Relative Fluency (unfelt vs felt) in Active Inference

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Abstract. For a growing number of researchers, it is now accepted that the brain is a predictive organ that predicts the content of the sensorium and crucially the precision of—or confidence in—its own predictions. In order to predict the precision of its predictions, the brain has to infer the reliability of its own beliefs. This means that our brains have to recognise the precision of their predictions or, at least, their accuracy. In this paper, we argue that *fluency* is product of this recognition process. In short, to recognise fluency is to infer that we have a precise 'grip' on the unfolding processes that generate our sensations. More specifically, we propose that it is changes in fluency — from unfelt to felt — that are both recognised and realised when updating predictions about precision. *Unfelt fluency* orients attention to unpredicted sensations, while *felt fluency* supervenes on—and contextualises—unfelt fluency; thereby rendering certain attentional processes, phenomenologically opaque. As such, fluency underwrites the precision we place in our predictions and therefore acts upon our perceptual inferences. Hence, the causes of conscious subjective inference have unconscious perceptual precursors.

Key words: Predictive Processing, Active Inference, Fluency, Felt fluency, Unfelt Fluency

How living organisms adapt to a constantly changing environment is a recurrent question since Darwin (1859) and von Uexküll (1934). Active Inference is an attempt to understand this adaptation from the point of view of brain function, cognition and behaviour. Active inference accounts for the way in which all living organisms manage to minimize surprise (i.e., the discrepancy between predicted and observed outcomes) via the perception-action loop. To do that, brain constantly generates predictions about the sensorium to, effectively, produce an error or surprise signal (Clark, 2013b; Friston et al., 2011; Hohwy, 2013). This prediction error is large when sensory inputs do not correspond to what was anticipated. The ensuing prediction error can be minimised in one of two ways. First, it can be used to revise beliefs or representations of the causes of sensations to produce more accurate predictions, as in perception. Second, one can act upon the world to generate sensations that are closer to predictions (Adams et al., 2013; Friston et al., 2016; Friston et al., 2011; Lanillos et al., 2021; Parr et al., 2022; Seth, 2013). In other words, both action and perception can be seen as in the service of minimising prediction error or surprise.

However, not all prediction errors are equal: some predictions may be very precise, or some sensory input may be very imprecise. This means that the imperative is not simply to minimise prediction errors but only those that convey precise information relevant for belief updating—or affordance for action (Limanowski, 2017; Parr et al., 2018; Parr and Friston, 2017a; Seth and Friston, 2016; Smith et al., 2019a; Sterzer et al., 2018). This account foregrounds the importance of precision; more specifically, precision-estimation and the ensuing precision weighting of prediction errors (Clark, 2013a). In terms of Bayesian belief updating, the relative precision of prior beliefs and sensory evidence determines the degree of belief updating. A prior belief that is held with great precision will be resistant to updating by a relatively imprecise prediction error. Neurophysiologically, the implicit sensitivity to prediction errors is thought to be mediated by the excitability of neuronal populations encoding prediction errors (e.g., via the action of classical modulatory neurotransmitter systems and associated fast synchronous interactions in electrophysiology). Psychologically, this evinces a kind of selection that can be read as attentional selection or, its complement, sensory attenuation (Feldman and Friston, 2010). We will pursue the psychological reading of precision.

To assess the precision of its predictions, brain relies on its own beliefs; that is to say about the precision of its prior predictions. The core idea developed in this paper is that fluency—the subjective experience associated with any cognitive treatment—plays a key role in prediction because it reflects or recognizes the precision of predictions and, in so doing, underwrites precise belief updating. However, we argue that it is not fluency itself that is firstly perceived but rather changes in fluency expectation. This change instantiates attentional set or mediates attentional selection (or attenuation) in response to violations and unexplained prediction errors.

We begin by rehearsing the principles underlying active inference. We then review the works that foreground the importance of fluency in cognitive processes; particularly those concerning relative fluency. Finally, we suggest that if fluency underwrites the optimisation of precision in (Bayesian) belief updating, it is non-felt fluency (surprise) that play a key role in updating predictions about precisions—and furnishing a sense of felt fluency.

About Active Inference

Active inference is formulation of Predictive Processing (PP), applied to the perceptual, cognitive and enactive functioning of the brain. As above, it inherits from the foundational insights of Hermann von Helmholtz (1867) that cognitive processes are inferential processes (for a synthesis, see Hutchinson & Barret, 2019; Wiese & Metzinger, 2017).

It is now widely accepted that PP provides a theoretical framework that accounts for many aspects of human and animal cognition in a way that no model has done previously (Clark, 2013b, 2018; Friston, 2009, 2010; Hohwy, 2016; Knill & Pouget, 2004; see also, Friston, 2010; Hutchinson & Barrett, 2019; Wiese & Metzinger, 2017).

Over the past decade, numerous studies have highlighted its relevance in major areas of psychology: vision (Rao & Ballard, 1999; Walsh, McGovern, Clark, & O'Connell, 2020), perceptual illusions (van Heusden, Harris, Garrido, & Hogendoorn, 2019), memory (Hindy, Ng, & Turk-Browne, 2016; Parr & Friston, 2017b), attention (Ainley, Apps, Fotopoulou, & Tsakiris, 2016; Feldman & Friston, 2010; Kanai, Komura, Shipp, & Friston, 2015; Parr & Friston, 2019), motivation (Tate, 2019), emotions (Joffily & Coricelli, 2013; Barrett, 2017; Ridderinkhof, 2017; Wilkinson, Deane, Nave, & Clark, 2019), action (Friston, Daunizeau, & Kiebel, 2009; Shadmehr, Smith, & Krakauer, 2010), theory of mind (Friston & Frith, 2014), social interactions (Kahl & Kopp, 2018), and language (Kuperberg & Jaeger, 2016; Mitsugi & Macwhinner, 2016). It is important to note that traditionally these psychological functions are considered in isolation (they would be autonomous processes). As soon as active inference makes it possible to account for each of them, it is not necessary to consider that these psychological functions are not so different.

Active inference[1] provides an account of one of the major characteristics of living systems: that is a generalised kind of homeostasis or self-organisation that can be read as minimizing the discrepancy between current sensations and predictions based on previous information that has been assimilated under a generative or world model entailed by the brain. But, minimizing discrepancy (e.g., prediction errors) is not a passive process, living systems actively control their sensed environment to maintain their internal equilibrium: i.e., *active inference*. Technically, active inference is a process theory for embodied brains that is an application of a variational principle of least action (called the *free energy principle*, Friston, 2009; Friston & Stephan, 2007; Friston et al., 2012).

[1] For a complete review read: Parr, Pezzulo, Friston (2022)

Active inference is an instance of the Bayesian brain hypothesis (Doya, 2007): under which brain is a predictive system grounded on a generative model, which scaffolds Bayesian belief updating of probabilistic representations of how the hidden (i.e., unobservable) causes in the world generate (i.e. unobservable) sensations. This belief updating corresponds to inferring the causes of sensations. That is to say, a probabilistic generative model of the dependencies between (unobservable or hidden) causes and (observable or sensory) consequences allows us to recognise the causes of sensations—and generate predictions of sensations given their causes. Hierarchical generative models entertain nested causes of an increasingly abstract and domain-general nature at successive levels of the hierarchy; usually, with a separation of temporal scales (Friston et al., 2017b; Hasson et al., 2008; Kiebel et al., 2008; Poeppel et al., 2008; Ramstead et al., 2018).

Under hierarchical models, recognition or perception is mediated by top-down predictions and bottom-up prediction errors; where prediction errors are used to update (Bayesian; i.e., subpersonal) beliefs about hidden causes of the sensorium—and the synaptic weights that encode the causal regularities of the world. In short, our brain infers, from sensory inputs, an internal probabilistic model of the world (i.e., the body/environment system). In turn, this internal probabilistic model allows us to anticipate sensory inputs and to evaluate the discrepancy between current sensations and those predicted under our generative models.

The brain constantly generates predictions and ensuing prediction error or surprise signals. As noted above, prediction errors can be reduced in two ways: by changing predictions or by selectively action-sorting sensory inputs (Friston, 2010). These two ways of minimising prediction error have been referred to in terms of perceptual and active inference, respectively. Both are in the service of minimising prediction errors or variational free energy (Ramstead et al., 2022), which can also be read as maximising (a lower bound on) the statistical evidence for the generative model. In philosophy, this has been referred to in terms of self-evidencing

(Hohwy, 2016); namely, acting or selectively sampling the sensorium to maximise the evidence for our generative models of the sensed world.

Crucially, the brain has to make predictions about the precision of its own predictions. These precision predictions are necessary to weight prediction errors in a Bayes optimal fashion; namely, in proportion to the precision or reliability of the information they contain. This means that inference—i.e., Bayesian belief updating—is driven by precision-weighted prediction errors. The idea is that the more precise a prediction is expected to be, the prediction errors that result should be afforded more weight. Psychologically, this kind of precision weighting is often equated with attentional set (see Ainley et al., 2016; Clark, 2018; Feldman & Friston, 2010; Kanai et al., 2015). Physiologically, it is thought to rest upon the same synaptic gain mechanisms that underwrite attentional selection.

In order to assess the precision of its predictions, our brain must have subpersonal beliefs about the precision of its own predictions and therefore has to infer the reliability of its own beliefs. This means that our brains have to estimate the precision of their predictions. This estimation is ubiquitous in all inference settings. Perhaps the simplest example would be in statistics, where one has to estimate the standard error—of some group mean or expectation—based upon the sum of squared prediction errors. Please see (Kanai et al., 2015) for an example of this precision encoding or uncertainty quantification as implemented in the brain—as a model of attention in separating feature from ground.

In short, predicting precision is a key aspect of inference, in the sense of estimating the certainty. We consider that if fluency plays a key role in predicting precision, it is relative fluency that plays a key role in revising predictions about precision.

About fluency and relative fluency

In the field of memory, Jacoby and colleagues (Jacoby & Dallas, 1981; Jacoby, Kelley & Dywan, 1989; Jacoby & Whitehouse, 1989; Kelley & Jacoby, 1990, 1998; Whittlesea, Jacoby & Girard, 1990) leveraged the ideas of Hermann von Helmholtz (1867)—in the field of perception—that cognitive processes are inferential processes (see also Brunswik, 1956). They were the first to suggest that the experience of memory originates in an inference based on a phenomenological cue, *fluency*. Fluency is generally defined as the subjective (metacognitive or qualitative) experience of the level of ease with which our own cognitive processes proceed (Alter & Oppenheimer, 2009; Reber & Schwarz, 2001)[2].

But fluency is phenomenologically transparent to its own causal source, in the sense that it does not represent such a source (Metzinger, 2003). Introspecting fluency will not reveal what brought it about, it is only a subjective feeling. This is why assigning it a source must rely on an attributional process (the *fluency attribution heuristic*, Jacoby & Dallas, 1981). This attributional process relies on an inference: if fluency is felt, its origin can only be what I am aware of, the processed stimulus. Consequently, *felt fluency* leads to the orientation of attention to the stimulus selected for processing (Turo, Collins & Brouillet, 2022)[3].

As predicting precision is a key aspect of inference (see above), fluency could play a key role in active inference. Indeed, it informs the cognitive system about expectations toward the stimulus, according to the properties of the stimulus and past experiences. In short, fluency

[2] Several empirical studies suggest that fluency is involved in a wide variety of judgements (for an overview, see Alter & Oppenheimer, 2009). Furthermore, it has been shown that fluency is evinced at different levels—and entails diverse contents that allow people to experience the world as unitary (see Winkielman, Ziembowicz & Nowak, 2015). Fluency has been referred to as *perceptual fluency*, when it involves perceptual processes (Jacoby & Whitehouse, 1989), *conceptual fluency* when it involves semantic processing (Whittelsea, 1993) and *motor fluency* when motor processes are involved (Yang, Gallo & Beilock, 2009).

[3] It was highlighted that: in a distance judgment task the stimulus will be perceived as closer (Alter & Oppenheimer, 2008; Mrkva, Travers & van Boven, 2018), in a memory judgment task the stimulus will be considered as old (Lanska, Olds & Westerman, 2014; Brouillet et al., 2022), in a hedonic judgment task the stimulus will be judged as positive (Reber, Winkielman & Schwarz, 1998; Milhau, Brouillet & Brouillet, 2013) and aesthetic (Reber, Schwarz & Winkielman, 2004; Zhang et al., 2022).

is interpreted as a metacognitive signal that tells us that there is minimal error in the execution of the current process.

The idea that fluency is an integral part of active inference was implicit in the work of Hesp, Smith, Parr, Allen, Friston and Ramstead (2021). In their work, they demonstrate that hierarchical Bayesian networks, solved using active inference (Friston, Parr & de Vries, 2018), make it possible to account for emotional valence. To evince this, they formalized emotional valence as a state of self that is inferred on the basis of fluctuations in the estimated confidence (or precision) that an agent has in its generative model that informs his decisions. According to their results, they propose that it would be changes in processing fluency across different domains that that would be at the root of affective states.

Based on the idea that fluency can be seen through the lens of Helmholtzian inference — that underlies predictive coding — Brielmann and Dayan (2022) proposed a computational model of aesthetic value. They consider that stimuli that are predictable (under the generative model) are those that are processed fluently. Indeed, the brain continuously predicts the next sensory input and greater fluency corresponds to a precise match between predictions and the sensory input. Thus, fluency can be thought as signifying a resolution of prediction errors, or at least, as a signal of smaller prediction errors and greater precision. Moreover, according to the so-called hedonic marking fluency, increasing fluency is the main determinant of how positively a sense experience is evaluated.

In the model they proposed, they adapted the generative model to make the processing of specific stimuli more fluent, that is to say more predictable. To do that they operationalized processing fluency as the likelihood of a stimulus, given the system state at a given time. Technically, this corresponds to increasing the precision of the likelihood model. In two experiments, their model was able to capture the classic effects observed in the literature on aesthetic evaluations. In turn, these results support the idea that sensory experiences associated with smaller prediction errors (i.e., greater precision), for which fluency is the marker, are more pleasurable.

While Brielmann and Dayan's model supports the idea that fluency is an intrinsic part of predictive processing, it seems important to consider the distinction proposed by Whittlesea and Leboe (2003) between *absolute fluency* and *relative fluency*[4] to explain the role of fluency from an active inference perspective.

Absolute fluency refers to an increasing degree of fluency (e.g., the speed of processing), which results in a subjective feeling of fluency (c.f., recognising that one is becoming increasingly fluent)[5]. The works mentioned in the preceding paragraphs considered absolute fluency. In distinction, relative fluency refers to a violation of expectation and consequent surprise: for example, you expect something to appear immediately, and it doesn't, but then appears after a delay. In this case, that something will seem more fluid than if it had appeared immediately. Cinema often uses this phenomenon to keep viewers spellbound

According to the SCAPE model (Whittlesea, 1997), the *discrepancy attribution hypothesis* (Whittlesea, 2002, 2004; Whittlesea & Leboe, 2000, 2003; Whittlesea & Williams, 1998, 2000, 2001a, 2001b) furnishes an account of this phenomenon[6]. For example, in their core experiment, Whittlesea and Williams (1998) wanted to highlight the role of surprise in creating a sense of familiarity. In the first phase (experiment 3) they asked participants to learn a list composed of real words (e.g., *table*), orthographically regular non-words (e.g., *hension*), and orthographically irregular non-words (e.g., *stofwus*). Then, in a second phase, participants

[4] Westerman (2008) uses the concept of relative fluency in a significantly distinct sense from Whittlesea and Leboe (2003): fluency is relative to a benchmark (the proportion of fluent items to non-fluent items)

[5] A priming task is a good example: if we present the word "doctor" and immediately after the word "nurse" we will feel a sense of fluency whereas if "nurse" is preceded by the word "tree" that will not be the case.

[6] Since several researches have supported the discrepancy attribution hypothesis (Aßfalg & Bernstein, 2012; Aßfalg, Currie & Bernstein, 2017; Breneiser & Mcdaniel, 2006; Brouillet et al., 2017; Brouillet, Servajean, Josa, Gimenez, Turo & Michelland, 2023; Brouillet, Rousset & Perrin, 2022; Bruett & Leynes, 2015; Chen & Mo, 2002; Goldinger & Hansen, 2005; Hansen, & Wänke, 2013; Hansen, Dechêne & Wänke, 2008; Joordens, Ozubko, & Niewiadomski, 2008; Thomas, Lindsey, & Lakshmanan, 2010; Wänke & Hansen, 2015; Wilbert & Haider, 2012; Willems & Van der Linden, 2006).

were presented with old items (i.e., presented in the first phase) and new items (i.e., not presented in the first phase but with the same characteristics as the old items). Subjects were asked to perform three tasks on each item: to pronounce it, to decide if it were a word or non-word (lexical decision task), and to decide if it had been presented in the first phase.

It is the results on the new words that are most interesting. They revealed that the real words were pronounced more easily than the other two types and that the orthographically regular non-words were pronounced more easily than the orthographically irregular non-words. Results on the lexical decision task showed that real words were judged more rapidly than orthographically regular non-words and these ones more rapidly than orthographically irregular non-words. They highlighted that there were more false alarms (i.e., new words are judged as having been presented in the first phase when they were not) for orthographically regular non-words than for real words and for orthographically irregular non-word. The difference between real words and orthographically irregular non-words was no significant.

If feeling of familiarity was only associated with absolute fluency of processing, then the proportion of new items judged as old (called false alarm) should have been higher for real words than orthographically regular non-words. But it is the opposite that was observed. To explain what they called the *Hension Effect*, the authors evoke the *discrepancy attribution hypothesis*: the surprise associated with the pronounceability of the orthographically regular non-word, while their perceptual identification is more difficult than for real words (they do not exist in the lexicon), generates a feeling of familiarity. This is because—in the context of a recognition test—participants cannot attribute surprise to its source, so they attribute the fluency felt to the most obvious source, the stimulus, that is consequently regarded as having been present in the learning phase.

It is important to note that felt fluency—related to the pronounceability of orthographically regular non-words—is relative to the fact that their perceptual identification was difficult (non-felt fluency), hence the term “relative fluency” used by the authors. It is the surprise that emerges from the gap between a phenomenal sense of non-felt fluency and a phenomenal sense of felt fluency that orients attention to the ongoing sensory processing.

Recently, Brouillet et al. (2023) observed similar results (Experiment 2, new words) to those of Whittlesea and Williams (1998). However, their results show that the gap between non-felt fluency and felt fluency acts both anteriorly (forward) and posteriorly (backward). They manipulated the discrepancy between conceptual and perceptual fluency, using an adaptation of the sentence stem paradigm (Whittlesea, 1993): words to be recognized were predictable or non-predictable and Gaussian noise (Reber et al, 1998) was used to manipulate the readability of the words. With a noisy background (no-perceptual fluency), participants were more likely to judge a new word as old for predictable words (conceptual fluency) than when the background was noiseless (perceptual fluency). This situation is similar to that of Whittlesea and Williams (1998): non-felt fluency (no-perceptual fluency) precedes felt fluency (conceptual fluency). But, when the background was noiseless (perceptual fluency), participants were more likely to judge a new word as old for non-predictable words (no-conceptual fluency) than for predictable words (conceptual fluency). In this situation non-felt fluency (no-conceptual fluency) follows felt fluency (perceptual fluency). Taken together these results suggest that it is relative fluency that orients attention to surprising sensory input and accompanying phenomenology. In the context of a memory task — as the surprise is transparent to its origin — participants attribute the source of phenomenal sensations to prior experience with the stimulus.

In the same vein, Brouillet, Milhau, Brouillet and Servajean (2017) tested the discrepancy hypothesis through the effect of motor fluency that preceded the words to be recognized. In this paradigm, participants had to perform a fluent gesture (e.g., dominant hand and ipsilateral gesture) or a non-fluent gesture (e.g., dominant hand and contralateral gesture) just before the recognition task. The gesture had no relationship with the meaning of the words. The results showed that ipsilateral side gestures (high motoric fluency) were easier to execute than contralateral side gestures (less motoric fluency), and that words which followed an ipsilateral side gesture were more likely to be reported as recognized than words that followed a contralateral side gesture. The results on new words are, once again, interesting. When they appear on the screen it is non-fluency that is experienced but before the word appeared, participants have experienced fluency. This discrepancy generates a non-specific signal that automatically triggers the search for an explanation. Since participants cannot firmly attribute this nonspecific signal to its source, they attribute it to the most salient source—the stimulus—and thus they infer that the word was on the learning list and report that they recognize it.

In further paper, Brouillet, Rousset and Perrin (2022) showed an effect of discrepancy through the transfer of the motor feeling of fluency linked to the participants' past interactions with the environment, independently of the stimulus in progress. In this paradigm, they constructed an experiment that comprised two steps. Firstly, participants had to perform a perceptual discrimination task (distinguishing a square from a circle) that involved a fluent gesture (ipsilateral side) or non-fluent gesture (contralateral side) to respond. Motor fluency vs. non-fluency was implicitly associated with the colour of the geometric shapes (blue vs. magenta). Second, they had to perform a classical memory recognition task: learning a list of pseudo-words and recognize them among new pseudo-words. During the recognition phase, pseudo-words (Old and New) appeared, either with the colour associated with motor fluency or with the colour associated with non-motor fluency. Results highlighted that pseudo-words presented in a colour associated with an ipsilateral gesture (motor fluency), lead to more frequent "old" (i.e., learned) responses, than non-words presented in a colour associated with a contralateral gesture (non-motor fluency). Again, it is particularly interesting that new pseudo-words were recognized as old — when they were presented in the colour associated with a fluent gesture. This strengthens previous results: it is the discrepancy between colour (felt fluency) and new pseudo-words (non-felt fluency) that leads participants to attribute the origin of the phenomenal experience to pseudo-words, and to infer that they must be old words. So, these results show that the cognitive system uses motor fluency — engendered by preceding actions — even if these past actions have no link with items processed. On the other hand, they show that the cognitive system is sensitive to the gap between non-felt fluency and felt fluency, which results in a deployment of attention to current sensory inputs and in the context of recognition task they judge items as old.

Wilbert & Haider (2012) were the first, to our knowledge, to brought out a link between fluency and (the processing of) prediction errors. The authors used the discrepancy hypothesis to explain the feeling of having committed an error. Their assumption was that a subjective discrepancy between the expected and the experienced feeling of typing triggers a search process for the cause, resulting in the attribution of the discrepancy to a typing error. To show this, participants had to type visually presented letters, one at a time. After having finished typing, they were asked to judge whether or not they had correctly typed the actual word (or pseudo-words). Results show that it is the perceived violation of an expectation regarding fluency of typing that leads to the subjective experience of having made a mistake (e.g., expecting to type pseudowords slowly and typing them quickly and correctly).

But the most interesting result, for our purposes, was obtained in their experiment 4. Its aim was to find out whether an expectation violation in itself is sufficient to produce the subjective feeling of having made an error, or whether this subjective feeling results from the attribution of the perceived expectation violation to a cause. Instead of only asking participants to judge the correctness of their typing after typing the letters, they were asked to first judge whether their typing matched their expectations. When a participant reported that their typing differed from their expectations, they were asked to choose between two alternatives: a) they had to decide whether the strange sensation was due to a mistake being made or to some other non-specific cause, b) they had to decide whether the strange sensation was due to a mistake being made or to a strange sequence of letters in the word. Two conditions were thus manipulated: a non-specific origin of the strange sensation vs. a specific origin of the strange sensation. Results showed that in the unspecific condition, the rates of false alarms (i.e., respond that the stimulus is present when it is not) and misses (i.e., the stimulus is present but there is no response) were higher for pseudo-words—hard to pronounce (unfelt fluency) but easy to type (felt fluency)—than for lexical words. By contrast, in the specific condition (given an increased rate of misses for pseudo-words), the rate of false alarms did not differ between pseudo-words and lexical words. This is particularly interesting, because it is the false alarms that are based on an attribution of a cause when a strange feeling during typing is experienced. Conversely, for misses, a judgment about a cause is not necessary, because it corresponds to the situation in which participants decided they did not commit an error, even though an error was made. As the authors point out, the results of this experiment provide clear evidence that participants do not rely on only the error signal when they have to judge whether or not they correctly typed a word. Rather, they seem to be influenced by perceiving a discrepancy between expected fluency and experienced fluency of their processing, which they then resolve by searching for a cause that can best explain the current situation (i.e., answer the question asked). In short, the judgment of having made an error is, by itself, the result of an attribution of a cause associated with expected fluency which turned into experienced fluency.

In short, all these experiments show that the phenomenological perception of a gap directs attention, and that the fluency experienced is merely the consequence of a non-felt fluency or an expected fluency. This is why we consider that there is a close similarity between what the SCAPE model tells us about cognitive functioning, via the discrepancy hypothesis, and the theoretical framework of active inference. Indeed, according to the active inference account, these experiments support the idea that non-felt fluency or expected fluency leads, via the heightening of felt fluency, to a revision of precision expectations (i.e., surprise or unresolved prediction errors); namely, an active updating of attentional set. Consequently, the results observed following the presence of a gap between non-felt fluency and felt fluency resonate with the principles of active inference. Thereafter, we shall refer to *unfelt fluency* as non-felt fluency.

Unfelt and felt fluency in active inference

According to the *discrepancy attribution hypothesis* and *active inference framework* it seems obvious that *surprise* plays a key role in cognitive processing. It is important to specify that surprise is not a state (i.e., an emotional state of mind induced by an unexpected event). Surprise is an attribute of sensations, technically known as self-information or surprisal (Levy, 2008; Tribus, 1961): it is a warning signal which, on the one hand, informs the system that there is a gap between what is observed and what is predicted and, on the other hand, leads a redeployment of attention to the unfolding of the process being inferred. In short, the more a prediction is contradicted by the sensory evidence, the more sensitive we are to the ensuing prediction errors. As a result, it follows a stimulus-bound change in attentional set.

These subpersonal changes can then be recognised as *unfelt fluency*; namely non-conscient recognising a change in attentional set; i.e., recognising when our attention is drawn to something we cannot explain—or did not predict. On this reading, *unfelt fluency* is phenomenologically transparent (surprise) until it is rendered opaque by the mental action that attends its recognition, *felt fluency*. Mental action in this instance refers to top-down or endogenous attention (Limanowski, 2017; Limanowski, 2022; Limanowski and Blankenburg, 2013; Metzinger, 2003). In other words, although *felt fluency* may be phenomenologically transparent, it may render *unfelt fluency* opaque, in the sense that I can report "I lost a fluent grip on this task because my attention was distracted". The explicit nature of felt versus unfelt fluency is not unlike the distinction between endogenous and exogenous attention. Please see (Jiang et al., 2013; Limanowski, 2017; Solms and Friston, 2018) for further discussion.

To our knowledge, there are relatively few studies that illustrate the importance of *unfelt fluency* for active sensing and perceptual synthesis. If the work of the Whittlesea's team has paved the way, it is, in our opinion, a direction of travel where the discrepancy between what is expected and what is perceived does not directly concern the processing of stimuli but how these stimuli are processed. Indeed, these studies allow us to understand, on one hand, that the cognitive system considers the fluency felt regardless of its origin and, on other hand, that *unfelt fluency* underwrites perceptual synthesis because it operates as a non-conscious process that orients attention, even if its origin is not the stimulus processed (but rather the precision with which stimuli can be predicted).

The emerging story here is that there is an intimate relationship between hierarchical predictive processing; particularly of precision, fluency and attention during an active engagement with the sensorium. In brief, we have pointed to evidence that suggests the estimation of the precision of various sources of evidence (e.g., prediction errors) in Bayesian belief updating in the brain is crucial for an optimal balance of prior beliefs and sensory evidence. This optimal balance rests on predicting the precision of prediction errors in perceptual hierarchies that, when optimal, constitutes *unfelt fluency*. From a psychological perspective, this can be likened to exogenous attention. In a hierarchical setting, the recognition—and implicitly instantiation—of optimal precision renders *unfelt fluency* opaque and implies a hierarchically deeper representation of fluency; namely *felt fluency*. Because predictive coding formulations of active inference rest upon ascending prediction errors and descending predictions, felt fluency can be read as inferring some fluent processing at lower hierarchical levels while, at the same time, issuing top-down predictions that place priors over the mediation of *unfelt fluency*; namely, precision at lower levels of the hierarchy. Because, neurobiologically, this kind of precision control is thought to be mediated by modulatory neurotransmitter systems: e.g., monoaminergic systems such as dopamine, norepinephrine, et cetera (Moran et al., 2013; Parr and Friston, 2017a), there is a close connection between the notion of *felt fluency* and *felt uncertainty* as articulated in certain applications of active inference to sentient behaviour (Solms, 2018). For example, Solms (2019) assimilates consciousness to a sense of uncertainty. In Solms' thesis, felt uncertainty is mediated by ascending neuromodulatory systems which represent the dénouement of hierarchical processing in the brain (Solms, 2021).

To summarize, the theoretical considerations concerning active inference, in particular the need for the organism to make predictions about its own predictions on the one hand, and to assess the precision of its predictions on the other hand, have allowed us to propose that *unfelt fluency* is used to assess the precision of our predictions and the feeling of fluency supervenes on—or is an attributional inference about—the resulting optimisation of active inference; i.e., fluent or skilled exchange with the sensorium, which is experienced as a precise grip on the world of affordances (Bruineberg and Rietveld, 2014).

Conclusion

The aim of this paper was to propose, based on both theoretical considerations and experimental works, that felt fluency, the subjective metacognitive experience associated to the causes of the ongoing process, can be read as recognising and contextualising unfelt fluency; where unfelt fluency optimises predictions of the precision of sensory processing. On this view it is unfelt fluency that instantiates attention, in response to unresolved prediction errors or surprise.

In summary, our sentient behaviour can be understood in terms of active inference under a generative model that includes a certain cognitive set called *fluency*. This cognitive (or attentional) set *is both cause and consequence* of a fluent, precise predictive processing of sensory exchanges with the world. It is a *cause* because it provides top-down—i.e., prior—constraints on the precision of processing at lower levels of the hierarchy. These predictions of precision ensure the (Bayes) optimal deployment of attention and, consequently, precise and confident action selection. At the same time, it is a *consequence* of lower-level processing when prediction errors are lower than predicted. This "prediction error of prediction errors" furnishes bottom-up messages that revise (Bayesian) beliefs about cognitive or attentional set, and a suitable adjustment of the precision at lower levels. See (Feldman and Friston, 2010; Kanai et al., 2015; Parr and Friston, 2017b, 2019; Parr et al., 2020; Smith et al., 2019b) for a technical discussion and illustration using simulations and numerical experiments. In other words, changes in unfelt fluency (i.e., precision) induce felt fluency.

The key aspect of this context-sensitive predictive processing is that the cause of felt fluency—c.f.: felt uncertainty (Solms, 2018)—arises from internal inferences about the precision of predictive processing, *not the sensorium*. This means that a sense of fluency cannot be attributed to its subpersonal cause—and is therefore plausibly attributed to the sensorium. This formulation gracefully accommodates attribution theories of fluency while, at the same time, emphasising the causal role of changes in the precision or unfelt fluency of predictive processing. A closely related perspective on the key role of inferred precision can be found in computational accounts of phenomenology and metacognition. For example, (Sandved-Smith et al., 2021) offer a computational phenomenology of mental action, modelling meta-awareness and attentional control that is formally consistent with the current account of fluency. Specifically, the authors propose a model of meta-awareness and attentional control using hierarchical active inference. They "cast mental action as policy selection over higher-level cognitive states and add a further hierarchical level to model meta-awareness states that modulate the expected confidence (precision) in the mapping between observations and hidden cognitive states.” In so doing, they differentiate between “the capacity to explicitly notice the current content of consciousness” (c.f., felt fluency) and attentional processes *per se* (c.f., unfelt fluency).

Having made these connections, we proposed that *unfelt fluency* could be considered as the cue that increases precision in our own predictions because it is the cause of inferences. To support this proposition, we have presented several experiments that endorse this view. Firstly, it seems that the cognitive system is nothing more than an inferential process associated with the monitoring and recognition of the ongoing process and the resulting subjective feeling of (felt) fluency. Secondly, it seems that cognitive system uses felt fluency, which supervenes on—and contextualises—unfelt fluency, for attributing precision to its inferences (predictions). Thirdly, unfelt fluency seems to underwrite a foundational kind of cognitive or attentional set, since it is used even when not directly related to the processed stimulus but to the ongoing process associated with the individual's activity.

If the core role of inference advanced by von Helmholtz—that any mental state is realised by unconscious inference—then the causes of the subjective (conscious) inference must have unconscious perceptual precursors. It was James (1890) who suggested that consciousness was preceded by a state of pre-consciousness, called the *fringe of consciousness*, which shapes this consciousness (see, Mangan, 2003). On the current view[7], this fringe of consciousness would include unfelt fluency; namely, the subpersonal (possibly pre-conscious) changes in precision at low levels of hierarchical processing. This level of processing has a crucial and adaptive function because it signals whether or not you need to allocate more attention to ongoing processes.

[7] See, Reber, Fazendeiro & Winkielman (2002) who have linked fluency to Fringe of Consciousness.

Perspective

We have pursued the idea that the experience of fluent processing reflects the degree to which beliefs are updated. Our theoretical treatment of fluency rests upon current formulations of the predictive brain, with a special focus on the encoding of uncertainty — or its complement, precision (e.g., inverse variance). This theoretical treatment can be contrasted with more descriptive approaches to the Bayesian brain and rational (or bounded rational) decision-making: e.g., (Ernst and Banks, 2002; Kahneman and Tversky, 1973). Predictive coding (and active inference) commits to a neuronal process theory that foregrounds the explicit estimation—and neuronal representation—of Bayesian beliefs (Friston et al., 2017a; Shipp, 2016). Bayesian beliefs in this setting are subpersonal (i.e., they are not propositional or folk psychology beliefs): they are implicit probability distributions encoded by neuronal activity and synaptic gain (Friston et al., 2006). This is an important issue from two perspectives.

First, there is an explicit appeal to priors in the ensuing Bayesian inference that explains apparently irrational decision-making in terms of hierarchical inference. In other words, unlike appeals to Bayesian statistics as a description of decision-making, c.f., (Gardner, 2019), active inference tries to explain any given (e.g., perceptual) decision in terms of the appropriate priors that are inherited from experience: technically, for any given choice behaviour and loss function there are always some Bayesian priors that render the behaviour Bayes optimal—this is known as the complete class theorem (Brown, 1981; Wald, 1947). Second, this neuronally plausible explanation for belief updating foregrounds the importance of encoding a belief that includes its precision. This is the key aspect of the current account of *felt* and *unfelt* fluency that rests upon the observation that belief updating entails estimating or inferring the precision of beliefs. This precision can be read as a subpersonal 'confidence' in various beliefs or expectations during belief updating (Bays and Wolpert, 2007; Feldman and Friston, 2010; Limanowski and Friston, 2018; Mathys et al., 2011; Moran et al., 2013). However, optimising this subpersonal, unfelt ‘confidence’ rests on mental action, which equips it with a certain phenomenology that we associate with felt fluency.

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