevance realization: why agency and cognition are fundamentally not computational**. *Front Psychol* 2024, **15**:1362658.

13. Johnson T, Zhou S, Cheah W, Mansell W, Young R, Watson S: **Implementation of a perceptual controller for an inverted pendulum robot**. *J Intell Robot Syst* 2020, **99**:683-692.
• This study involved the same robotic device — a simple inverted pendulum — that was controlled by three different software controllers, one of which was a perceptual control system, and one of which utilised prediction. The PCT pendulum appeared as though it was preparing itself to counteract disturbances, yet it did not implement prediction.

14. Mansell W, Curtis A, Zink S: **Observers fail to detect that behavior is the control of perception: a computer demonstration of unintended writing**. *J Exp Psychol Gen* 2019, **148**:e23.

15. Marken, R (2024): **PCT vs Free Energy**; ⟨http://Discourse.iapct.org/t/pct-vs-free-energy-specification-versus-prediction/16088/52⟩.

16. Marken R, Kennaway R, Gulrez T: **Behavioral illusions: the snark is a boojum**. *Theory Psychol* 2022, **32**:491-514.

17. Matić A, Valerjev P, Gomez-Marin A: **Hierarchical control of visually-guided movements in a 3D-printed robot arm**. *Front Neurorobotics* 2021, **15**:755723.

18. Moore, RK (2019): **Vocal Interactivity in Crowds, Flocks and Swarms: Implications for Voice User Interfaces**; arXiv preprint arXiv:1907.11656.

19. Parker MG, Weightman AP, Tyson SF, Abbott B, Mansell W: **Sensorimotor delays in tracking may be compensated by negative feedback control of motion-extrapolated position**. *Exp Brain Res* 2021, **239**:189-204.
• People can track a target better when the disturbances to their cursor are predictable, for example, if they are in the form of a sine-wave pattern. A perceptual control system was trained to simulate human data in these circumstances, and the closest match to human data was produced by a system that adjusted its current perception of the target location by a function of the target speed, without probabilistic prediction.

20. Parker MG, Willett AB, Tyson SF, Weightman AP, Mansell W: **A systematic evaluation of the evidence for perceptual control theory in tracking studies**. *Neurosci Biobehav Rev* 2020, **112**:616-633.

21. Pinheiro AP, Schwartze M, Gutierrez-Dominguez F, Kotz SA: **Real and imagined sensory feedback have comparable effects on action anticipation**. *Cortex* 2020, **130**:290-301.

22. Powers WT: Living Control Systems III: The Fact of Control. CT: Benchmark Publications; 2008.

23. Powers WT, Clark RK, Farland RLM: **A general feedback theory of human behavior: part I**. *Percept Mot Ski* (1) 1960, **11**:71-88, https://doi.org/10.2466/pms.1960.11.1.71

24. Powers, W.T. (1973). Behavior: The control of perception. Aldine.

25. Rieger M, Boe SG, Ingram TG, Bart VK, Dahm SF: **A theoretical perspective on action consequences in action imagery: Internal prediction as an essential mechanism to detect errors**. *Psychol Res* 2024, **88**:1849-1858.

26. Schultz J, Frith CD: **Animacy and the prediction of behaviour**. *Neurosci Biobehav Rev* 2022, **140**:104766.

27. Tang DL, Parrell B, Niziolek CA: **Movement variability can be modulated in speech production**. *J Neurophysiol* (6) 2022, **128**:1469-1482.

28. Teufel C, Fletcher PC: **Forms of prediction in the nervous system**. *Nat Rev Neurosci* 2020, **21**:231-242.

29. Tschantz A, Barca L, Maisto D, Buckley CL, Seth AK, Pezzulo G: **Simulating homeostatic, allostatic and goal-directed forms of interoceptive control using active inference**. *Biol Psychol* 2022, **169**:108266.

30. Yon D, Frith CD: **Precision and the Bayesian brain**. *Curr Biol* 2021, **31**:R1026-R1032.

31. Yoo SBM, Hayden BY, Pearson JM: **Continuous decisions**. *Philos Trans R Soc B* 2021, **376**:20190664.