This paper is now published in: Perspectives on Psychological Science

<https://doi.org/10.1177%2F17456916211031926>

Shamay-Tsoory, S. G., & Hertz, U. (2022). Adaptive Empathy: A Model for Learning Empathic Responses in Response to Feedback. Perspectives on Psychological Science: A Journal of the Association for Psychological Science, 17456916211031926.

Adaptive empathy: A model for learning empathic responses based on feedback

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Abstract

Empathy is usually deployed in social interactions. Nevertheless, common measures and examinations of empathy study this construct in isolation from the person in distress. In this paper we seek to extend the field of examination to include both empathizer and target in order to determine whether and how empathic responses are affected by feedback and learned through interaction. Building on computational approaches in feedback-based adaptations (e.g., no feedback, model-free and model-based learning), we propose a framework for understanding how empathic responses are learned based on feedback. In this framework, *adaptive empathy*, defined as the ability to adapt one's empathic responses, is a central aspect of empathic skills, and can provide a new dimension to the evaluation and investigation of empathy. By extending existing neural models of empathy, we suggest that adaptive empathy may be mediated by interactions between the neural circuits associated with valuation, shared distress, observation-execution and mentalizing. Finally, we propose that adaptive empathy should be considered as a prominent facet of empathic capabilities with the potential to explain empathic behavior in health and in psychopathology.

Your son had a harsh day at school and fell apart when he came through the door. He recounts that he failed the final math exam. You empathize with his distress and wish to calm him down. You offer him ice cream. He angrily refuses. You explain to him that he did his best. He doesn't respond. You promise to help him next time. He starts to calm down. You're on the right track. Next time, you will not start by offering ice cream.

It is widely agreed that empathy is critical for healthy social relationships. In counseling and psychotherapy literature, being able to become 'tuned' with clients is essential for their recovery (e.g. Rogers, 1957). In developmental psychology, empathic reactions of parents are crucial for childhood development (Levy, Goldstein, & Feldman, 2019) and in social psychology, empathy is associated with helping others (e.g. Morelli, Rameson, & Lieberman, 2014). Although the studies of empathy highlight its fundamental role in relationship outcome, little research directly explored how empathic reactions dynamically change during relationships and shaped by feedback. Here we hold that *adaptation* of the empathic responses based on feedback is a core component of empathic capacity, which we refer to as *Adaptive Empathy*. Relying on recent literature on reinforcement learning models, we propose that choice of empathic response may be adapted based on prediction errors, i.e. difference between actual and expected distress relief, and suggest how such models may capture different aspects of adaptive empathy. We further suggest how different brain networks may support this adaptive process, and how this concept may expand our understanding of psychopathologies.

Feedback-Based Adaptation as an Empathic Skill

Empathy is a multifaceted construct that encompasses both the cognitive and the emotional reactions of one individual (the empathizer) to the observed experiences of another (the target) (Decety & Jackson, 2004; Shamay-Tsoory, 2011). Behavioral and neuroimaging findings have led researchers to identify two broad types of empathic reactions. One is *emotional empathy*, which is characterized by feeling other people's emotions. The other is *cognitive empathy*, which is characterized by understanding

other people's thoughts and motivations (Cuff, Brown, Taylor, & Howat, 2016; Gonzalez-Liencre, Shamay-Tsoory, & Brüne, 2013; Smith, 2006). While definitions of emotional and cognitive empathy vary, the main objective of all empathic capabilities is clearly related to responding to the emotional state of another person. Empathy is thought to have evolved as a response that promotes distress reduction among group members (Decety, Bartal, Uzefovsky, & Knafo-Noam, 2016; Eisenberg & Miller, 1987; Reeck, Ames, & Ochsner, 2016; Telle & Pfister, 2016; Zaki, 2020; Zaki & Williams, 2013). Empathic skills have been shown to play a major role in promoting well-being (Morelli, Lieberman, & Zaki, 2015), parenting (Atzil, Gao, Fradkin, & Barrett, 2018) and easing intergroup tensions (Influs et al., 2019). It has also been implicated in a variety of psychiatric disorders, such as depression, autistic spectrum disorder (ASD), schizophrenia, borderline personality disorder and psychopathy (Gonzalez-Liencre et al., 2013).

Despite a long tradition of studying empathy in social interactions in the fields of social (Stinson & Ickes, 1992; Thomas, Fletcher, & Lange, 1997) and developmental (Hastings, Zahn-Waxler, Robinson, Usher, & Bridges, 2000) psychology, the vast majority of paradigms testing empathy in neuroimaging and cognitive experiments involve passive observation of a suffering target. Typical studies of empathy evaluate a participant through a single reaction to pictures, questionnaires or vignettes depicting others in distress (e.g., Perry et al., 2011, Figure 1A). Focusing on a single empathic response in isolation from the target has been useful in identifying different aspects of empathy. For example, this approach facilitated differentiating between a shared distress network activated during emotional empathy and a mentalizing network activated during cognitive empathy (Eres et al., 2015; Shamay-Tsoory, 2011). Here we suggest that as empathy is associated with relationships with others (Zaki, 2014), it must be examined in the context of dynamic interactions between empathizer and target over time. In such a context, an empathizer can detect the effects of his or her initial empathic response and adapt this response accordingly (Figure 1B). At the heart of our approach is framing empathy as a process that involves a feedback loop, where the likelihood to provide a specific empathic reaction changes during, and across, interactions based on feedback from the target (Main, Walle, Kho, & Halpern, 2017; Tamir & Thornton, 2018; Zaki, Bolger, & Ochsner, 2008) (Figure 2). For example, telling a distressed target to calm down may be helpful in diminishing distress for certain individuals, but for others such a response may backfire and make them more agitated. Indeed, in real-life social interactions empathy does not end when the

empathizer perceives the target's distress or deploys an empathic response (Main et al., 2017; Zaki et al., 2008).

Figure 1 - Illustration of empathic response

Empathic responses to another's distress. In many experimental paradigms empathy is examined in isolation, in response to a set of static vignettes (A). However, in real life we are often face to face with the distressed person (B1) and can provide an empathic response to relieve the distress (B2). This live interaction allows us to detect the effect of our empathic response on the other person, and its effectiveness in relieving the distress, and use this information to adjust our current and future empathic responses, resulting in adaptive empathy. Illustration by Yali Ziv.

The empathizer's responses are received by the target and can cause changes in the target's distress level. The empathizer then observes a consequent change in the target's distress level, triggering a new cycle of empathic response. This cycle can span multiple instances of distress relief during the course of an interpersonal relationship (Goldstein, Weissman-Fogel, Dumas, & Shamay-Tsoory, 2018) or a therapeutic relationship (Barrett-Lennard, 1981). Indeed, as evidenced by parental care, such a cycle can last a lifetime (Atzil et al., 2018). Therefore, we suggest that *adaptive empathy*, defined here as the ability to adjust one's empathic responses appropriately during (online) and after (offline) social interactions, is a core aspect of empathy that should be investigated in addition to static empathic responses. By focusing on adaptive empathy, we argue that empathic reactions are flexible and shaped by feedback.

Here, we synthesize models of empathy with models of learning to propose an integrative neural model of adaptive empathy. Inspired by recent computational accounts of social behaviour (Lockwood, Apps, & Chang, 2020; Lockwood & Klein-Flügge, 2020; Olsson, Knapska, & Lindström, 2020; Tamir & Thornton, 2018; Zhang, Lengersdorff, Mikus, Gläscher, & Lamm, 2020), we suggest three modes in which adaptive empathy can operate, namely open-loop, model-free and model-based adaptation. Within these modes we examine how this framework can be used to characterize different types of learners, e.g. rigid, flexible, and biased, and how one learner can display different adaptive empathy profiles across domains. Measures of adaptive empathy, we suggest, may enhance our understanding of the current prevalent static measures of cognitive and emotional aspects of empathy and propose applications of this approach for understanding psychopathology. Finally, we contend that developing new paradigms for assessing adaptive empathy can expand our understanding of empathy in real-life and encourage the development of novel computational and experimental approaches to investigate empathy.

Modes of adaptive learning - A computational approach to examine learning and adaptation in empathy

To understand and characterize empathy as an adaptive learning process, we adopt methods and frameworks from research in the fields of learning and control (Lockwood & Klein-Flügge, 2020). Computational approaches to learning and adaptation use such mechanisms as reinforcement learning, internal models and predictive coding to track trial-by-trial learning from responses, outcomes and feedback (Huang & Rao, 2011; Rescorla & Wagner, 1972; Sutton & Barto, 2012; D. Wolpert, Ghahramani, & Jordan, 1995). These approaches are based on the notion that actions are selected based on their value and that the value of an action is updated by observing its outcome on a trial-by-trial basis. Actions become associated with outcomes through dynamic interactions with the environment, and these associations are used to guide policies for choosing actions that are most likely to lead to desirable outcomes (Daw, Niv, & Dayan, 2005). These models can therefore be used to characterize the way in which feedback from a distressed target, as well as contextual signals from the environment, can cause empathizers to adapt their initial empathic responses during empathic interaction.

Considering that empathy represents a set of reactions aimed at achieving distress regulation, it is suitable for characterization using a learning framework. Research on empathy indicates that it contains all the elements of a regulatory mechanism (Atzil et al., 2018; C. Heyes, 2018). An external event, someone else's distress, signals a disturbance, a divergence from an optimal state, which needs to be regulated by triggering an empathic response. Empathic responses can be covert (change in mood, emotions and thoughts), but are frequently overt (detectable facial or body expression, verbal responses) and are communicated back to the target. Importantly, the choice of response is guided by experience and expectation of its effectiveness in relieving the distress. After an empathic response has been deployed, feedback about the response's effect is communicated in a similar manner: the target may show diminished distress, no effect or increased distress. On the basis of the target's response the expected effectiveness of the response may be updated, and a new response is being deployed. This cycle can go on until distress is diminished, updating the expected effectiveness of empathic responses for future interactions. The extent to which such a course of action takes place, the domains in which it operates, and the types of information it incorporates, may lead to different modes of adaptive empathy – open-loop, model-free and model-based (Figure 2). In the following sections, we provide some detailed examples of situations in which adaptive empathy is deployed, drawing on the different computations underlying adaptation and learning.

Figure 2 – Three models of adaptive empathy

Adaptive empathy relies on transmission of distress signal from a target (light orange) to the empathizer (light blue). In open loop models, the distress signal triggers an empathic response, but this response is not shaped by feedback about the effectiveness of the response in relieving distress. In model-free feedback models, the empathizer adapts her empathic response in line with incoming feedback about the target's current level of distress. Model based feedback loop further enhances adaptive empathy by incorporating knowledge about the target's beliefs, perspective, and internal state to select the appropriate empathic response.

Open-loop empathy

The simplest mode of adaptive empathy we consider is an open loop account. In this mode, no feedback-dependent learning takes place. That is, the empathizer is unlikely to change the expected effectiveness of empathic response after observing its effect on a target (Figure 2). In such cases, the empathic responses may have been triggered automatically by the distress signal, but do not change over the course of interaction. The initial response may be habitual, and automatically deployed which triggers a cascade of reactions (De Waal & Preston, 2017; Simone G. Shamay-Tsoory, 2011). Indeed, during affective sharing, i.e., sharing the physical pain of another, the target's emotions automatically trigger a corresponding emotional state in the empathizer. The automatic responses elicited by distress cues from the environment may be due to associative learning between sensory cues and somatic responses (Heyes, 2018) and these responses can in turn prepare for actions (e.g. escape or prosocial responses). Automatic reactions such as mimicking (Jospe, Flöe, & Lavidor, 2018) are evident even when the target is not present. For example, we can share the distress of a victim we observe on the news even if we have no previous knowledge of this person and no chance of interacting with her in the future. Importantly, such automatic responses may be manifested as biases or priors in a model-free (or model-based) mode of adaptive empathy, as we will discuss below (Figure 3). The hallmark of open-loop mode is the lack of adaptation, a rigidity in the deployment and update of empathic response when facing the target's feedback.

Neuroimaging investigations of automatic reactions to the pain of others have revealed that in several brain areas responses to one's own pain resemble one's responses to the pain of others (Figure 4). Such studies show that the anterior insula (AI) and the dorsal-anterior/anterior-midcingulate cortex (dACC/aMCC) are activated

in both experienced and observed pain (Bernhardt & Singer, 2012; Lamm, Decety, & Singer, 2011). Such responses may trigger allostatic responses in the empathizer, concerned with diminishing his own distress, engaging the hypothalamic–pituitary–adrenal (HPA) axis (Atzil et al., 2018; Heuser & Lammers, 2003; Keramati & Gutkin, 2014). This consistent response of the shared distress network suggests that it is not readily affected by feedback and will be triggered whenever a distress signal is apparent. Note, however, that this network may change and adapt over time, perhaps by means of top-down control from other networks. Nevertheless, it does not seem to exhibit the hallmark of online adaptation during interaction.

Closing the empathy loop: Model-free reinforcement learning

The main mode of adaptive empathy we discuss is a feedback loop model in which observations of the outcome of our empathic responses inform and affect our future empathic responses (Daw et al., 2005; Tamir & Thornton, 2018; D. Wolpert et al., 1995). Unlike the open-loop model, this model assumes that empathic responses are deployed based on their predicted outcome, i.e., on their expected ability to relieve the target's distress (Figure 2). The outcome of each response is compared with its expected outcome, and any mismatch between expectation and outcome serves as a prediction error used to adapt future responses. In the case of an unexpected outcome, its value is updated. For example, when a reassuring response (e.g., handholding) does not lead to the expected reduction in distress, the response's expected outcome is updated such that it is less likely to be deployed in the future. Such update may take place based on associative learning where the association between empathic response in a specific state, e.g. towards a specific person, and its distress relief is learned over time. This version is referred to as model-free reinforcement learning, or feedback control, where associations of actions and outcomes are learned without incorporating contextual knowledge (Daw et al., 2005; D. M. Wolpert, Doya, & Kawato, 2003).

One example of model-free feedback mechanism of adaptive empathy is synchronization. While the empathizer initially uses automatic mimicry in an open-loop manner (Jospe et al., 2018), over time the behavior of the empathizer becomes aligned and synchronized with that of the target. During synchronization, empathizers can adjust their body posture, tone of voice, and advice content to the target (Barrett-Lennard, 1981), thus potentially relieving the target's distress (Kühn et al., 2010, 2011; Ramseyer & Tschacher, 2011). Feedback and conditioning were shown to affect the

emotional facial expression in response to other's distress (Englis, Vaughan, & Lanzetta, 1982; Levenson, 1996). For example, participants were shown to adapt their emotional facial expression to the one displayed by the distressed person, even when it counters their initial response, e.g. when the distressed person appears to be smiling when experiencing pain (Englis et al., 1982). Building on models of social alignment it was suggested that, during social interactions, a predictive coding mechanism is geared to maximize alignment in movement, emotion, and cognitions with others (Simone G. Shamay-Tsoory, Saporta, Marton-Alper, & Gvirts, 2019). This indicates that alignment with others serves as the optimization principle, and achieving alignment reduces prediction errors, and makes the environment more predictable (Koban, Ramamoorthy, & Konvalinka, 2019).

Feedback does not have to be directly experienced during a dyadic interaction, and may be acquired through observational learning (Burke, Tobler, Baddeley, & Schultz, 2010; Hertz, 2021; Olsson et al., 2020; Schmid, Chatterjee, Hilbe, & Nowak, 2021). The classical work of Bandura (Bandura, 1969) indicates that through the observation of another's behavioral outcomes we may gain knowledge about the possible consequences of related behaviors. In the context of empathy, it is thus possible that observing an unsuccessful empathic reaction of a person may shape the observers' future empathic reactions. In observational empathic learning, observing the demonstrator's empathic responses can serve as a vicarious unconditioned stimulus (US), resulting in an association between the affective experience of the observer and the specific environmental context (Olsson et al., 2020). Notably, it was demonstrated that vicarious fear responses are positively associated with trait empathy (Olsson et al., 2016).

The observation-execution system was shown to be engaged during such adaptive online interaction (Cook, Bird, Catmur, Press, & Heyes, 2014). In motor synchronization, continuous updating requires the existence of a system that observes the target's behavior and automatically activates the empathizer's own representations of this behavior. In turn, output from this shared representation automatically proceeds to motor areas of the brain where responses are prepared and executed (Preston & de Waal, 2002). The inferior frontal gyrus (IFG) as well as the inferior parietal lobe (IPL), which are frequently mentioned as playing a role in emotional empathy (Korisky, Eisenberger, Nevat, Weissman-Fogel, & Shamay-Tsoory, 2020; Simone G. Shamay-Tsoory, 2011; Vachon-Preseau et al., 2012), also participate in observation-execution processes, among them the ability to observe and correspondingly execute specific actions. The IFG was found to participate both in

synchronized finger tapping (Fairhurst, Janata, & Keller, 2013) and in synchronous speaking (Jasmin et al., 2016). Research has demonstrated increased activity in the IPL during both motor (Cacioppo et al., 2014) and emotional (Korisky et al., 2020; Nummenmaa, Hirvonen, Parkkola, & Hietanen, 2008) synchronization. Synchronization is heavily dependent on constant observation and behavioral updating, including predictions of the other persons' behavior (D. M. Wolpert et al., 2003). In addition to the role of the IFG in synchronization, Hein et al. (2015) reported activity in the IFG during learning of empathic responses. The authors show that this learning was driven by classical prediction errors, whose impact on empathy signals was mediated by an increase in positivity toward the out-group member. Notably, activation in the observation-execution system was reported to be coupled between individuals during synchrony. Studies using the second-person approach ([Redcay & Schilbach, 2019](#)), demonstrate inter-brain coupling in the observation-execution system in various types of tasks that involve social interaction. For example, evidence from hyperscanning fNIRS studies points to inter-brain coupling in the IFG during synchronized singing (Shimada et al., 2015). Likewise, studies using dual-EEG show inter-brain coupling in the alpha/mu band (8 to 12 or 13Hz) during synchronized class participation (Dikker et al., 2017). Inter-brain coupling in the alpha/mu band may represent activity in the observation-execution system (Astolfi et al., 2010; Dumas, Nadel, Soussignan, Martinerie, & Garnero, 2010).

A model-free account of adaptive empathy can account for a number of behavioural patterns (Figure 3). To demonstrate these patterns we consider an adaptation of a two-armed bandit task, often used in learning and decision making studies (Hertz, Bahrami, & Keramati, 2018). In a social task, one is faced with a distressed target (Figure 1), and has to choose one of two empathic responses to deploy. One response leads to distress relief, while the other does not. A learner may learn over time which empathic response is most efficient, increasing its expected relief value over time (Figure 3A). Learners may differ in the rate of learning, with some being very flexible and adapting quickly, while others are more rigid and display very little behavioral adaptation. Another distinction has to do with the learner's initial response, which can be described as her prior on the effectiveness of the empathic response, which biases her initial selection (Figure 3B). In such a case the initial bias in likelihood of choosing the response may indicate such priors. Importantly, such initial bias may be the result of lifelong experience (Heyes, 2018), but unlike the open-loop account, here a change and adaptation in behavior occur as the response outcome is revealed. Finally, dynamic responses can differ within learners, as they may be more flexible when learning about one state-action pairs, for example learning in a person-

specific manner (Farmer, Hertz, & Hamilton, 2019; Thornton, Weaverdyck, & Tamir, 2019), but slower to learn across other states (Figure 3C). For example, one may be slower to learn that a different response will be more effective for high intensity distress and another for low intensity distress (Shafir, Thiruchselvam, Suri, Gross, & Sheppes, 2016), than that a response may affect different people in a different way. Finally, it is possible that a mixture of these effects will be apparent, with people having both different learning rates and initial biases in different domains.

All these patterns can arise from using a single, and simple, learning model, by changing the values of parameters such as learning rate and starting condition (and decision noise which is not discussed here, but see (Daw, 2011; Findling, Skvortsova, Dromnelle, Palminteri, & Wyart, 2019). It is therefore possible to use a simple experimental paradigm, where the states at hand are manipulated and a learning model is fitted to participants' responses, to uncover the different adaptive empathy style and constraints displayed by an individual (Lockwood & Klein-Flügge, 2020). Such patterns may include overall slow or rigid adaptation, overall flexibility, or domain specific biases. These can be used to validate and enhance the current measures of empathy, emotional or cognitive, or reveal how previous experience and background may shape future relationships (Levy et al., 2016) by investigating biases in empathic responses. In addition, extending the computational framework to more elaborate models of learning, for example Bayesian accounts of learning under uncertainty (Diaconescu et al., 2014; Siegel, Mathys, Rutledge, & Crockett, 2018), may help characterize adaptive empathy by examining the way empathizers adapt their learning rate in face of volatile scenarios or persons.

There are a number of brain regions known to support associative learning, in non-social and social domains (Behrens, Hunt, & Rushworth, 2009; Olsson et al., 2020). Most notably, the ventral striatum (VS) was shown to track prediction errors in value based decisions (Delgado, 2007; Izuma, Saito, & Sadato, 2008; Schönberg, Daw, Joel, & O'Doherty, 2007), which is at the heart of the learning model described above. Social rewards were also shown to elicit such responses in the VS (Hertz et al., 2017; Klucharev, Hytönen, Rijpkema, Smidts, & Fernández, 2009; Wake & Izuma, 2017). Prediction error related to social behaviour of others were also associated with activity in other brain areas, such as the right temporal-parietal junction (rTPJ) (Behrens, Hunt, Woolrich, & Rushworth, 2008; Bellucci, Molter, & Park, 2019; Koster-Hale & Saxe, 2013) and medial prefrontal cortex (MPFC) (Hertz et al., 2017). These brain areas, part of the brain social system, were associated with learning about others' traits, while

activity in the brain's valuation system (including VS and ventromedial frontal cortex (VMPFC) (Lebreton, Jorge, Michel, Thirion, & Pessiglione, 2009) were associated with social rewards. In the case of adaptive empathy, the processing of empathic response prediction errors may be displayed in both these networks, as one learns about the response most effective to a specific person engaging the brain's social system, but can also be processed in the brain's valuation system, if relieving others' distress is rewarding. Indeed, the balance in the engagement of such networks during empathic response learning may be associated with individual differences in prosocial tendencies and motivations (Lockwood et al., 2017). The participation of the observation-execution system as well as reward-related signals may support a feedback-loop learning process, in which alignment serves as a learning signal leading to changes in empathic responses based on feedback (Simone G. Shamay-Tsoory et al., 2019).

Figure 3 – Model-free adaptive empathy patterns

Adaptive empathy can rely on feedback-based learning model, where an empathic response is selected based on its expected effectiveness in relieving the target's distress, and this effectiveness is learned based on the response outcome, using an associative mechanism. Such a model can give rise to a variety of learning patterns.

(A) Differences in learning rates can lead to a more flexible pattern of adaptive empathy, where the learner adapts quickly to the target, or more rigid pattern of adaptation where learning rates are low. (B) Empathizers can have some initial bias in their response selection (a priori) based on their previous experiences. These biases may change the starting point of the empathic adaptation process, but can still leave room

for adaptation as the interaction unfolds. (C) Adaptation may have different learning profile for different domains. For example, an empathizer may learn quickly about the best empathic response to a specific person, but fail to learn that a similar response is useful across similar distress intensities or in similar situations.

Expanding the loop: Model-based empathic learning

The model-free feedback-loop model of adaptive empathy does not require holding and updating a representation of the targets' beliefs and perspective. It requires learning about state-action pairs, where states could be different persons, different scenarios that triggered the distress (physical pain, disappointment, grieving, and so on), or different emotion intensity. However, during empathic interaction one may also use a representation of the other person's perspective and beliefs (Den Ouden, Frith, Frith, & Blakemore, 2005; Frith & Frith, 2003). Incorporating such information about the target's beliefs and internal states into the learning process is referred to as model-based learning (Daw et al., 2005; Gershman, Norman, & Niv, 2015; Wolpert et al., 2003) (Figure 2). A model-based mode of adaptive empathy which can therefore rely on previous knowledge of human behavior as well as on a mentalizing process in which mental states are inferred and attributed to specific persons. This knowledge, in turn, is applied when reacting to the behavior of others. This process, also known as theory of mind (ToM), has been shown to be affected by culture and developmental stage (Frith & Frith, 2003; C. M. Heyes & Frith, 2014). ToM requires high-order cognitive abilities such as cognitive flexibility (Decety & Jackson, 2004; Simone G. Shamay-Tsoory, Tomer, Goldsher, Berger, & Aharon-Peretz, 2004) and episodic memory (Perry et al., 2011). In model-based learning, rather than simply updating the expected outcome of a response based on the current outcome and state, the learner also maintains an internal model of the target's beliefs, traits and goals, and uses this model for adaptation. For example, a person may be distressed because he thinks he is more severely sick than he really is. Recognizing this gap may be useful in providing an empathic response, either by not underestimating what the empathizer knows is an exaggerated distress, and also by choosing a reaction that will help the target realize his distress is misplaced. A physician dismissing a patient by telling him he suffers from hysteria is failing to use model-based empathy, as does a physician giving in to the patient by subscribing unnecessary treatment.

One example of an empathic response that relies on ToM is the recommendation of a regulation strategy for the target. Levy-Gigi and Shamay-Tsoory (2017) showed that regulation strategies chosen by the empathizer in the context of long-term romantic relationships were more effective at reducing distress than those selected by the target. Moreover, higher levels of trait cognitive empathy predicted successful regulation of the target's emotions, suggesting that the ability to implement previous knowledge about the target is an important factor in distress relief. Borrowing from the two-step decision task (Sharp, Foerde, Daw, & Shohamy, 2016), commonly used to distinguish model-based and model-free learning, we can test whether empathizers use only the target's expressed distress signal, and to what extent they incorporate knowledge about the target's state when making their decision. For example, one can observe that when her toddler states that he is hungry, only about 70% of the times providing him with a snack will relieve his distress, while sometimes he is finally being contented with a nap. This random pattern can be a source of frustration to her, as snack is the best response that can be inferred from the state and outcome – with association of 70%. However, she may realize that in many cases, 30% of the time, her son states that he is hungry when he is in fact tired. Incorporating this knowledge, his mother may be able to relieve her son's distress with a snack or a nap, according to her son's activities during the day (Figure 4).

Figure 4 – Model-based adaptive empathy

Model free mode of adaptive empathy (right) associates expressed distress signals with the effectiveness of empathic responses. An empathizer may learn in this manner that when his toddler states that he is hungry, giving him a snack will relieve his distress on 70% of the times (blue arrows), while on 30% of the times this response is not effective (red arrows), which makes it the most effective response most of the time. This will lead him to use the response ‘snack’ whenever his child says he is hungry. A model-based empathizer (right) learned that her child’s inner states of ‘tired’ and ‘hungry’ sometimes (30% of the times) generate inappropriate distress statements (red arrow). By incorporating this knowledge, and her knowledge about events prior to the statement, she can recognize inappropriate statements and provide the most effective response. When her child states that he is hungry immediately after a snack, a model-based response will be a nap. When her child states that he is hungry after having a nap, the most effective response will be a snack.

Considering that model-based learning requires representing the mental states of others (e.g., beliefs, desires, intentions, and so on), this type of learning may be

mediated by the mentalizing brain system (Abu-Akel & Shamay-Tsoory, 2011). The network associated with mentalization involves the medial prefrontal cortex (MPFC), the temporal lobe (TPJ), and the posterior superior temporal sulcus (pSTS) (Dulau, 2015; Simone G. Shamay-Tsoory, 2011; Singer, 2006; Van Overwalle & Vandekerckhove, 2013). The brain areas implicated in mentalizing have also been shown to underlie tracking other people's behavior and learning about others (Bellucci et al., 2019; Olsson et al., 2020). Likewise, Hallam et al. (2014) demonstrated that the left anterior temporal pole and the MPFC are active during a task of interpersonal emotion regulation. Evidence from strategic social games suggests that the prefrontal cortex, including the MPFC and the dorso-lateral prefrontal cortex (dlPFC), are engaged in building models of social interactions and relations (Hampton, Bossaerts, & O'Doherty, 2008; Hertz et al., 2017; Kumaran, Banino, Blundell, Hassabis, & Dayan, 2016), and their activity represents depth of strategic reasoning (Coricelli & Nagel, 2009; Yoshida, Seymour, Friston, & Dolan, 2010). It therefore appears that the mentalization system may contribute to choosing a regulation strategy, as it is necessary to understand the target's mental state in order to try to change it (Zaki, 2020; Zaki & Williams, 2013).

A model of adaptive empathy

As we demonstrated above, we propose an adaptive empathy framework that considers three learning modes (Figure 2). When the empathizer observes someone in distress, an automatic distress mechanism, such as the shared distress network, is activated and can provide empathic responses in an open-loop manner. State dependent responses, learned in a model-free manner through previous experiences, may also provide initial empathic response based on expected effectiveness. Once feedback is available, an observation-execution system may participate, adjusting the empathic response according to the target's response and updating the expected effectiveness of the response according to the current state, e.g. person, emotion intensity, and environmental cues, in a model-free manner. In addition, the mentalizing system may come into play when the empathizer cognitively adopts the perspective of the other (Simone G. Shamay-Tsoory, 2011). The mentalizing system may be used to incorporate knowledge about the target's point of view, beliefs, and inner states, to inform the decision on the most effective empathic response in a model-based manner.

It is important to note that these modes of response are not mutually exclusive, and may operate one at a time or simultaneously, as suggested in the learning and

cognitive control literature. For example, in the classic two-step decision task used to identify model-based and model-free decision-making patterns in humans (Daw, Gershman, Seymour, Dayan, & Dolan, 2011), participants usually exhibit a mixture of model-based and model-free patterns. It is possible that cognitive and emotional empathic responses rely on open-loop patterns, model-free learning and model-based learning. The exact contribution of each may be flexible and appropriate to the task at hand. However, the examples given in figures 3 and 4 describe how experimental paradigms that can be useful in disentangling complex pattern of dynamic empathic responses, and evaluate the contribution of different mode of response under different experimental conditions.

While several other neural networks may mediate adaptive empathy, the proposed framework immediately points to four candidate core brain networks that are associated with different computations supporting the different modes of adaptive empathy suggested above (Figure 5): a shared distress network that is automatically activated following detection of distress in the target (open-loop), an alignment system responsible for adjusting responses to the target over time (model-free), and a mentalizing network that tracks understanding the other's mental state in a social context (model-free and model-based). The fourth system is the reward/valuation system which follows and reacts to changes in the world, mostly those associated with rewards, which may track changes in the target's distress based on feedback. The role of the reward system may be to assign value to the empathizer's reactions and therefore contribute to adapting the responses based on feedback from the target. The valuation system may assign value not only based on the relieve of the target's distress, but also to the consequent self-distress (Lamm et al., 2011). It may be that other brain networks, such as the social brain network, may perform the same computation of change detection. These networks represent different computations associated with our framework, and future research may examine their role during empathic interaction. One possibility is that the engagement of the valuation system will be dependent on the social motivation of the empathizer, modulated by their prosocial tendencies (Crockett, Siegel, Kurth-Nelson, Dayan, & Dolan, 2017). It may also be that different networks provide distinct behavioural effects, with the observation-execution network providing fine-detail short term adaptations within an interaction, and the mentalizing and social brain areas contributing to long term effects, carried from one interaction to the other.

Note that although we focus here on the brain networks that participate in empathy, it is highly likely that these same networks also mediate the target's behavior.

For example, the observation-execution network facilitates *mutual* alignment between the target and the empathizer. In addition, a person in distress may track the expected responses of a specific empathizer. For example, we may expect a close friend to hug us when we are in distress but be put off by similar behavior of a stranger.

Figure 5 – model of adaptive empathy

Our proposed model incorporates four core brain networks which may underlie different components of adaptive empathy. Shared distress network (light yellow), including ACC and Insula, and HPA axis (not depicted in the illustration) may operate as automatic distress detection, open-loop component. Observation-execution network (light green), including IFG and IPL, may underlie dynamic model-free adaptations, for example during imitation and synchronization. Mentalizing network (light blue), including MPFC and rTPJ, may track person specific responses' effectiveness, and incorporate internal models of the person in distress to inform the empathic response in a model-based manner. Change detection in the valuation and reward system (light red), including the ventral striatum and vMPFC, may detect the outcome of the selected empathic response, and send change signals to adapt future responses.

Out of the loop: Psychopathologies that involve impaired adaptive empathy

Beyond characterization of adaptive empathy dimension in the general population, the proposed adaptive empathy framework can be used to understand the social deficits presented in different psychopathologies in terms of how they are related to malfunctioning aspects of the adaptive process. Since empathy requires both emotional identification and emotional sharing (Bird & Viding, 2014), it could be the case that an individual is incapable of discerning changes in the target's emotion (e.g. Coll et al., 2017) and therefore would fail to learn how to adapt the empathic response. Similarly, variations in the tendency to learn from social feedback (Olsson et al., 2020) or in adaptation of learning rates according to environmental or person specific volatility (Diaconescu et al., 2014; Siegel et al., 2018) could also account for poor adaptive empathy. One example of a population which may exhibit difficulties in adaptive empathy is autism spectrum disorder (ASD), a condition that affects the way individuals interact with other people. Although research has repeatedly demonstrated that individuals with ASD exhibit aberrant empathy (e.g., S. G. Shamay-Tsoory, Tomer, Yaniv, & Aharon-Peretz, 2002), evidence regarding the exact empathy deficit found in ASD is conflicting. While individuals diagnosed with ASD have been shown to exhibit difficulties in mentalization (Baron-Cohen, 2002; Fletcher-Watson, McConnell, Manola, & McConachie, 2014; Frith & Frith, 2003; Gaigg, 2012; Jones, Happé, Gilbert, Burnett, & Viding, 2010; Ponnet, Roeyers, Buysse, De Clercq, & Van Der Heyden, 2004; Schwenck et al., 2012), some researchers have suggested that individuals with ASD exhibit preserved (e.g., Mazza et al., 2014) and even heightened (Adler, Dvash, & Shamay-Tsoory, 2015) emotional empathy. Yet they have been shown to demonstrate poor performance on tasks that involve synchrony (Cheng, Kato, & Tseng, 2017; Feldman, 2007; Fitzpatrick et al., 2016; Marsh et al., 2013). The adaptive empathy approach may resolve these contradictory findings. It is possible that individuals with ASD have difficulties with adaptive empathy. Poor feedback-based learning capacities in the social domain may impair their ability to synchronize and mentalize, while their shared distress response remains intact. In line with this notion, Bolis and Schilbach (2017) suggested that people with ASD show difficulties in real-time interactions that require generation of adequate behavioral responses in the context of ongoing and reciprocal behavior. This implies that individuals with ASD may be capable of appropriately detecting the distress of others (open-loop), serving as input to the empathic processes. Yet they may have problems aligning (model-free) and selecting the correct response as well as problems incorporating and inferring the mental state of other people (model-based). Indeed, Rosenthal et al. (2019) recently characterized specific impairments in model-based mentalizing among ASD

participants, showing that ASD participants demonstrated specific impairments in using their estimates of agent belief to understand agent intentions.

Examining model-based and model-free empathy in ASD may help lay the foundations for developing a new hypothesis to explain social deficits in ASD in terms of an adaptive empathy disorder. The clinical implication of such a hypothesis is that interventions for improving social deficits in ASD should focus on training individuals to react to feedback from a change in response.

Future directions: Adaptive empathy as an empathic skill

An important implication of focusing on the impact of feedback on empathy is the notion that such adaptation of the empathic response is an important empathic skill. Indeed, adaptive empathy is crucial for social interactions as adaptation of empathic responses may help regulate a target's distress by providing a more attuned and appropriate response (Figure 1). Future studies can demonstrate what types of response can be adapted, to what extent and for how long, and how this adaptive skill is related to trait empathy scales. Such studies can ultimately lead to new interventions that focus on training adaptive empathy.

We propose here three modes that are associated with different types of empathic computation (open-loop, model free and model based learning) which may rely on different neural networks and their interaction (Figure 5). Adaptive empathy may therefore include a variety of computational, cognitive, and neural features, and their combination may give rise to complex behaviors. We suggest that taking the dynamic dimension of empathy into account can enhance our understanding of the empathy construct, for example by examining the relationship between adaptive empathy and trait empathy, which is currently tracked using questionnaires and non-interactive tasks, and relate adaptive empathy with other social behaviors such as prosocial learning (Crockett, Kurth-Nelson, Siegel, Dayan, & Dolan, 2014; Lockwood, Apps, Valton, Viding, & Roiser, 2016). It may also help construct more ecological experiments, examining how empathy may operate in real-life interactions. As model-based learning was shown to be dependent on developmental stages (Decker, Otto, Daw, & Hartley, 2016), in line with the development of ToM (Frith & Frith, 2003), our framework may be useful to examine development of empathic trait and skill in children and adolescents. As we focus on social interactions, our approach directly lend itself to examining parent-child interactions and how the adaptive empathy skills of parents impact development of these skills in their children (Atzil et al., 2018; Levy &

Feldman, 2019). Finally, such tasks can also be used to characterize specific social deficits in clinical populations, adding a new dimension to the assessment and description of psychopathologies such as autism spectrum disorders (ASD). It is important to note, that we do not address other important aspects of empathy, and social learning in general, such as social motivation and social perception. Motivation plays an important role in the decision to engage and provide an empathic response (Cameron et al., 2019; Hughes, Zaki, & Ambady, 2017; Mccall & Singer, 2012). Indeed, engaging in an empathic interaction can be taxing (Coetzee & Klopper, 2010), and sometimes the role of empathy is to realize when not to engage. Detection of distress signals is also crucial in the triggering of empathic process, making the two concepts confused in some cases (Coll et al., 2017), and problems in detection of emotional signals can lead to deficits in empathic behaviour, while enhancing social saliency may result in increased empathy (Abu-Akel, Palgi, Klein, Decety, & Shamay-Tsoory, 2014; Iria & Barbosa, 2009; Simone G. Shamay-Tsoory & Abu-Akel, 2016). While both these concepts, and many others, are important to describe engagement in empathic interaction, they fall beyond our current scope. We show here that even when assuming an intact ability to detect distress signal and contextual information as well as motivation to engage in an empathic interaction, This new approach may provide a much-needed new dimension of empathy to explain how this construct operates in real-life social interactions.

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