

An active inference account of protective behaviours during the COVID-19 pandemic

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Abstract

Newly emerging infectious diseases like the coronavirus (COVID-19) create new challenges for public healthcare systems. Prior to effective treatments or vaccination, countering the spread of these infections depends on mitigating, protective behaviours. Previous work has shown that the enacting protective behaviours depends on beliefs about individual vulnerability, threat severity, and one's ability to engage in such protective actions. However, little is known about the genesis of these beliefs in response to an infectious disease epidemic, and the cognitive mechanisms that may link these beliefs to decision making. Active inference is a recent approach to behavioural modelling that provides a framework to understand the behaviour of agents in situations that require planning under uncertainty. In this paper, we suggest that the active inference framework can explain how agents update their beliefs about the risks during an outbreak and thereby commit to protective behaviours.

Keywords

Active inference; Bayesian inference; COVID-19; Coronavirus; Health belief; Epidemic; Belief; Free-energy principle; Pandemic; Outbreak.

Introduction

Emerging infectious diseases like COVID-19 that are caused by the novel coronavirus (SARS-CoV-19) create new challenges for public healthcare systems. Without a treatment and vaccination, countering the spread of these diseases depends largely on protective behaviours on the part of individuals and groups, such as social distancing, respecting quarantine, wearing masks, frequent handwashing, and travel restrictions (1–6). These individual and social measures can reduce transmission rates, and subsequently alter mortality rates and the number of active cases (7,8). Mathematical modelling and analysis of individual behaviour at the population scale during previous epidemics suggests that the degree to which protective behaviours are enacted, especially social distancing, effectively predicts the timing and course of global disease trajectories (9). Conversely, the inferred prevalence of the virus and accompanying fear predicts behaviour on a population-level (10). This straightforward observation has a profound implication; namely, that of a circular causality, in which protective behaviours modulate transmission and spread of infection, while the prevalence of infection in turn induces protective behaviours (5,11,12).

Previous work suggests that committing to protective behaviours depends on perceived risks (i.e., beliefs about individual vulnerability and threat severity) and on the estimated availability and efficacy of protective actions (i.e., beliefs about the efficacy of the response and about people's ability to engage in such protective actions) (13–15). These models include situations where individuals believe protective behaviours are effective, but are not be able to enact them (e.g., wanting a mask but not having one, or wanting to social distance but being stuck in prison). They assume that if a person believes that the infection can be prevented, that infection can be avoided with protective behaviour, and that they have the means to carry out those behaviours, then this person is more likely to perform protective behaviours (16–18). During a pandemic, information from several sources, such as media, government, and interpersonal

relationships, can increase awareness of the risks associated with the disease and whether preventive measures should be adopted (19). However, little is known about the genesis of these beliefs in responses to an epidemic, and about the cognitive mechanisms that may link these beliefs to decision-making and action. In order to develop sanitary strategies, it may be useful to gain better understanding of the mechanisms that define the association between perceived risk and protective behaviour.

The *active inference framework* is a novel approach to behavioural modelling that integrates embodied perception and action, belief updating, and decision making (20,21). It addresses the problem of inferring (unobserved or hidden) states of the world, learning the statistical structure of the world, and acting in an appropriate manner based on a set of preferred outcomes and probabilistic beliefs about an uncertain and changing environment (20). Active inference casts action, perception, and cognition as minimizing quantities called variational and expected free-energy. The former minimizes the divergence between predicted and observed sensory outcomes and the latter minimizes the divergence between preferred and observed sensory outcomes of actions – based upon a model of how sensory data are generated under distinct plausible behaviours (22). According to active inference, the brain deploys a form of (variational or Bayesian) inference to infer the unobserved causes of its sensory data, and to select action sequences (policies) that actively change the world to bring about expected or preferred sensory outcomes (22). In other words, action and perception work hand-in-hand to minimise free-energy, or to get the agent as close as possible to its preferred sensations.

Active inference provides a formal framework to model how agents update their probabilistic models of the world by collecting sensory data that are generated by the consequences of action. It thereby provides a mathematical description of the cognitive and behavioural adaptation of a biological agent to its environment (23–25). In short, active inference provides a framework for studying the behaviour of individuals and groups in situations that require decision making

under uncertainty (20). In this paper, we suggest that the enaction of protective behaviours by the general population can be explained by in this principled way.

Active inference in the brain?

In the cognitive neurosciences, active inference provides a formal framework for understanding the choice behaviour of individuals under uncertainty. This theory proposes that the dynamics of the brain minimize variational and expected free-energy (22). In information theory, free-energy provides an upper bound on self-information (a formal measure of surprise) where expected surprise is known as entropy or uncertainty. Crucially, minimizing free-energy is equivalent to maximizing Bayesian model evidence, i.e., the probability of sensory exchanges with the environment under a model of how those sensations are caused (26). Accordingly, the brain maintains an internal representation of all the relevant statistical variables in the environment. This representation rests on a probability distribution over hidden states – and the observable consequences generated by those variables; such (probabilistic) models are called *generative models* because they represent the causal factors that generate sensory data. Based on sensory observations, the brain can update its representations, with an algorithmic process equivalent to an approximate form of Bayesian inference about the (hidden) state of its environment. This inference corresponds to minimising free energy or maximising the evidence for the generative model.

Active inference assumes that perception and action are two major ways in which free-energy is minimized (27). Heuristically, perception makes internal representations more like the data that the brain acquires. Reciprocally, action makes the data closer to the preferred distribution that is represented internally. Action (or policy selection) involves inference premised on a generative model that represents the expected sensory consequences of action, where the

sequence of actions that is selected is the one that best reduces (expected) free-energy. This is sometimes referred to as planning as inference (28). This notion supposes that the brain is capable of predicting the perceptual feedback that would be produced by adaptive actions. It infers the hidden states that cause sensations, and chooses actions that minimize expected surprise in the future (26). For that purpose, the brain accumulates sensory evidence; and perception corresponds to updating probabilistic beliefs or representations about the current state of the world. In action, rather than inferring the causes of sensory data, the brain infers actions that are expected make sensory data accord with its preferences about sensory input (i.e., avoid surprises expected in the future). The value of each policy is then evaluated in terms of its expected free-energy (i.e., surprise), such that the policy that leads to the least expected free-energy is the one that is selected. Behaviour therefore depends on beliefs about future states and outcomes under each policy. Actions realize these predicted outcomes, eliciting new evidence from the world (29).

Free-energy minimization has been proposed as an explanation for collective behaviours premised on shared cultural, social, and trans-personal conventions (30,31). Crucially, these accounts explain collective (multiagent or ensemble) behaviour in terms of individual actions premised on a shared generative model. Recall that a generative model specifies the manner in which typical sensory data are caused, especially by action. To share a generative model means to share such sets of expectations. In this way, social conformity comes from individual inferences premised on a shared model and from the enactment of those expectations via environment-modifying actions (30,31).

How to protect yourself during an outbreak?

In the context of an outbreak, people generate a number of beliefs about the risk of infection given large amounts of available, but ambiguous, evidence (32,33). These evidence come from

local sources that are communicated through personal connections, and global sources that depend on extrinsic factors like the media (16,17,34). According to these sources, people update beliefs about the chances of being infected, the seriousness of the disease, the efficacy and availability of protective actions, and their ability to commit to such protective actions (35–37). Numerous studies have shown that these beliefs are a major determinant of protective behaviours like social distancing, mask wearing, and handwashing, or for the respect afforded to collective rules, like mandatory quarantine and travel restrictions (10–13,15).

Two competing theories of health-protective behaviour have been proposed to explain the link between beliefs and health actions: the health belief model (HBM) and the protection motivation theory (PMT) (35,38). They are value-expectancy theories, based on the assumptions that people want to avoid illness and believe that behaviours will prevent illness. They describe the cognitive processes that mediate behaviour in the face of a threat and suppose that the motivation to protect oneself is the proximal determinant of these behaviours (39). These theories have been applied extensively in numerous frameworks in medicine, nutrition, or cybersecurity, to predict various health-related behaviours (40). The health belief model (HBM) assumes that health behaviour depends on the perceived threat, the perceived benefits of health behaviour, and the perceived cost of health behaviour, comprising economic, social, and psychological costs, such as anxiety, shame, or discomfort (41,42). Protection motivation theory (PMT) supports HBM theory by incorporating several additional factors. It refines these assumptions and includes beliefs about self-efficacy as well as the conviction that one can successfully execute the behaviour required to produce predicted outcomes (35,43).

PMT suggests that people's motivation to engage in precautionary actions is influenced by two major factors: threat appraisal and coping appraisal (44). Threat appraisal encompasses beliefs about vulnerability, a subjective estimate of the chances of contracting a disease (how likely one is to get the illness), and beliefs about the severity of a disease (how serious the illness is).

Coping appraisal involves beliefs about the efficacy of the response, protective actions that are available, and beliefs about self-efficacy; that is, one's ability to effectively engage in such protective actions (35). PMT thus includes the beliefs of individuals regarding their ability to respond to the threat, and about the efficacy of this response to that threat (39). Explicitly, these beliefs cover the self-vulnerability ("my chances of getting Covid-19 are high"), the severity of the pathogen ("pneumonia resulting from coronavirus is a serious condition"), the perceived benefits ("handwashing could reduce the risk of contracting COVID-19"), but also the cost involved in carrying out that behaviour ("social distancing will make me sad").

These beliefs can be represented in a hierarchical structure defining their entailment relations, where beliefs about the ability of individuals to protect themselves influence beliefs about individual vulnerability or about the dangerousness of a pathogen. In this structure, each belief is embedded in a network of causal dependencies. If you believe that potential infection will only have mild effects on you, then the perceived efficacy of coping strategies is reduced (since they reduce an already low risk). If you believe that coping strategies are effective, then your perceived potential risk of infection must be low. This dependence ensures that one's motivation to remain healthy can influence coping appraisal, predicted vulnerability, and perceived severity, but also perceived benefits and predicted costs. In other words, the motivation to realize protective actions may sensitize individuals to threat signals, while a lack of motivation may desensitize individuals to such signals. On the other hand, the consequences of action could influence the strength of protective motivations. If, after realizing action, perceived costs were higher than perceived benefits, the perceived threat would be expected to increase. In turn, the perceived threat could strengthen motivation to enact protective behaviours, leading to a self-reinforcing feedback loop.

These theories have been successfully applied to understand the evolution of behaviour during past outbreaks of severe acute respiratory syndrome coronavirus (SARS) (45–47), influenza A

virus subtype H1N1 (H1N1) (48–50), and Middle East respiratory syndrome (MERS-CoV) (51,52). In the 2009 H1N1 outbreak, the belief that the virus could be spread by indirect contact was directly associated with a greater use of hygienic measures and social distancing (48). This belief increased the perceived vulnerability of an individual, but also indirectly increased the predicted response efficacy and self-efficacy. During the early stages of the COVID-2019 pandemic, a study conducted in South Korea showed that the enactment of precautionary behaviours was strongly associated with perceived risks, and with beliefs about the efficacy of those behaviour (53). The majority of respondents (51.3%) reported that their perceived risk of infection was “neither high nor low,” 48.6 % reported that they believed that the severity of illness would be “high,” and 19.9% reported that they believed it would be “very high.” In this sample, 41.5% were avoiding crowded places, 50% reported cancelling social events, 63.2% reported always wearing a facial mask, and 67.8% reported always practicing hand washing. Interestingly, the average perceived severity score was higher than perceived vulnerability. Another study that was conducted in Iran showed that both threat appraisal and coping appraisal predicted protective behaviour (54). These findings suggest that, whether for old epidemics or for the current coronavirus crisis, a high perceived risk and a good coping appraisal are strongly associated with social response.

Towards an active inference account of protective behaviour

Epidemics are massive generators of uncertainty. Infectious diseases are generally perceived as less controllable than chronic life-style diseases such as diabetes, cancer, or heart disease (55). When facing an epidemic, individuals appraise the characteristics of the threat itself, and their ability to act against that threat (56). First, the threat is generally assessed in terms of dangerousness. Second, the predicted effectiveness of protective strategies and the perceived

vulnerability to infection each modulate the salience of the threat. Proportional to threat salience, one of the central emotional responses to a pandemic is fear (57–60).

We suppose that the brain continuously mobilizes beliefs about the severity of the illness, the probability of infection, the efficacy of the behaviour to reduce the probability of infection, and finally, the probability of infection if a new behaviour is adopted. Individuals could also reduce their fear by updating these beliefs. This conception may be associated with previous models of perceived risk that distinguish between an “automatic” emotional reaction (a quick and automatic feeling about risk), and a slower cognitive reaction (a more explicit, calculative appraisal of risk (61,62)). The first automatic type of response corresponds to belief updating about the risk, i.e., increased estimated likelihood of risk; whereas the second, deliberative response may be more associated with explicit policies (beliefs about actions), i.e., appraisal of coping strategies. These reactions (updating beliefs vs. action-oriented decision making) could then be qualified as adaptive (e.g., following group advice, seeking information) or maladaptive behaviours (e.g., denial of risk, avoiding new information).

Active inference offers an attractive framework for integrating uncertainty, emotion, belief, and action (26). Interestingly, most theories based on active inference associate negative emotions, such as fear, with inferences about increases in (expected) free-energy over time, where expected free energy (i.e., surprise) can be read as uncertainty (63). In this computational formulation of *affective* inference, a hierarchical generative model is used in which negative affective states are modelled as “states of self,” i.e., higher-order states that are inferred on the basis of lower-order beliefs (i.e., “I must be stressed because I can't decide what to do next”). The expected free-energy can then be read as a kind of internal estimate of “how well I am doing” – such that increases in expected free-energy suggests poor performance, i.e., a failure to resolve uncertainty or realise preferred sensory states.

Crucially, an agent can evaluate the degree to which it trusts the expected free-energy that it is generating. Heuristically, if consistently higher-than-anticipated levels of expected free-energy are generated under that model, then it is not a particularly good model. Under this conception, negative emotional states indicate that the agent's attempts to secure preferred outcomes have been consistently thwarted. This entails that the agent's predictive grip on its world is lacking. Negative emotion is therefore a sign that the agent is losing its predictive grip. This model of emotional valence—as hierarchical inference about irreducible expected free-energy (i.e., uncertainty)—provides an account of how emotional states nuance posterior beliefs during Bayesian inference (63). This is usually cast in terms of emotional states predicting the predictability or *precision* of lower level representations.

A loss of certainty about states of affairs—and how to respond—corresponds to a loss of precision in representations or probabilistic beliefs. Precision is an important attribute of probabilistic beliefs and can be thought of as the opposite of uncertainty (e.g., inverse variance). In active inference, the precision of a belief has itself to be inferred, where this inference corresponds to attention. In other words, affording a representation greater precision corresponds to attentional selection. Technically, the precision assigned to various sources of evidence is a key quantity in Bayesian inference, ensuring that more reliable sources of evidence contribute to belief updating.

Beliefs about coping responses are crucial for understanding the mechanisms involved in emotional responses to pandemics (64). Beliefs about threat depend on evaluating the state of the environment and observing what happens to individuals, whereas beliefs about coping are compelled by the perceived response efficacy (the belief that the recommended behaviour will be protective) and one's own self-efficacy (the ability to perform the recommended behaviour). Individuals evaluate whether a protective action will mitigate the threat (response efficacy), their level of confidence in being able to carry that action out (self-efficacy), and also the cost

of this protective action. Beliefs about coping responses encompass beliefs about the threat, because if an individual is convinced that they could protect themselves from risks, this reduces fear (and uncertainty) associated with the threat. Active inference allows us to integrate beliefs about the risk (threat appraisal), beliefs about action (coping appraisal), and decision making. It suggests that the brain could minimize free-energy (i.e., beliefs about high vulnerability and beliefs about high severity) by fulfilling its prediction about the availability of protective actions, and predictions about the ability to engage in such protective actions.

Adaptive and maladaptive behaviours as free-energy minimization

In active inference, optimal behaviour entails actions that resolve uncertainty and achieve preferred, unsurprising outcomes. These behaviours can be specified in terms of policies that minimize the free-energy expected when pursuing them (20,29). If the brain seeks to minimize free-energy, it can select protective behaviours, which fulfil predictions about the threat and about coping responses. In short, the brain chooses policies that minimize uncertainty about future outcomes, by minimizing the free-energy expected following action. Crucially, expected free-energy can be decomposed into epistemic and pragmatic terms that can be alternatively expressed in terms of *risk* and *ambiguity*.

Here, risk scores the difference between predicted and preferred outcomes, where preferred outcomes and those that are least surprising a priori (e.g., avoiding infection). Ambiguity reflects the uncertainty about observations, given their causes. Therefore, choosing policies to minimise expected free-energy maximizes preferred outcomes while, at the same time, avoiding ambiguous situations, such as ‘being in the dark’ (i.e., this has the effect of driving the agent to seek the most salient or informative observations). These two aspects of expected free-energy can be regarded as uncertainty of a specific and non-specific sort that pertain to

specific prior expectations about preferences (i.e., risk) and a generic ability to infer states of the world (i.e., ambiguity). Mathematically, risk corresponds to the expected ‘cost’ of a policy.

On this account, the outcomes of protective behaviours confirm beliefs about the ability of coping to achieve preferred outcomes, and reduce uncertainty. Reduction of negative affect (e.g., fear) via free-energy minimization will reinforce protective behaviour in the future (29). The realization of protective behaviours thus forms a loop of belief-confirmation and epistemic habits. This account could explain why protracted experience of threat reduces perceived risk, in the sense that fulfilment of predictions about coping strategies reduces uncertainty about policies, independently of some variation in the threat itself (65). Protection motivation arises when beliefs about response efficacy and self-efficacy outweigh cost, and when protective actions effectively fulfil predictions about severity and vulnerability. Dovetailing with this account, studies carried out during SARS epidemics show that the perceived response efficacy and self-efficacy were strongly associated with protection behaviours (45–47). During the COVID-19 pandemic, results from a national cross-sectional online survey of 1420 Australian adults in March 2020 show that protection behaviours were associated with a higher rating of perceived effectiveness of behaviours and higher levels of perceived ability to adopt social distancing strategies (66). This association between precautionary behaviours, perceived severity and perceived self-efficacy was also found in a study which investigates the impact of online information during the pandemic (67).

However, in order to minimize free-energy, the brain can adopt other strategies, especially when there are no plausible coping policies. These strategies encompass maladaptive behaviour, such as avoidance, or maladaptive beliefs, such as denial or wishful thinking (68,69). In these cases, individuals entertain internal actions or policies (e.g., attentional mechanisms) that control emotions rather than limiting risks—which also minimizes free-

energy, albeit maladaptively if the resulting beliefs are not attuned to the real risks present in the environment (70). In other words, by changing the confidence or precision afforded certain beliefs, the brain can effectively ignore sources of evidence, leading to a decrease in the perceived threat (e.g., ignoring cues that would otherwise suggest the situation is dangerous). These maladaptive behaviours and beliefs allow together individuals to avoid or reduce the threat, and therefore maintain a low free-energy. High perceived risk will elicit protective behaviour only when the individual has sufficient confidence about coping efficacy. If there is high uncertainty about these coping strategies, perceived risk may produce a greater level of maladaptive responses.

In the early phase of the outbreak, the discrepancy between predictions and sensed outcomes will largely increase free-energy, producing uncertainty and fear (71,72). Faced with this uncertainty, the choices of policies are limited. The need to reduce uncertainty may encourage individuals to ignore (i.e., reduce the precision of) evidence of risk, resulting in some reassuring underestimation of the severity of the epidemic (73). These attenuated or biased beliefs can be understood as nuancing the risk (and ambiguity) of the world. In effect, this kind of—possibly some personal—denial is a Bayes-optimal response to a world that cannot be predicted or explained

This phenomenon could explain the discrepancy between sensory evidence and people's cognitive representations of risk at the beginning of COVID-19 epidemic (65,70,74). In February and the beginning of March, a large proportion of the European public did not consider the novel coronavirus to be a significant threat—sometimes attributed to an unwarranted exceptionalism (i.e., “This could not possibly happen to us”) (75). This collective denial has been difficult to understand, given the accelerating death count in China, Italy, and France (76). During this period, many Europeans developed maladaptive beliefs, such as “the virus is like influenza”, “it only affects old people”, or “it will never come through the border”.

In the same way, while epidemiologists pointed out risks of infection ranging from 11% to 19% during the 2009 H1N1 outbreak, the majority of people believed that they were unlikely to get infected and to infect others (77), and felt that the pandemic did not affect their daily habits (78).

Cognitive sciences offer some understanding of the emergence of adaptive or maladaptive behaviours toward health threats (79,80). Several studies show that individuals with reduced ability to think about the future are more likely to engage in health behaviour when positive outcomes are immediate, and negative outcomes are seen as only having effects on the long term. Alternatively, individuals with a greater ability to think about, and project themselves into the future are more likely to undertake health behaviours when immediate outcomes are negative, and long-term outcomes are positive (81).

Another important variable is the perceived level of the threat, and the confidence placed in (i.e., precision afforded) the efficacy of coping strategies. If the level of threat is believed to be too high, and the precision of expected outcomes from protective policies is believed to be too low, the threat itself then could inhibit the protective action. This phenomenon is particularly apparent in the context of screening for serious diseases such as cancer or HIV (82). Screening tools then provide information on the risk, but if the risk is confirmed, the individual knows that the possibility of reducing risk is low. In other words, there is a balance between reducing the uncertainty of risk, and the risk of increasing uncertainty. Avoidance and denial are then a quick and effective way to resolve uncertainty. By not performing the screening test, the individual protects himself from the possibility of bad news. The fear of death and physical pain—as a result of being diagnosed with cancer or HIV—can lead to denial and hinder screening behaviour.

Some studies have shown that compliance to protective behaviour result from people's capacity to obey the rules, opportunity to break rules, and people's intrinsic motivations, comprising

moral support and social norms (83,84). During the pandemic, individuals share group membership with other agents: in this setting, protective behaviours may become a socially approved norm, and social conformity is an adaptive strategy to cope with this kind of uncertain environmental situation (85,86). This cognitive mechanism includes the tendency towards increased appraisal of information from socially relevant agents (e.g., people who elicit epistemic trust), and to imitate these agents (87,88).

However, other lines of evidence suggest that maladaptive behaviour can carry rewards, such as intrinsic pleasure and social approval, which can maintain maladaptive behaviour (68). This account is crucial to understand the factors which determine whether people accept or reject control or protection measures (89). This highlights a complicated interplay between prior preferences (that determine risk) and the need for clarity (that resolves ambiguity) when selecting a course of action. Crucially, prior preferences can span many domains, from the prosocial to the autonomic (25,30,31,90).

From theory to guidelines for global health policies

Despite its idealizations, active inference furnishes some perspectives on developing guidelines for global health strategies. In response to the COVID-19 pandemic, governments across the world have adopted measures to slow the spread of the virus. The behavioural response of individuals during epidemic is one of the major variables to limit the spread. Collective measures targeting these behavioural responses are critical to decrease mortality, and reduce the overburdening of health care systems (91). Indeed, behavioural responses to the prevalence of infection are a crucial component of some epidemiological models; especially those that are able to predict societal or institutional responses to the epidemic (5,92).

Extensions of active inference to social phenomena may shed light onto individual reactions to the uncertainty of the pandemic. Facing a pandemic, individuals coordinate and cooperate with each other, supporting group decisions based on shared goals. Beliefs about risks and protective actions are a crucial part of the shared expectations—to which an individual or group implicitly appeal when they choose a behavioural policy. Individuals acquire these expectations through shared experience in a social or epistemic community; and crucially, individual behaviour is shaped by the social subgroups which embrace their social identities (93). These shared expectations could explain social conformity in protection behaviour, by generating automatic behavioural responses in accordance with preferences, values, and goals that are characteristic of an epistemic community (94). For the group, the relevance of protective actions may therefore been associated with beliefs about generalised individuals vulnerability, and in turn the display of protective action in the group may sensitize individuals to threat signals.

Later, protective behaviour may be characterised by environmental cues that denote specific actions to be accomplished, given that certain cues are perceived (31). The idea here is that observing our peers to be doing this or that increases the likelihood that we will engage in the same behaviour. If this is correct, governments should promote the spread of positive appraisals of public protective behaviour (e.g., the obligation to wear a mask in public places), so as to produce “epistemic pressure” leading to behavioural conformity (75,79). In line with this view, a study carried out during the spread of COVID-19 revealed that promoting collectivism may be a way to increase engagement in protection behaviours (95).

Moreover, if action fulfils predictions based upon perceptual inference, and if the brain favours actions that minimize expected free-energy, then the prediction of the effectiveness of the action—in relation to risk and ambiguity—is crucial. Therefore, the major role of health policies and communication should be to increase the precision of various beliefs, i.e., resolve uncertainty about the expected outcomes associated with protective behaviour. Namely, such

beliefs have to underwrite confidence about coping outcomes. Accordingly, a meta-analytic review showed that both threat and coping appraisals were significantly associated with protective behaviour, but this association was stronger for coping appraisal than threat appraisal, and especially for self-efficacy (40). Alternatively, self-efficacy and response efficacy were negatively correlated with maladaptive behaviour which inhibits protection motivation.

In this setting, governments may have to improve their health message (96–99). During COVID-19 outbreak, a study carry out in 9,000 citizens in Italy dramatically shows that mass media communication plays a major role in updating beliefs about pandemic (100). It is crucial for health public policies to deliver mass health advice, not only about risk, but especially about the effectiveness of protective behaviours. Individual behaviours, such as handwashing, mask wearing, and social distancing, *must be framed as effective* (when they are found to be effective). The balance between adaptive and maladaptive response toward an infectious disease depends on the balance between the threat appraisal and the expected risk. Then, the predicted cost, both economic and cognitive, has to be presented as low to facilitate these actions.

Conclusion

Cognitive and theoretical neuroscience may have something useful to offer when fighting the COVID-19 outbreak. Epidemics emerge from interactions between pathogens and epistemic agents. Collective and individual protective measures especially require a fundamental shift in human beliefs and behaviour. Although we are well aware of the biological processes involved in the propagation of most pathogens, it is difficult to model the cognitive and the behavioural processes of individuals. Insights from the computational and social neurosciences are then critical to enrich models of public health intervention strategies.

Active inference offers a unifying framework to understand how the individuals generate beliefs about risks and commit to protective actions. It assumes that the brain minimizes expected free-energy, a proxy for uncertainty. For that, the brain constantly makes inferences to predict the consequences of action, and update its beliefs based on what the senses relay back. With action, the brain actively samples the world to ensure its predictions become a self-fulfilling prophecy. Protective behaviours, but also maladaptive behaviours, may furnish a way to reduce this uncertainty. In this present work, we suggest that increasing the perceived efficacy of protective behaviour, i.e. increasing the precision of beliefs about a consequence of protective action is a priority for our collective fight against COVID-19.

This formulation acts as a bridge between theoretical models of cognition and epidemiological models—and offers a perspective on the importance of propositional and sub-personal beliefs in mitigating epidemic crises. Mathematical formulations of these cognitive mechanisms could improve the predictive validity of computational models used in epidemiology, if suitably equipped with behavioural responses and the uncertainty. Our brain possesses a set of prodigious adaptive systems to fight against ecological threats: it is up to us to understand them, so that we can improve our defences.

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