# Psychological and Neural Mechanisms of Stay/Leave Decision Making

by


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III. Amber Heijne & Alan G. Sanfey (in preparation). Social versus nonsocial reinforcement learning: Resisting against the effect of priors.

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# Chapter 1

## *General Introduction*

Every day, people are faced with a constant stream of decisions, such as perceptual decisions (i.e., look at street signs to navigate), habitual decisions (i.e., going to work every day), consumer decisions (i.e., buy Pepsi rather than Coca Cola), financial decisions (i.e., buying health insurance), medical decisions (i.e., getting a risky surgery), moral decisions (i.e., donating to charity) and social decisions (i.e., asking someone out on a date). Understanding how people make decisions is highly relevant to society such that it can help people to make better decisions; and it is highly interesting on a scientific level, such that it increases knowledge about the internal workings of the human mind and brain.

A challenge for decision making researchers, however, is that no decision is exactly the same as another, such that a large variety, and combination, of predictors can output a large variety of behaviors that may even differ within and between individuals. For example, the decision to buy health insurance may depend on the cost of insurance, my general health, the norm that one should have health insurance, my perception of the risk associated with not having health insurance; and even if all those factors are the same today as tomorrow, I might not decide to buy health insurance but I will tomorrow. To study decision making processes, it is therefore useful to focus on more basic type of decisions that may form the foundation of many (higher-order) different types of decisions.

One such basic type of decision is the decision to maintain a currently chosen course of action, or rather to switch to an alternative course of action; or alternatively put, the decision to stay or leave. In fact, the decision to stay or leave implies a behavioral change and has a broad potential for application. That is, I make a stay/leave decision when I decide to get health insurance even though I never did, but also when I rush to catch my usual train to work (i.e., stay) rather than taking the next train; when I decide to stay in academia (i.e., stay) or find a job in industry (e.g., leave).

Given that the decision to stay or leave applies to many different types of decision problems, it has received attention from different research fields, using different perspectives and methodologies and even using different species. To illustrate, social psychologists built theories about potential determinants of social relationship maintenance; mathematicians have build formulas with which they can compute when an agent should continue a course of action or explore alternative courses of actions to maximize its payoffs; and animal researchers have investigated how animals decide to exploit a current food patch or rather explore the environment for potentially better food patches.

Because of this wide-spread attention for stay/leave decision making however, the information available on this topic is highly shredded. While this means that different scholars have already solved different parts of the stay/leave decision making puzzle – that we can use to our advantage -, it also poses a big challenge. That is, to provide a complete account of stay/leave decision making, we have to bridge the gaps between different pieces of information; reconcile potentially opposing insights about stay/leave decision making from different contexts; and incorporate theories, methods and findings from research that was not even designed to study stay/leave decision making per se but may help to put things in perspective. The only way to pose this challenge is to take on an interdisciplinary research approach that integrates knowledge and tools from different fields.

I will use a Neuroeconomics approach which entails that I use knowledge and tools from the fields of Psychology, Economics and Neuroscience to gain a better understanding of stay/leave decision making. To explain why this approach is advantageous, let me describe the strengths and weaknesses of each of the three fields.

### *PSYCHOLOGY*

The strength of the field of psychology is that, for more than a century, psychologists have closely and systematically observed animal and human behavior; and that they have build extensive and useful theories about how behavior is shaped by our environment. Some weaknesses of this field however are that these theories do not make specific predictions about behavior that can be tested; and that measurement of behavior often has included self-report questionnaires and hypothetical scenarios of which the validity has been questioned.

### *ECONOMICS*

The strength of economics is that it has the mathematical tools to transform theories to formal models which with specific behavioral predictions can be made; and that it provides sophisticated experimental paradigms (i.e., economic games) with which the predictions of these models can be tested. A weakness of this field however is that, for a long time at least, Economists have build models that describe what a purely rational and selfish agent would do. Not surprisingly, the predictive value of these models is rather weak.

### *Neuroscience*

The strength of the field of neuroscience is that it can (a) provide biological back-up for existing mechanistic theories of human behavior; (b) help to disentangle alternative mechanistic explanations for the same behavior; and (c) help to formulate new and well-informed hypotheses about the underlying mechanisms of human behavior. A weakness of this field however is that it is relatively young and that a clear brain region to brain function mapping is missing. It is therefore difficult to neural activation and psychological theories and economic models of human behavior our necessary to make sense of activated brain regions.

### *Neuroeconomics*

What becomes clear from the above is that the three disciplines both need as well as complete each other. By combining the three disciplines when investigating stay/leave decision making processes, I will therefore be able to provide a more complete account of these processes. Specifically, in the present study I will use knowledge and tools from Psychology, Economics and Neuroscience to form a more unified understanding of (a) how our experiences shape the likelihood of staying versus leaving; (b) how prior expectations affect these temporal dynamics of stay/leave decision making; and (c) how nonsocial stay/leave decision making mechanisms relate to the decision to stay with or leave a social relationship partner.

The field of psychology provides important information on stay/leave decision making from two perspectives. One is relevant to the decision to stay with or leave a social relationship partner specifically, and that is the literature on relationship maintenance; the other is the literature on (operant) conditioning, which demonstrates how animals' behavioral decisions can be shaped by trial-and-error learning processes and is potentially relevant to how people's experiences change their likelihood of staying versus leaving.

The branch of social psychology has provided a wealth of literature on how a variety of factors may affect social behavior in general, and many of them have also been found to affect social relationship maintenance. A list of these predictors includes individual factors such as one's personality traits or attachment style; affective states such as social (i.e., empathy, guilt, envy, embarrassment) and emotions in general (i.e., joy, sadness, anger, disgust); social motivations, such as reciprocation, fairness, equality and belongingness); social norms, such as what everybody does (e.g., descriptive norms) or what one is ought to do (e.g., injunctive norms); social or psychological distance towards a social interaction partner (i.e., close friends, family members or romantic partners versus distant colleagues, acquaintances and strangers); perceptual and contextual factors (i.e., facial characteristics of an interaction partner, smells, sounds); mindsets, such as an approach or avoidance mindset or mindfulness; and habits.

We can thus assume that the list of factors influencing *social* stay/leave decision making is large, and that pretty much any factor known to influence behavior may also influence the decision to stay with or leave a social partner. Unfortunately however, although this list may be useful, it cannot predict when someone is going to stay or leave, and it fails to provide a unified theory or mechanism explaining why all these factors affect relationship maintenance in some way or another. Surprisingly enough, the field did start off with more explanatory theories on social relationships and relationship maintenance that may help to explain why one would decide to stay with or leave a social relationship partner.

One of the earliest theories on social relationships (Interdependence Theory; Thibaut & Kelley, 1958; Kelley & Thibaut, 1978) started with the notion that people need each other; and that this state of mutual dependence leads people to form and maintain social bonds with each other. Essentially, this theory thus transforms social relationship to a form of economic commitment (e,g., social exchange) in which people exchange and reciprocate each other's resources. Even more, according to this theory, people keep track of relationship rewards (e.g., exchanged resources that are reciprocated) and costs (e.g., exchanged resources that are not reciprocated). For instance, reciprocated trust would be a relationship reward while unreciprocated trust would mean a relational cost. Somehow, the combination of rewards and costs would then make up a relational outcome, which would be compared against a comparison level to evaluate these relationship outcomes.

Logically, one would decide to stay when relationship outcomes are high and leave when they were low. Indeed, the *Investment Model* (Rusbult, 1980; 1983; Rusbult & Farrel, 1983; Rusbult & Johnson, 1986) extended *Interdependence Theory* to relationship maintenance. Specifically this model stated that the resources invested in a relationship (e.g., investment size), the rewards obtained from the relationship (e.g., satisfaction level) and the comparison level (e.g., quality of available alternatives) together made up a person's commitment level, or in other words, a person's intention to maintain the relationship. In the next decades of research on relationship maintenance, support for the *Investment Model* was found such that the Investment Model variables were consistently found to predict relationship maintenance and even actual relationship maintenance in various types of social relationships well (for reviews see Cate et al., 2002; Le & Agnew, 2003; Le et al., 2010), but also a variety of other factors were linked to relationship commitment and maintenance (see Cate et al., 2002; Ogolsky & Bowers, 2012).

As stated above, the Investment Model conceptualized Thibaut and Kelley's comparison level as the 'quality of availability alternatives' and was later even typically conceptualized as the availability or attractiveness of alternative romantic partners in *romantic* relationship maintenance (Johnson & Rusbult, 1989). However, this was not in line with Thibaut & Kelley's original account of the comparison level which, they stated, was based on people's prior beliefs about relationships. While this expectations account of social relationship evaluation was the biggest addition that *Interdependence Theory* made to existing social exchange theories (Emerson, 1976), it was completely ignored in all subsequent research on relationship maintenance that was even indirectly build upon this theory.

Even more, a different role of prior expectations and beliefs in cognition and behavior was found in the Confirmation Bias which was defined as peoples' tendency to behave in ways that confirms their prior beliefs, such that they search for information that confirms rather than discredits their beliefs; that they weight information consistent with their beliefs stronger than belief-inconsistent information when updating their beliefs; and that they may remember information that is in line with their prior beliefs and forget information that is not in line with their beliefs. Importantly, Interdependence Theory and the Confirmation Bias make opposing predictions about how prior beliefs or expectations affect stay/leave decision making and I will get to that in Chapter 2 and 3.

Another account of *Interdependence Theory* that did not get any attention in later research on relationship maintenance is their claim that relationship outcomes are based upon relationship rewards and costs. Even more, no research exists that investigates *how* relationship rewards and costs, over time, change one's likelihood of staying with or leaving. Interestingly, some insights into this question come from an entirely different branch of psychology, which is the field of animal psychology. That is, animal psychologists have demonstrated how trial-by-trial experiences of animals change their trial-by-trial likelihood of repeating a behavior (e.g., stay) or to avoid it (e.g, leave).

This line of research all started when E.L. Thorndike (Thorndike, 1901) observed his cats trying to escape from puzzle-boxes and realized that they learned to repeat (e.g., stay with) actions that had turned out to be effective and avoid (e.g., leave) actions that had been less effective to get out of the boxes. Thorndike then formulated the *law of effect,* which stated that '*responses that produce a satisfying effect in a particular situation become more likely to occur again in that situation'*. Even more, consistent with this law, the behaviorist B.F. Skinner than provided extensive experimental evidence that rewarding (i.e., giving a food reward) specific actions (i.e., pressing a lever) increased the likelihood that an animal would perform an action again, whereas not rewarding or even punishing (i.e., giving the animal an electrical shock) an action would lead the animal to not perform the action again.

Even more, after reviewing literature on animal learning, two experimental psychologists theorized that it is not a positive or negative outcome of an action per se that changes the likelihood of an animal repeating a behavior, but rather the fact that the outcome was expected or not (e.g., temporal difference learning; Rescorla & Wagner, 1972). That is, once an animal learned to associate pressing a lever with receiving a food reward, learning will stop as long as the behavior keeps being followed by the expected reward. However, only when the reward is *unexpected* (i.e., even better than expected or worse than expected), the rat will update the expected value of the behavior (i.e., learn). Thus, actual outcomes are thus constantly compared to expected outcomes to update behavior. Interestingly, albeit on a different level, this account shows close resemblance to Thibaut & Kelley's proposal that actual relationship outcomes are compared to people's prior beliefs about relational outcomes (e.g., comparison level).

To sum up, the field of psychology, on the one hand, provides us with the insight that a higher order type of stay/leave decision making, which is the decision to stay with or leave a social relationship partner, may depend on value-considerations. It is less clear however how different factors together make up the decision to stay or leave; and specifically, the role of prior experiences on subsequent social stay/leave decision making remains unclear. However, observations about animal learning behavior indicate how positive and negative experiences may shape decision making through the deviations of actual experiences from expected experiences. An open question however is whether positive and negative relationship experiences shape the likelihood of staying with versus leaving a social partner in the same way.

## ECONOMICS

A cornerstone of the field of economics is the concept of value and the idea that people choose options that are most valuable to them (e.g., value-maximization). Interestingly, this concept is in line with psychological theories that stated that suggest that stay/leave decision making in social relationship depends on value-considerations; and with operant conditioning theories which demonstrates that the likelihood of an animal performing a specific action depends on the associative value of those actions. The field of economics, however, provides some important contributions to the concept of value-based decision making.

One issue with the notion of value-based decision making or value-maximization is that if one always stays with the option with the highest expected value, he or she will never learn if there are better options out there. Deciding to exploit the option with the highest known expected value may thus lead to suboptimal outcomes. How does an agent balance exploitation with exploration? In fact, different research fields (i.e., animal literature, machine learning, game theory) have concerned themselves with this decision problem, which led not only to the development of reinforcement learning models, but also to mathematical solutions for the exploitation/exploration trade-off. Very briefly, the generally accepted way to compute a decision makers' choices in any learning task is to update the expected value of each option, once it gets chosen, with reinforcement learning models, and to transform the expected values of each choice option to selection probabilities on a trial-by-trial basis (Sutton & Barto, 1998). Specifically, the softmax selection rule is used to give options with a relatively high expected value, a higher chance of being selected.

A second issue is the question what is value made off? Traditional economists assumed that valuable options were options that increased outcomes to the *self*. However, when game theorists started to investigate strategic decision making in social economic games, they found that people often did not choose options that were maximally valuable to the self, but instead were valuable to another person. For example, when people were asked to share money with another person (e.g., the Dictator Game), traditional economists predicted that those people would keep all money to themselves but in reality people did decide to share and some even shared their money equally with others. While at first these social decisions were labeled as being irrational, economists later acknowledged that social motivations also may be valuable to the self. For example, concepts such as equality or fairness (Thompson & Loewenstein, 1992; Loewenstein et al., 1993) can be valuable, because equity is socially accepted and because behaving in equitable ways would thus increase one's social reputation, which in turn is valuable to the self (Boero, et al., 2009). Thus, following modern economist theories, social value may impact decision making in the same way as nonsocial value does. To illustrate, reinforcement learning models have also been able to predict decision making in social learning tasks, such as the learning of social norms (Xiang, et al., 2013), the emotional valence of faces (Lin et al., 2013), social approval (Jones et al., 2011) and a person's trustworthiness (Delgado et al., 2005; Fareri et al., 2012b; Fouragnan et al., 2013).

In the previous paragraph I already mentioned one economic game that was typically used by game theorists to investigate social strategic decision making (e.g., the Dictator Game). Importantly, game theory provides a large collection of these economic games that are both simple as well as highly sophisticated in simulating social interactions between people in which they can behave selfishly or prosocially; and thus could be used to study social behavior in other contexts as well.

To highlight, the Dictator Game (Kahneman et al., 1986) which originally was used to measure irrationality, is now used to measure equitable behavior. Specifically, in this game in which an endowment is shared between two players, the first mover (e.g., the Dictator) receives a personal endowment (i.e., 10 Euros) at the start of the game and is asked if, and if so how much, he/she wants to share some of the money with the recipient. The second mover (e.g., the recipient) then simply receives the money the Dictator decided to share, but is otherwise entirely passive. Several extensions of this game are also used such as the Ultimatum Game (Güth, et al., 1982) in which the first mover (e.g., the Proposer) receives an endowment which he/she can decide to share with a second mover (e.g., the Responder), but after which the Responder may decide to accept the money or reject it in which case both players receive no money.

Even more, another popular game (especially in the context of social learning) is the Trust Game in which the first mover (e.g., the Truster) receives an endowment and decides to transfer some of that money to the second mover (e.g., the Trustee). Any transferred money is then multiplied by a factor (i.e., usually three or four) after which the Trustee may decide to transfer back some of the multiplied money to the Trustor. Importantly, the amount of money the Trustor transfers is a measure of his/her trust in the Trustee; and the amount of money the Trustee sends back is a measure of his/her trustworthiness. That is, if the Trustor trusts the

Trustee to reciprocate half of the money, he/she should invest the entire endowment (with the risk of ending up with no money), but if the Trustor expects the Trustee to keep any transferred money, he/she should not invest any money. The field of Game Theory also provides a variety of other economic games, such as the Prisoners' Dilemma, Public Goods Games and the Stag-Hunt Game that measure cooperativeness, and many other games designed to measure specific strategic social decisions.

In sum, the field of economics thus offers solutions to the exploitation/exploration trade-off that typically arises when one needs to make a value-based (i.e., stay/leave) decision without knowing the long-term expected values of each option. Even more, the field suggests that socially valuable choice options are also valuable to the self; and provides an extensive collection of economic games that can be used to study actual stay/leave decision making between people.

## NEUROSCIENCE

In line with psychological theories of (stay/leave) decision making and economic theories about decision making in general, the field of neuroscience provides neural support for the idea that, at least a large variety of both individual and social decisions depend on value considerations. That is, a large share of the brain regions typically found to contribute to various decision making tasks (Knutson et al., 2000; Rushworth, et al., 2011) are also typically implicated in the representation of value (see Bartra et al., 2013).

Even more, neuroimaging studies in both primates and humans suggest that the brain uses a common currency for value (Chib et al., 2009; Izuma et al., 2008; Kim et al., 2011; Levy & Glimcher, 2011; Lin et al., 2012; Sescousse et al., 2014), such that the subjective value of decision options and their outcome value is represented by the same brain regions irrespective of their nature. To illustrate, activation in especially the ventromedial prefrontal cortex / medial orbitofrontal cortex (vmPFC / mOFC) and striatum correspond to the subjective value of foods (Kringelbach et al., 2003; O'Doherty et al., 2000; O'Doherty, et al., 2002; Plassman et al., 2007, 2010; Small et al., 2001, 2003) and drinks (McClure et al., 2004; Plassman et al., 2008), odors (Anderson et al., 2003; de Araujo et al., 2005) and musical tones (Blood & Zatorre, 2001) and money (Knutson et al., 2000, 2001a; 2001b; Pessiglione et al., 2006), but also moral value (Shenhav & Greene, 2010) and social value such as  the value of viewing attractive faces (Kampe et al., 2001), getting social approval/acceptance (Jones, et al., 2011), donating money to charity (Moll et al., 2006; Hare et al., 2010), equitable treatment (Tabibnia et al., 2008), altruistic punishment (deQuervain et al., 2004), reciprocation of trust by trustworthy others (Phan et al., 2010) or sharing rewards with close others (Fareri et al., 2012b). In addition, lesions in ventromedial frontal lobes in humans is associated with disrupted value-maximization in food decision making tasks (Camille et al., 2011).

Importantly also, neuroscientists have provided biological support for temporal difference learning models (see Lee et al., 2012) which suggest that experiences may shape decisions based on prior positive and negative experiences associated with each decision. That is, electrophysiological studies in non-human primates demonstrated that the firing rates of dopamine receptors in the primate brain (e.g., midbrain and ventral tegmental area) corresponded to prediction errors these animals experienced (see Asaad & Eskandar, 2011; Schultz et al., 1997; 2000). Moreover, a similar neural prediction error signal was later replicated in the human brain in nonsocial (Abler, et al., 2006; Berns et al., 2001; O'Doherty et al., 2003; Delgado et al., 2000) and social contexts (Harris & Fiske, 2010) such that activation in the human striatum also corresponded to the experience of prediction errors. Importantly, the striatum is known for its richness in dopamine receptors, and a solid link between the neurotransmitter dopamine and learning has therefore been proposed (Glimcher, 2011).

Consistent with this, individual difference in striatal responsiveness to prediction errors is associated with individual differences in learning (Schönberg, et al., 201?); is diminished when prior information about choice options is available and less learning takes place (Biele et al., 2011; Doll et al., 2009; Fareri et al., 2012; Fouragnan et al., 2013; Li et al., 2011). Furthermore, genetic variations in dopaminergic genes are associated with individual differences in learning rates (Krugel et al., 2009) and exploration/exploitation (Frank et al., 2009; Sallet & Rushworth, 2009).

However, quite some debate still exists about the exact role of each region (see Rushworth et al., 2009; Rushworth et al., 2012). An illustrative example is the debate on the role of the anterior cingulate cortex (ACC) in decision making. The ACC is not necessarily implicated in the *representation* of value, but appears to play an important role in value-based decisions even so. Some suggested roles of the ACC are that it signals decision conflict (Pochon et al., 2008) which is the case when the values of alternative choice options lie close together (see also Kolling et al., 2013). Alternatively, a recent popular function of the ACC is that it represents the value of switching, foraging or exploration (Kolling et al., 2013; Hayden et al., 2011), but that function has been disputed already (Shenhav et al., 2014). Another proposed function is that the ACC signals the cost associated with specific decisions, and may therefore contribute to cost-benefit trade-offs (Croxson, et al., 2009; Kennerley, 2012). Potentially related to this latter claim are that, in a social context, it has been found that ACC activation is increased when people decide to break rather than reciprocate trust (Baumgartner, 2009).

In sum, the field of neuroscience has provided biological back up for many psychological and economic theories and models of value-based decision making and indicate that the value of choice options and their outcomes is independent of the nature of these options and outcomes, such that socially valuable options are represented by neural signals in the same areas as individually valuable options. However, the exact role of each brain region is not entirely clear yet, which makes interpretation of neural activation associated with value-based decision making a challenge.

## Overview of studies

### Study 1a

The most fundamental assumption underlying theories of relationship maintenance is that people strive to maximize what they get out of their relationships (Thibaut & Kelley, 1978). However, although extensive support exists, no experimental testing of this assumption yet exists. Since all research in my dissertation is based upon the assumption that stay/leave decision making is value-based, I will test in Study 1a whether indeed experimental manipulations of actual relationship outcomes affect the time one decides to stay with a specific social partner; and whether this is similar to how outcomes of nonsocial resources affect the time one decides to exploit those resources.

### Study 1b

The effect of prior beliefs on stay/leave decision making is unclear. That is, while Interdependence Theory considered prior beliefs as a frame of reference against which relationship outcomes would be compared, the existence of a Confirmation Bias suggests that prior beliefs could guide stay/leave decisions such that they would be in line with prior beliefs. In study 1b, I will investigate how prior beliefs affect stay/leave decision making specifically.

### STUDY 2

The purpose of Study 2 is then to investigate whether stay/leave decision making about social partners is affected by temporal difference learning models; and to investigate exactly how prior beliefs affect learning processes underlying both social and individual stay/leave decision making.

### STUDY 3

Finally, in Study 3, I will investigate the neural mechanisms underlying stay/leave decision making by using fMRI. One goal of this approach is to find stronger support for the claim that stay/leave decision making is value-based; and to investigate in what ways the decision to stay with or leave a social partner relates to individual stay/leave decisions.

# Chapter 2

## *How social and nonsocial rewards affect stay/leave decision making: The influence of actual and expected rewards*

The paper investigated whether deciding to stay with or leave a social relationship partner, based on a sequence of collaborative social interactions, is affected by (1) observed and (2) anticipated gains and losses associated with the collaboration; and, importantly, (3) whether these effects differ between social and nonsocial contexts. Participants played a social or nonsocial version of an iterated interactive and collaborative economic game in which they were free to stop collaborating with a social or nonsocial agent whenever they wanted. In Study 1, we manipulated both social and nonsocial agents' probability of success in the game and demonstrated that participants decided to stay longer rather than shorter with both social and nonsocial agents with a higher probability of success. In Study 2, we induced prior expectations about specific social and nonsocial agents, while keeping objective performance of all agents equal, and found that, in both social and nonsocial context, participants decided to stay longer with high expectancy agents compared with low expectancy agents, and even believed the high expectancy agents to have a higher probability of success than the low expectancy agents. Importantly, results demonstrated that, in a social context, both prior expectations about and actual behavior of a partner affected stay/leave decision making, whereas in a nonsocial context, the effect of prior the influence of actual experienced gains and losses was ignored and participants followed prior expectations blindly.

People typically group together: they work together, become friends, join sports teams and fall in love. However, as we all know from daily life, these social relationships we form with others do not always function the way we would like. That is, collaborations with colleagues turn out to be inefficient, friends let us down, we lose important games with our sports team and we fight with our romantic partners. As a consequence, people will at some point be faced with the decision to maintain or terminate a social relationship.

Deciding to either stay with or leave a social partner is one of the most complex social decisions a person must make. Numerous aspects feed into the decision process (see Cate, Levin & Richmond, 2002), such as individual factors (i.e., personality traits), relationship factors (i.e., investments in and satisfaction with a partnership), or even external factors (i.e., the influence of social networks). Additionally, the decision is often made in highly uncertain circumstances, as the decision-maker does not know what the future consequences will be of staying or leaving at the time of decision. We propose that, in general, people will be more likely to stay in relationships the more they are getting out of them; and as people cannot know what a relationship will bring for the future, we additionally propose that people are also more likely to stay in relationships the more they *expect* to get out of them, regardless of whether these expectations are being met or not.

Previous research supports the idea that people stay longer in relationships the more they get from them. That is, based on the proposition that people try to maximize their returns from social relationships (Kelley & Thibaut, 1978), researchers have consistently demonstrated that self-reported satisfaction with real-life social relationships (which may capture subjective returns of a relationship) is one of the most important predictors of (intended) relationship maintenance (see Le & Agnew, 2003; Le et al., 2010). The fact that these findings are based on different types of real life relationships (e.g., personal and work relationships, and even nonsocial commitments) supports the ecological validity of the link between relationship returns and stay/leave decisions. However, as experimental testing of the *causal* link between relationship returns and stay/leave decision-making is lacking, the first goal of this paper is to establish that stay/leave decision-making is indeed affected by the outcomes one gains from a social partnership.

A related set of research examines the circumstances under which participants stop playing with an interaction partner in iterated economic games such as the Prisoner's Dilemma (e.g. Macy & Tksvoretz, 1998; Macy & Boone, 1999). However, this line of work has mostly concerned itself with the question whether including an option to exit, that is, to dissolve a partnership, affects cooperative or trust decisions. In contrast, our goal is not to investigate how the option of leaving a partner affects cooperation levels, but rather whether the competence levels of partners in collaborative settings affect subsequent decisions to either stay or leave.

Given that people are more likely to stay in social relationships the higher the relationship returns are, it makes intuitive sense that people will also be more likely to stay in social relationships the higher they *expect* the relationship returns to be. This also follows from the softmax selection rule in reinforcement learning (Sutton & Barto, 1998), which predicts that a decision maker becomes more likely to select an action the higher the expected returns of that action are. Moreover, the idea that expectations guide decision-making also has been shown in other contexts, such as those of fairness, trust, and cooperation. That is, psychological descriptions about a specific partner (Marchetti et al., 2011) or information about what a typical partner would do (Sanfey, 2009) influence the rejection of unfair offers in the Ultimatum Game. Explicit descriptions of a person's moral character (Delgado, Frank & Phelps, 2005) and implicit assessments of a social partner's trustworthiness based on his or her facial features (Van 't Wout & Sanfey, 2011) influence how much trust a person puts in a social partner in the Trust Game. Additionally, people are more likely to cooperate with partners in a Prisoner's Dilemma when they perceived these partners as cooperative based on a brief informal conversation beforehand (Frank, Gilovich & Regan, 1993). The second goal of the present paper is therefore to investigate whether, and how, expectations about relationship returns affect decisions to stay in a social relationship. Specifically, we will focus on those situations in which decision makers have exaggeratedly low or high prior expectations about a partner.

An important question to this effect is *how* expectations might affect decisions to stay with or leave a social partner. One possibility is that when prior expectations and actual returns of a partnership do not match, people may become either positively surprised or disappointed about the partnership (e.g., experience positive or negative prediction errors), as a function of whether they received a greater or a lesser amount than they expected from the partnership. Having overly low prior expectations – and thus getting more from a relationship than expected - may then increase the likelihood of staying, because beliefs about relationship returns were raised. In contrast, having overly high prior expectations – and thus getting less from a relationship than expected - will increase the likelihood of leaving, because beliefs about relationship returns were lowered. This way of updating expectations is typical for associative learning (Sutton & Barto, 1998).

Another possibility is that the influence of prior expectations on stay/leave decisions is guided by the Confirmation Bias. The Confirmation Bias is the tendency for people to gather, remember, and interpret information in line with their existing beliefs (Plous, 1993; see also Lord et al. 1979; Ross et al. 1975; Snyder & Cantor, 1979). Although different conceptualizations of the Confirmation Bias have been proposed (e.g. see Baron 2000), we use the more broad definition stated above. In the context of stay/leave decisions, this could mean that when people have prior expectations about a partnership, they perceive the returns of that partnership in line with those expectations, irrespective, to some extent, of the actual returns. Specifically, having high prior expectations about a partnership could lead those positive behaviors of a partner to be treated as a confirmation of the existing belief, whereas negative behaviors by the same partner may either be not noticed, not remembered, or perhaps dismissed as noise. Conversely, having low prior expectations about a partnership could lead negative aspects of the partnership to be seen as a confirmation that the partnership is not productive, whereas positive aspects of the partnership are in turn dismissed. In this way, having overly high prior expectations about relationship returns can increase the likelihood of staying, whereas too low prior expectations can increase likelihood of leaving the relationship. While seemingly counterproductive to optimal decision-making, much experimental support exists for the confirmation bias. That is, the confirmation bias can maintain or even strengthen beliefs even when contrary evidence is available, and decision-making errors due to this bias have repeatedly been found (Higgings & Bargh, 1987; and see Ask & Granhag, 2007 for an example).

Though we propose rather deliberative, or even "coldhearted", mechanisms underlying decisions to stay with or leave a social partner, we would not necessarily argue that deciding to stay with or leave a social partner is precisely the same as deciding to abandon a monetary investment that is or is not paying off. Instead, we expect additional mechanisms to be at play when deciding about social partners as opposed to non-human agents. For example, when a social relationship is not paying off, feelings of bonding or perhaps guilt may prevent someone from leaving the social partner even though this may be the optimal decision in terms of pay-offs. Indeed, feelings of social bonding have been reported even in experiments in which participants merely had to synchronize their finger tapping (see Marsh et al. 2009). These feelings presumably do not occur when deciding about a purely probabilistic resource, without human efforts underlying the payoffs. The third goal of this paper is therefore to directly compare effects of anticipated and observed gains and losses on stay/leave decision making between social and nonsocial contexts.

As it is both ethically and practically impossible to experimentally investigate the effects of actual and expected relationship returns on actual stay/leave decisions in real-life social relationships, we simulate real social relationships between participants in the lab. Specifically, we make use of a novel task, the Apple Game, designed to probe the questions of interest outlined above. In the Apple Game, a cooperative relationship is formed between two players, the participant and another, anonymous, partner. We use a free-choice paradigm to increase the ecological validity of the present research, with the participant free to leave their game partner at any moment in the experiment, at which point they are paired with another player. Moreover, the Apple Game has also the important cooperative characteristic that participants share a mutual goal, with nothing to gain for each by exploiting the other. We note this explicitly, because this is not the case in the standard tasks that simulate cooperative relationships between players. For example, to achieve the highest personal income people should decide to free ride in Public Good games; defect while the other cooperates in the Prisoner's Dilemma; not reciprocate trust in the Trust Game; or make the most unfair offers that still have a chance of being accepted in the Ultimatum Game. In contrast, in the Apple Game, to obtain the highest (personal) income, participants are required to cooperate, and failures to cooperate will negatively impact the income of both players.

In summary, in a first study, we test the hypotheses that (1) people decide to stay longer in partnerships the greater the returns of that partnership, and (2) additionally whether the degree to which these decisions differ as function of whether the other partner is a human or not. The second study then tests (3) whether, and how, prior expectations about returns of a specific partnership impact stay/leave decisions; and again (4) how this may change depending on whether the relationship is with another person or a non-human agent.

## STUDY 1: INTRODUCTION

In Study 1, we investigate whether actual relationship returns affect stay/leave decision making in a collaborative task. Furthermore, we directly compare this effect between social and nonsocial condition, to investigate whether the actual observed gains and losses experienced in a social collaboration affect stay/leave decision making to the same extend as how gains and losses affect stay/leave decision making in nonsocial contexts in which social motivations will not play a role.

## STUDY 1: METHODS & MATERIALS

### *PARTICIPANTS*

One-hundred and seventeen students (mean age = 19.6, 87% female) from Radboud University in Nijmegen, The Netherlands, were recruited via an online participant database. Participants participated in return for course credit, and were additionally incentivized to perform on the task by the allotment of a performance dependent monetary bonus to six randomly selected participants (7.60 Euros on average). An ethical approval is provided by the competent local ethics committee CMO regio Arnhem-Nijmegen (i.e. acknowledged Dutch Review Board) . This approval covers all so-called standard studies, which are defined as cognitive neuroscientific studies using EEG, MEG, MRI, and/or behavioral testing that do not apply any invasive intervention (e.g. medication) and include only healthy, legally competent adults (>18 years of age) as participants. The ethical approval is recently renewed and registered under MO2014/288, entitled: "Imaging Human Cognition".

### *PROCEDURE*

After receiving instructions about the task, participants started playing the Apple Game with, ostensibly, other participants. In the Apple Game, participants attempt to amass as many points as possible by catching virtual apples. Specifically, apples fall from random positions from the top of a computer screen and participants had to place their basket under the falling apple such that the apple will pass through the basket. Each apple took 1.69 seconds to reach the bottom of the screen, after which the participants receive feedback about whether they caught the apple (the basket turning green and displaying the word 'hit') or missed it (the basket turning red and displaying the word 'miss'). Please note that the speed with which apples fell and the unpredictability of where the apples would appear made the task quite difficult. Feedback remained on the screen for 1.52 seconds before a new apple then fell. In this manner apples fell continuously, one at the time. The specific timing intervals used were calculated based on the refresh rates of the computer monitor to ensure the graphics were smooth. The primary between-participant variable in the task was whether participants interacted with social partners or with nonsocial agents. In the social partner version, participants were coupled with another human, and both players attempted to catch the same apple with each of their own baskets. Only apples that were caught by *both* of the participants led to a reward (ten points awarded to both participants), whereas failure to catch the apple by either one (or both) of the participants led to punishment (e.g., five points are removed from *both* participants' scores). In this way, the success of a partnership was equally dependent on both of the interaction partners, and there was no way of exploiting a game partner. Feedback about the partner's performance was displayed simultaneously with feedback about the participant's own performance. Importantly, participants thus had no choice but to collaborate. This is an important feature of our study because we are investigating stay/leave decision making in collaborative relationships in particular. In the nonsocial agent version, participants experienced a tree dropping either ripe or unripe apples (i.e., the equivalent of hits and misses by the human partner). Only the catching of ripe apples led to reward (ten points awarded to the participant), whereas either catching an unripe apple or the failure to catch an apple led to punishment (five points removed from the participant's score). Importantly, and to match the feedback and outcomes of the social condition, participants did not know whether an apple was ripe until the feedback phase of the trial, during which the words 'ripe' and 'unripe' were displayed in the same way as catches and misses of the participant. As in the previous condition, trial feedback and overall performance were continuously updated and displayed in the top right hand corner of the screen.

Apples continued falling until the participant indicated that they wanted to leave a partner or until 100 trials had been played with the same partner. Participants could decide to leave a partner whenever and as often as they desired, with no associated cost. To indicate a leaving decision, participants pressed the ESC button on the keyboard and were then paired with another, randomly selected, partner or tree. A leaving cue (e.g., the letters ESC in red) was continuously displayed in the top left corner of the screen. Each time a partnership was ended, participants were asked to estimate the percentage of the apples both themselves (e.g., indicate on the slider below how much percent of the apples you think you caught') and their partner (e.g., 'indicate on the slider below how much percent of the apples your partner caught') had caught in the previous partnership (social condition); or the percentage of apples from the last tree (e.g., indicate on the slider below how much percent of the apples were ripe') that were ripe (nonsocial condition). Then, a new partner was introduced by means of a silhouette, along with an arbitrary ID-number. To ensure that participants only made leave decisions due to their dissatisfaction with a partner - and not because they, for example, were afraid they themselves would be left by partners - participants were informed that they alone had the opportunity to decide to leave. After 650 trials, or roughly 45 minutes, the Apple Game ended.

Importantly, and to manipulate relationship returns, the performance of each of the social partners was set such that they would perform well, moderately, or poorly. Specifically, social partners would catch 85%, 50% or 15% of the apples dropped respectively. Similarly, trees could be good, moderate, or bad in terms of how many ripe apples they produced, also dropping 85%, 50% or 15% of ripe apples respectively. Partner type was ordered pseudo-randomly with each of the three types occurring twice in every sequence of six partners.

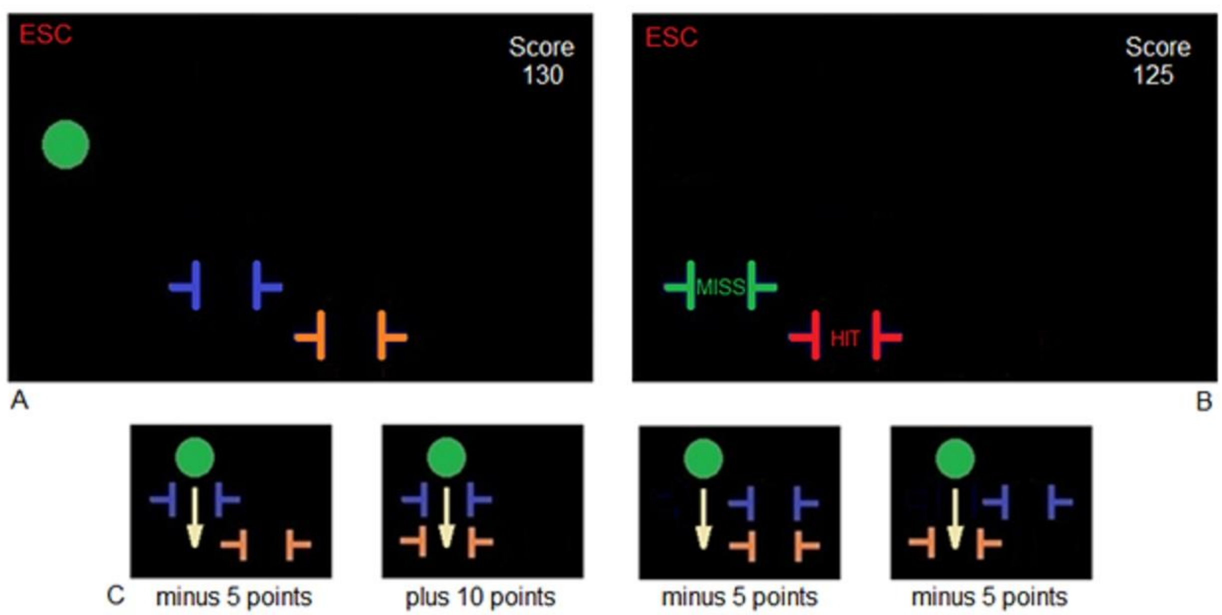


FIGURE 2.1 *On each trial, participants (A) first saw an apple falling from the top of the screen that they attempted to catch by moving their (blue) basket to right and left, while they saw their partner (orange basket) do the same. Once the apple hit the bottom of the screen, (B) feedback was given about the performance on the trial. A leave-cue was always present (ESC) and the score was updated at every trial. (C) Prior to the experiment, the potential outcomes of each trial with their respective consequences for the score were explained.*

## *DESCRIPTIVES*

Over the entire course of the experiment, participants left their social partners 6.67 (SD = 3.80) times and their nonsocial partners 5.61 (SD = 3.10) times on average. Forced leaves (i.e. after 100 trials with the same partner) occurred 5.41 (SD = 0.94) and 4.38 (SD = 0.88) times on average for participants interacting with social and nonsocial partners respectively. As a result, participants played with, on average, 12.09 (SD = 3.82) different social partners or 10.00 (SD = 2.99) different nonsocial partners over the entire experiment. Individual differences were quite large, with some participants never making a leave decision – and thus playing with only six different partners – while others decided to leave much more frequently and therefore interacted with up to twenty-two different partners. On average, participants who played the social version of the game, caught 60.54% (SD = 13.95) of the apples, and participants who played the nonsocial version of the game, caught 55.40% (SD = 15.86) of the apples. This difference was not significant ($t = 1.75$, $p = .084$).

## *STAY-LEAVE DECISIONS*

In the present study, participants were free to decide to leave a partner whenever they wanted. Therefore, we use the number of trials for which they decided to stay with a given partner as the dependent measure. However, there are two ways in which a partnership could be ended, namely when the participant pressed the ESC button or when the participant stayed for 100 trials, in which case the partnership was automatically terminated. The latter 'forced-leave' event was implemented because we found in pilot studies that participants never left a partner once they believed they found a good one and we wanted each participant to interact with partners of all performance levels at least twice. Indeed, also in the current study, 4.92%, 27.05% and 68.02% of, partnerships with, respectively low, moderate and well performing partners ended in a forced leave in the social condition; and in the nonsocial condition 3.66%, 35.11% and 61.23% of all partnerships with, respectively low, moderate and well performing agents ended in a forced leave. We treat these 'forced-leave' events as if the participant had decided to stay with a partner for 100 trials. In our analyses, these events are thus not qualitatively different from the partnerships that were terminated by the participants' themselves.

Since we have a mixed design with a highly unbalanced number of repeated measures per participant, the data were analyzed using a mixed-model approach. Specifically, we used the lmer function of the lmerTest package in R (Kuznetsova et al. 2014). Using the anova and summary commands within this package, we are able to compute F and p-values using the Kenward-Rogers approach (an option that is not available for the lme4 package that also is commonly used).

To investigate whether the number of trials for which participants decided to stay with their partners was affected by the performance of the partner, and whether this effect was moderated by partner type, we constructed a linear mixed model using the centered number of stay trials as the continuous dependent measure, and partner performance (high, moderate, or low; within-subject) and partner type (social or nonsocial; between-subject) and their interaction term as fixed effects. In addition, we took into account the centered number of partners a participant had already paired with at the time of each decision, and included this factor in the model. Moreover, we included a fixed intercept as well as a participant-specific random adjustment to that intercept to account for the repeated measures design. Lastly, we included random slopes for all within-subject factors (e.g., partner performance and partner number) in the model.

Results demonstrated that the number of trials participants decided to stay with a given game partner was significantly ($F = 487.97$, $p < .001$) affected by partner performance (participants stayed 25.00 rounds with low performing agents, 61.54 rounds with moderately performing agents and 98.54 rounds with high performing agents, collapsed across social and nonsocial partners). The difference in staying times between low and moderately performing agents ($t = 19.91$, $p < .001$) and the difference for moderately performing versus high performing agents ($t = 29.86$, $p < .001$) are both significant. The results also demonstrated that participants stayed significantly longer ($F = 3.97$, $p = .049$) with nonsocial (63.39 rounds) than social (60.43 rounds) agents.

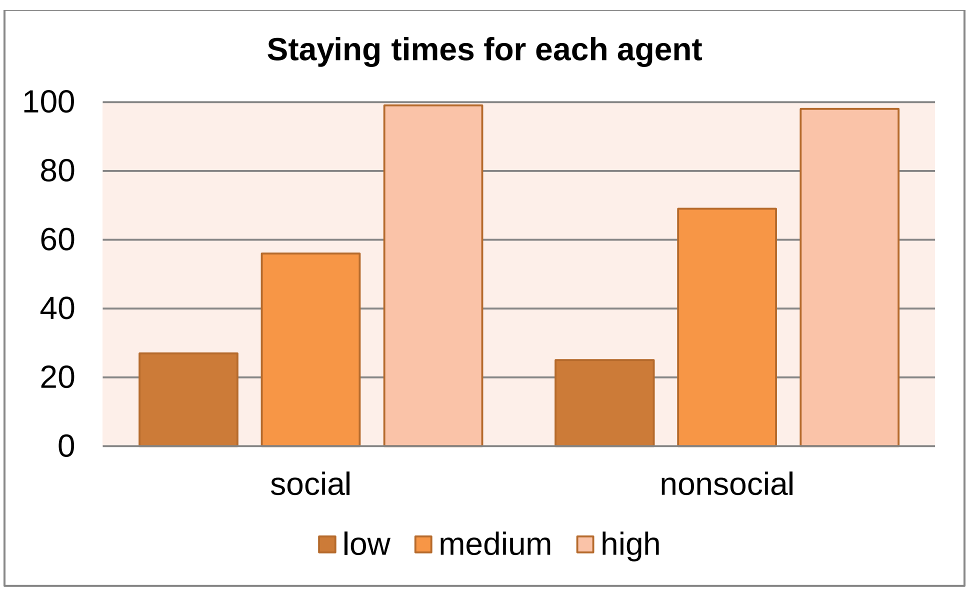


FIGURE 2.2 *Number of trials participants decided to stay with social and nonsocial agents that performed badly (e.g., 15% success), moderately (e.g., 50% success) or well (e.g., 85% success) in the game.*

Moreover, the modeling results also revealed a significant interaction effect between partner performance and partner type on staying times ($F$ = 6.65, $p$ = .002). As depicted in Figure 2, for both social and nonsocial agents participants stayed longer with their partners the better their performance at the game. Specifically, participants who played the social version of the game, decided to stay 26.62 rounds with the low performing, 55.57 rounds with the moderately performing and 99.09 rounds with the high performing social agents. Similarly, participants who played the nonsocial version of the game, decided to stay 24.72 rounds with the low performance, 68.67 rounds with the moderate performance and 97.69 rounds with the high performance nonsocial agents. The difference in staying times from moderate to high performance partners was not significantly different between social and nonsocial condition ($t$ = -0.69, $p$ = .490), but the difference in staying times from low to moderate performance partners was ($t$ = -3.36, $p$ = .001). In addition, the results showed that, overall, participants stayed significantly ($F$ = 49.50, $p$ < .001) shorter (coef. = -1.36) with their partners the more partners they already had.

### *ESTIMATIONS OF PERFORMANCE*

To gain insight into how participants actually processed their partners' performance, we examined if participants were aware of the difference in performance between the different partners, and whether the performance of social partners was evaluated in a similar way as performance of nonsocial partners. To test this, we set up a mixed model similar to that described above, but with estimations of partner's performances as the dependent measure.

The results show that participants indeed noticed the difference in performance between the different partners, with a significant main effect of partner performance on performance estimations ($F$ = 322.13, $p$ < .001). Participants believed the low, moderate and high performing agents as performing at 23.21%, 38.26% and 70.69% respectively. The differences in performance estimations between low and moderately performing agents ($t$ = 23.90, $p$ < .001), as well as between moderately and well performing agents ($t$ = -23.80, $p$ < .001) are significant. The main effect of partner type on performance estimations was also significant ($F$ = 8.74, $p$ = .004), but the interaction effect ($F$ = 2.74, $p$ = .069) between the two factors was not (see Figure 3). In addition, performance estimations did change ($F$ =15.12, $p$ < .001) as a function of the number of partners each participant already had interacted with (coef = 0.73).

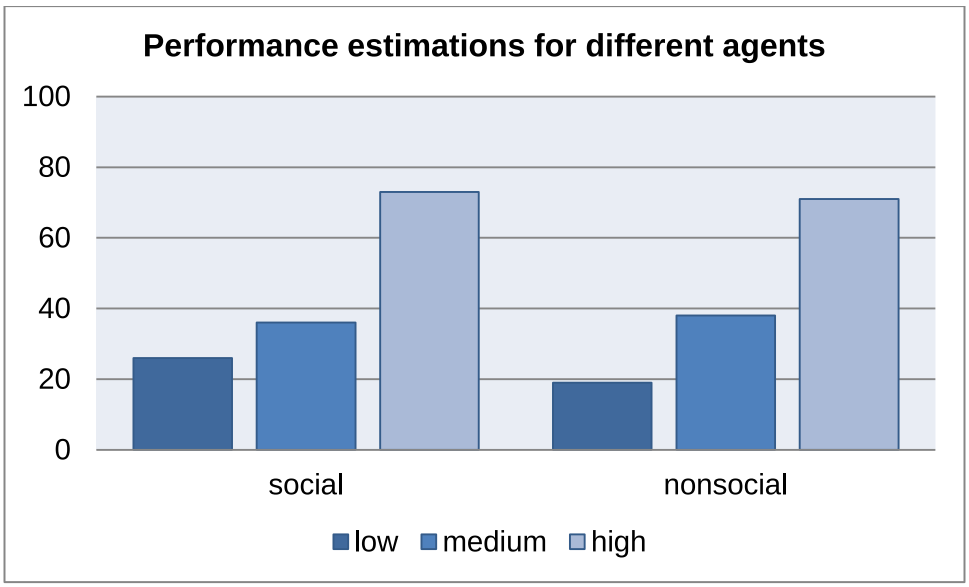


FIGURE 2.3 *Performance estimations (in percentages) of social and nonsocial agents that actually performed badly (e.g., 15% success), moderately (e.g., 50% success) or well (e.g., 85% success).*

## Study 1: Conclusion

Study 1 confirmed the initial hypothesis that people would decide to stay longer in partnerships the higher the actual returns of those partnerships. We found similar effects in both social and nonsocial conditions, however there were some subtle differences between interacting with either a social partner or a monetary resource. Interestingly, when estimating social partners' performance, participants underestimated the performance of moderate and high performing social partners, but overestimated the performance of low performing social partners.. However, when estimating the probability of success of a non-social agent, participants underestimated the performance of moderate and high performance monetary resources, but were quite accurate in estimating the performance of monetary resources with a low probability of success. In terms of staying times, we did not see such clear differences between social and nonsocial conditions. However, the increase in staying times from low to moderately performing partners was greater in the non-social than the social condition, likely related to the overestimation of the performance of low performing social partners. In contrast, the increase in staying times from moderately to high performing partners was greater in the social condition.

## Study 2: Introduction

Study 2 was conducted to investigate how the interplay between anticipated and observed gains and losses associated with a social collaboration affect stay/leave decision-making. Moreover, we compare these effects between social and nonsocial contexts to examine if expectations impact both social and nonsocial partnerships differently.

## STUDY 2: METHODS & MATERIALS

### *PARTICIPANTS*

Ninety-three students (mean age 20.2, 83% female) from Radboud University in Nijmegen, The Netherlands were recruited via an online database to participate in Study 2 in exchange for course credit. Five randomly selected participants additionally earned a performance-dependent monetary bonus, (7.52 Euros on average). Ethical approval was again provided by the same competent local ethics committee as in Study 1.

### *PROCEDURE*

As in Study 1, half of the participants were randomly chosen to play the social version of the task (i.e. purportedly with another experimental participant), while the other half played the non-social version (i.e. with a computer agent). The game was as described in Study 1 (above), with the following differences: (1) the actual performance of all social and nonsocial game partners was now set at 50%, that is, there were no objective performance differences between any of the partners; and (2) information about the prior performance of each game partner was provided at the start of each partnership. Every time a new partner (either a social or nonsocial agent) was introduced to the participant (by means of a silhouette and an associated ID-number), information about that agent's past performance was provided via both a 'star rating' and text information. Partners could have 1-, 2-, or 3-star rating, meaning that game partners, respectively, caught less than half (i.e., 0 – 33%), about half (i.e., 34 – 66%) or more than half (i.e., 67% - 100%) of the apples in the past (see Figure 2). During the instruction phase of the task, participants were told about the percentage rates for each category.


FIGURE 2.4 *Introduction screen of a new partner in Study 2. The silhouette is coupled with an arbitrary ID number, a star rating, and written information about the participant's past performance.*

## *DESCRIPTIVES*

Over the course of the experiment, participants left social partners an average of 6.62 (SD = 4.73) and nonsocial agents 6.91 (SD = 3.72) times. Forced leaves occurred on average 3.91 (SD = 1.22) and 4.13 (SD = 1.02) times interacting with social and nonsocial agents respectively. Moreover, in the social condition 21.24%, 35.35% and 42.41% of all partnerships with, respectively low, moderate and high expectancy partners ended up in a forced-leave; and in the nonsocial conditions these percentages were 2.55%, 39.96% and 57.48% for the low, moderate and high expectancy agents. As a result, participants played with, on average, 10.53 (SD = 4.19) different social or 11.04 (SD = 3.47) different nonsocial agents. The range across participants was relatively large, as observed in Study 1. Some participants never left their partners – and thus played only with six different partners over the course of the experiment - whereas others played, maximally, with twenty-three and twenty-one different social and nonsocial agents respectively. Participants in the social version of the game caught 66.25% (SD = 12.35) of the apples, and participants who played the nonsocial version of the game caught 70.20% (SD = 14.65) percent of the apples. This difference is again not significant ($t$ = 1.51, $p$ = .134), demonstrating that both versions of the task elicited similar performance from the participants.

## *STAY-LEAVE DECISIONS*

Analyses were performed in a similar manner as described in Study 1. That is, we again used a mixed-model approach, using the lmerTest package in R**.** The focus of this study was to investigate whether inducing prior expectations about specific interaction partners affected the stay/leave decisions made by participants, and whether this effect was different when playing with social or nonsocial agents. To investigate this, we built a linear mixed model with the centered number of stay trials as the continuous dependent measure, and with expectations (low, moderate or high; within-subject) and partner type (social or nonsocial; between-subject) and their interaction term as fixed effects. Also, we wanted to take into account the centered number of partners a participant had previously interacted with and included this factor in the model. In addition, as observations were nested within individual participants, we included a fixed intercept and a participant-specific random adjustment to that intercept to the model. Finally, we included random slopes for the within-subject factors expectations and partner number.

Results demonstrated that prior expectations about interaction partners had a significant impact on the number of trials participants played with their partners ($F = 260.53$, $p < .001$). More specifically, participants decided to stay 33.93 rounds with low expectancy, 60.03 rounds with moderate expectancy, and 83.55 rounds with high expectancy agents. Differences in staying times between low and moderate expectancy agents ($t = 16.28$, $p < .001$) and moderate versus high expectancy agents ($t = -21.82$, $p < .001$) were significant.

The main effect of partner type on stay trials was not significant ($F = 3.32$, $p = .072$), however there was a significant interaction effect of expectations by partner type on staying times ($F = 82.54$, $p < .001$). Participants who played the social version of the game decided to stay 51.54 rounds with low expectancy, 60.77 rounds with moderate expectancy, and 72.65 rounds with high expectancy partners. Participants who played the nonsocial version of the game stayed only 12.19 rounds with low expectancy, 69.12 rounds with moderate expectancy, and 98.24 rounds with the high expectancy agents. The increase in staying times from low to moderate expectancy partners was significantly different ($t = 16.62$, $p < .001$) between social and nonsocial condition, as was the increase in staying times from moderate to high expectancy partners ($t$ = -16.17, $p$ < .001). In addition, and as in Study 1, participants stayed significantly ($F$ = 89.93, $p$ < .001) shorter with their partners the more partners they already had interacted with (coef. = -3.33).

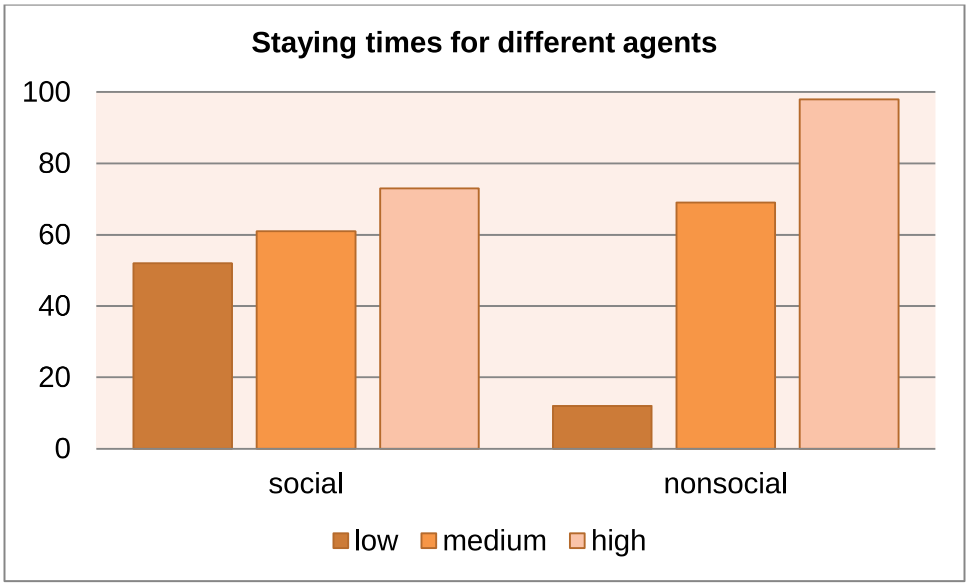


FIGURE 2.5 *Number of trials participants decided to stay with social and nonsocial agents for whom participants had low, moderate and high prior expectations, (in reality all performed at a 50% success rate)*

### *ESTIMATIONS OF PARTNER PERFORMANCE*

We assessed the degree to which participants' estimations of their partners' performance were accurate, based on the prior expectations they received about their partners. For this, we set up a mixed model with expectations, partner type and their interaction term as fixed factors; we included a participant specific random intercept and random slopes for expectations and partner number.

Results demonstrated a significant ($F$ = 139.48, $p$ < .001) effect of expectations on performance estimation. Participants estimated the low, moderate and high expectancy agents to perform at, respectively, 31.69%, 45.08% and 60.88%. The difference in performance estimations between low and moderate expectancy ($t$ = 16.55, $p$ < .001) and between moderate and high expectancy ($F$ = 15.34, $p$ < .001) agents are both significant. The effect of partner type on performance estimations was also significant ($F$ = 15.98, $p$ < .001), such that, overall, participants estimated the nonsocial agents (e.g., 51.25%) to perform better (e.g., 5.38 %, S.E. = 2.02) than the social (e.g., 42.09%) agents.

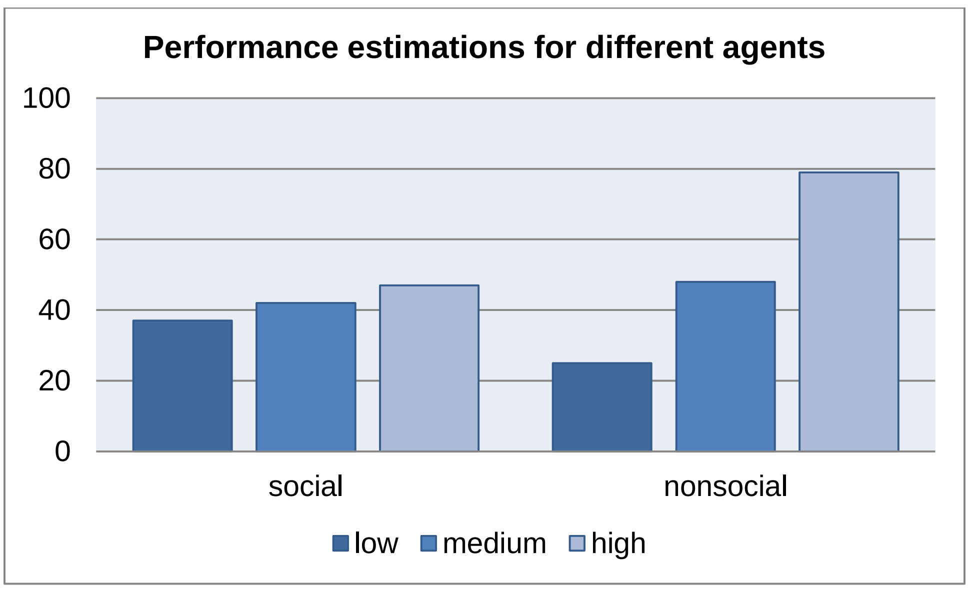


FIGURE 2.6 *Performance estimations (in percentages) for social and nonsocial agents for which participants had low, moderate or high prior expectations*

Moreover, the interaction effect of expectations by partner type on performance estimations was also significant ($F$ = 86.94, $p$ < .001). Participants estimated the social agents about which they had low, moderate and high expectations to perform at, respectively, 36.72, 42.33 and 47.10 percent. And, again more extremely, the low, moderate and high expectancy nonsocial agents were estimated to perform at, respectively, 25.48, 48.48 and 79.46 percent. Both the increase in estimated performance from low to moderate expectancy partners ($t$ = 12.08, $p < .001$) and the increase in estimations from moderate to high expectancy partners ($t$ = -11.32, $p < .001$) was significantly different between social and nonsocial conditions. In addition, performance estimations decreased significantly ($F = 9.54$, $p = .003$) the more partners the participants had already interacted with. (coef. = 0.61).

## STUDY 2: CONCLUSION

Study 2 confirmed the hypothesis that prior expectations about our interaction partners have an important impact on subsequent stay/leave decisions. That is, if participants had low prior expectations about social agents, they gave up on them relatively quickly, whereas they stayed longer with high expectation partners that might be expected given their actual performance. Interestingly, the effect of prior expectations on stay/leave decisions was much stronger for nonsocial agents than for social partners. Even though all agents performed at chance, with no agent actually better or worse than any other, participants stayed 10 more rounds with a social agent if they expected them to perform moderately as opposed to poorly. More dramatically however, when participants expected a nonsocial agent to perform badly, these partners were disposed with quickly (on average after just 12 rounds). In contrast, when participants expected a nonsocial agent to perform well, they stayed 98 rounds with those partners. Importantly, this pattern was also evident in participants' estimation of the agents' performance.

The aim of the present paper was to investigate whether decisions to stay with or leave social partners are based upon value-maximization motives, as suggested by some prior research (Kelley & Thibaut, 1978), and additionally to explore how prior expectations about the value of partners affects decisions to either stay with or leave them during an ongoing collaborative task. Consistent with our hypothesis, we first demonstrated that participants decided to stay longer in collaborative partnerships when those partnerships produced higher returns. Secondly, we demonstrated that, when the objective performance of all partners was equal, participants decided to stay longer with high expectancy as compared to low expectancy partners. In addition, our results demonstrated that even though prior expectations had a strong impact on stay/leave decisions in both social and nonsocial conditions, the effect was much more pronounced in nonsocial conditions.

In addition to existing literature that demonstrates that people who are more satisfied with their personal relationships are also more likely to (intend to) stay in them, Study 1 demonstrated a causal effect of relationship returns on *actual* decisions to stay with or leave a social partner. Moreover, Study 1 demonstrated that the relationship between cooperation and stay/leave decision making is bidirectional. That is, while previous decision making studies demonstrates that having the option to leave a social partner increases cooperation levels; Study 1 now also demonstrated that the level of cooperation of a social partner also affects the decision to leave.

In line with previous research, in this second study, the presence of false prior expectations about interaction partners led to suboptimal decision making, such that participants decided more quickly to leave the low expectancy partners, who were in reality no worse than other partners. Importantly, these results show that participants were affected by prior expectations but did not follow them blindly. That is, if participants were simply doing as they were instructed (e.g., following the information about partner performance) they should have immediately left low expectancy partners rather than staying for over 50 rounds with those partners. The fact that they were affected by prior expectations but still had moderate staying times for all partner types shows that they weighted both prior expectations and actual observations when deciding to stay or leave. Results demonstrate that participants were in fact more or less 'blind' to their actual observations in the *nonsocial* condition where they seemed to follow our prior expectancy induction much more extremely. Especially since we designed the two tasks in such way that *objectively* they were the same, even regarding the (monetary) type of outcomes, it is highly interesting to find any differences between social and nonsocial contexts at all.

The finding that the presence of prior expectations in sequential decision making tasks can lead to suboptimal decision making has been demonstrated by previous studies. For example, Doll et al. (2009) found that providing false information to participants about the probability of success of certain stimuli in a probabilistic learning task, led participants to erroneously select the high expectancy stimuli more often, and the low expectancy stimuli less often, than they should based on their actual probability of success. Similar results were found by Biele et al. (2011) when the false information was given to participants in the form of social advice. Also, Fareri et al (2012) and Fouragnan et al. (2013) both found that prior expectations about the trustworthiness of a social partner affected decisions in a repeated Trust Game, consistent with those expectations. Furthermore, these studies used computational modeling techniques to understand why the presence of prior expectations affected decision making.

These studies found that the presence of prior expectations can lead to suboptimal decision making because it inhibits learning. Specifically, by using a computational modeling technique they found that expectancy-consistent observations are weighted heavier than expectancy-inconsistent observations when people update prior beliefs about the probability of success of experimental stimuli or the trustworthiness of a social partner with actual observations. Our findings are consistent with those of these previous studies, and an interesting avenue for future research is to use similar data analysis techniques to look further into how prior expectations affect the learning processes underlying decision making about social partners in a collaborative context.

Extending these previous studies, the present research directly compared the influence of prior expectations on decision-making between social and nonsocial contexts. We explored potential differences between social and nonsocial conditions because it could be the case that when playing with other human partners specific social motivations might have led participants to decide to stay longer with their social partners than with nonhuman agents. It should be noted that, in the first study, we found no differences between both types of partner, observing that participants stayed with social partners equally as long as with non-social agents with similar performance levels. These findings suggests that motives of value-maximization affect decisions to stay or leave equally strongly across social and nonsocial contexts, with no evidence of social motivations modulating this effect between social and nonsocial context.

Even so, we did find that the effect of prior expectations on stay/leave decisions was much less pronounced in a social than in a nonsocial context. As we can rule out explanations for this effect related to differences in value-maximization motives and the influence of social motivations, we offer a simpler explanation of why this could be the case. It is possible that the social condition utilized more attentional focus than the nonsocial condition, and as a result participants had greater awareness of the actual performance level of the human partners, perhaps because social information is more salient in general. Potentially, a higher implicit baseline attentional focus in the social condition did not play a role in the first study because in both conditions participants had no prior knowledge about the social or nonsocial agents and had to actively pay attention to play the game optimally. In the second study however, prior knowledge about social and nonsocial agents was available, which diminished participants' attention to their game partners' performance. If indeed participants were implicitly more attuned to the performance of social rather than nonsocial agents, this implicit higher attentional focus in the social condition may explain why the effect of prior expectations on stay/leave decisions was less pronounced in this social condition.

Although highly speculative, another explanation of why participants were less affected by prior expectations in a social rather than nonsocial context could be that participants implicitly expected social, but not nonsocial, agents to be consistent over time in their probability of success. That is, the probability of success of a nonsocial agent could change, but why would a, supposedly, previously good apple catcher suddenly become less good at the game? This deviation from *consistency* might have made participants more likely to notice that social, but not nonsocial, partners' performance was not consistent with expectations; expectations that, importantly, were ostensibly based on a partner's previous task performance.

Another interesting finding is that prior expectations did not affect decision making per se, but rather the value estimations underlying value-based decision-making. If, as in previous studies, participants here also weighed expectancy-consistent observations more strongly than expectancy-inconsistent observations, it could be the case that participants considered successful trials by a high expectancy partner as evidence for the belief that the partner was a productive one, while misses by this partner were dismissed (i.e., 'everybody can make a mistake sometime'). Similarly, misses by a low expectancy partner then strengthened the belief that the partner was a poor one, while successful catches were considered lucky shots. To investigate whether prior expectations actually biased participants' perceptions of a relationship partner, participants were asked at the conclusion of each partnership to estimate the performance of the respective partners. In line with the above, we found that participants believed that the low expectancy partners caught fewer apples and the high expectancy partners caught more apples than other social partners, despite the absolute performance of all partners being identical. This suggests that the decisions themselves were based on these (mis)perceptions, with the expectations held by participants contributing to the beliefs as to the efficacy of the various partners. The present findings that stay/leave decision making in social collaborations is based upon value-maximization and that prior expectations bias both stay/leave decisions as well as beliefs about a person's collaborative value, has important implications for real-life social relationships.

Finally, we were somewhat surprised to see how loyal participants were to their game partners the task, with many participants staying the full 100 trials with their partners. Reasons why participants stayed so long with their partners in the game could be that the decision to stay was the default, with the decision to leave both consequential (you could not go back to a previous partner) and ambiguous (there was no information provided on what the future might bring). Since the decision to leave was ambiguous – and people are commonly observed to be ambiguity-averse – and had no way of undoing potential 'bad' decisions (i.e., leaving good partners), participants may have been hesitant to leave, and instead used the default option of staying. Future versions of this task, could endeavor to promote greater leave decisions by, for example, giving participants information about the pool of alternative game partners, giving them the opportunity to return to a former game partner, or even making the decision to stay more difficult, for example by requiring participants to pay to stay. Importantly, if one would plan to perform computational modeling analyses on participants' behavior in this task, these could be ways to acquire a greater balance between stay and leave decisions which is necessary to perform these types of analyses.

In conclusion, the present research demonstrated that (1) value maximization is indeed a fundamental aspect of stay/leave decision making in social relationships, and that (2) the prior beliefs we have about social partners guide subsequent stay/leave decisions via a Confirmation Bias mechanism. These findings are consistent with previous literature, but interestingly, the present paper showed that a well-known cognitive bias that people have was much less pronounced in a social than nonsocial context. It therefore seems that some aspect of social relationships somehow 'protect' people from the influence of prior expectations on social decision making in particular. An interesting direction for future research is to investigate more closely why this could be the case.

# Chapter 3

## *Social versus nonsocial reinforcement learning: Resisting against the effect of priors*

The present chapter investigated the effect of prior beliefs on social versus nonsocial reinforcement learning. To this end, participants played a 4-armed bandit task and an adapted (e.g., social) version of this task in which participants chose between 4 social partners and, on each trial, played a Dictator Game with the partner of their choice in the role of the recipient. Participants were more likely to select bandits or social partners about which they had very high expectations than any other bandits or social partners. However, the effect was less strong in the social learning task. Computational modeling analyses demonstrated that a Reinforcement Learning model that differentially updated belief-consistent and –inconsistent new events. Overall learning rates were higher in the social rather than nonsocial task, but only when prior beliefs were induced. The present findings suggest a stronger resistance against the effects of priors on social rather than nonsocial learning and decision making. Potential explanations are discussed.

People typically have prior beliefs about their social partners (i.e., based upon their age, skin color, nationality, facial characteristics, social group, social status or reputation) and these are known to influence our decisions about them. To illustrate, people are more likely to accept unfair behavior from people whom they believe to be generous (Marchetti et al., 2011); people are more likely to trust people whom they believe to be trustworthy (van ‘t Wout & Sanfey, 2011); and people are more likely to cooperate with people whom they believe to be cooperative (Frank et al., 1993).

The abovementioned examples are based upon one-shot interactions. However, consider the example from van ‘t Wout & Sanfey (2011). In their study, participants played a one-shot Trust Game with another person. The Trust Game is a two-player economic game, in which the first mover receives a personal endowment (i.e., 10 Euros) and may decide if, and how much, of that personal endowment he wants to invest in the second mover. Any money transferred is multiplied by some factor, after which the second mover may then decide to share the multiplied money with the first mover (e.g., reciprocate trust) or keep all money to himself (e.g., not reciprocate trust). Logically, the more the first mover trusts the second mover, the more he will invest in the second mover. Interestingly, van ‘t Wout and Sanfey (2011) manipulated facial trustworthiness of the second movers and demonstrated that the amount of money participants decided to invest was affected by their implicit assessments of a partner’s trustworthiness.

However, imagine you decided to invest a high amount of money in someone who looked trustworthy, but then found out that the he kept all money for himself. Would you update your belief about his trustworthiness and your decisions to trust him in a next round? Previous research demonstrates that, at least in the context of trust decisions, people tend to keep relying on their prior beliefs about a person's trustworthiness even when a person's actual decisions to reciprocate trust are inconsistent with those beliefs (see Delgado et al., 2005; Fareri et al., 2012; Fouragnan et al., 2013). Similar effects have been found when investigating the effects of prior beliefs in belief updating in nonsocial contexts (Biele et al., 2011; Doll et al., 2009; Li et al., 2011).

Interestingly, we found similar results in the previous chapter in which we investigated the role of prior beliefs on stay/leave decision making in both social and nonsocial contexts. That is, in that chapter participants played an interactive collaborative economic game with each other in which they were dependent on each other's game performance and could decide to leave a game partner whenever and as often as they desired. In line with the abovementioned literature, we found that inducing prior beliefs about a partner's game performance affected participants' decisions to stay with them even when objective performance of all game partners was exactly the same. Specifically, participants stayed longer with partners whom they believed to be good at the game and shorter with partners whom they believed to be worse at the game, even when all partners were equally good or bad.

Moreover, and importantly so, we demonstrated that the effect of prior beliefs on decision making in this chapter was heavily dependent on whether participants made individual or social stay/leave decisions. Specifically, although both decisions to leave a social partners as well as decisions to leave nonsocial resources (in a similar task) were affected by prior beliefs, the effect was less pronounced in the social context, in which participants seemed to take into account their partners' actual performance as well.

However, participants' decisions in the previous chapter were uninformative as to *how* prior beliefs affect learning mechanisms underlying stay/leave decision making, or more specifically, how prior beliefs and actual observations together are integrated into the decision making process; and importantly could not tell us *why* the effect of prior beliefs on stay/leave decision making was less strong in a social rather than individual stay/leave decision making context. To overcome these practical problems, we make use of a Reinforcement Learning framework (see Sutton & Barto, 1998) to investigate the effects of prior beliefs on stay/leave decision making in a social and nonsocial context.

Importantly, the reinforcement learning framework is a widely used (see Sutton & Barto, 1998) framework that provides mathematical models which can compute which decision an agent will make on a trial-by-trial basis based on its previous choices and the consequences these choices had. In other words, reinforcement learning models are able to mathematically represent how new observations update beliefs and decision likelihoods. Moreover, these reinforcement learning models have been used to study how prior beliefs affect belief updating in both social (Delgado et al., 2005; Fareri et al., 2012; Fouragnan et al.. 2013) and nonsocial (Biele et al., 2011; Doll et al., 2009; Li et al., 2011) context. Thus, using reinforcement learning models to investigate how prior beliefs are integrated into the underlying learning mechanisms of stay/leave decision making.

The goal of the present chapter is (1) to investigate how prior beliefs are integrated in the learning processes underlying stay/leave decision making; and (2) to explore why prior beliefs have a less strong effect on social rather than individual stay/leave decisions. Importantly also, to this end we make use of reinforcement learning models which are typically used in investigations of how beliefs and decision likelihoods are shaped by actual observations; and in research that investigates the role of prior beliefs on learning processes.

## *PARTICIPANTS*

Seventy-eight students (mean age = 24.46; 73.08% female) from Radboud University in Nijmegen, the Netherlands were recruited via an online participant database. Participants received a standard show-up fee of 8 Euros plus a performance dependent money bonus which was 2.98 Euros on average (SD = 0.78) and ranged between 2.05 and 5.01 Euros.

## *TASK*

Participants played two versions of the 4-armed bandit task. One in which prior beliefs about choice options (e.g., social partners or slot machines) were induced prior to starting the task, and one in which this was not the case (e.g., no priors task). Moreover, half of the participants could, in both versions, choose between four slot machines (e.g., the traditional or nonsocial version) and the other half of participants could, in both versions, choose between four social partners. All versions (e.g., social priors, social no priors, nonsocial priors, nonsocial no priors) consisted of 125 trials each.

In the nonsocial version of the game (without prior beliefs) participants were, on each trial, presented with four slot machines and were asked to choose one of them (max 7 seconds). Next, they waited for (2 seconds) and viewed (4 seconds) how much money the slot machine of their choice paid out. After an inter-trial-interval (2.5 seconds), a new trial started in which participants could again choose between the four same slot machines. Participants thus won some amount of money on each trial. In addition, they were told, prior to starting the game, that different algorithms represented the four slot machines and that, therefore, these slot machines could differ in their likelihood of generating relatively high sums of money.

The structure of the social version of the game (without prior beliefs) was exactly the same as the structure of the traditional version described above. However, rather than choosing between four slot machines on each trial which paid out some amount of money, participants chose between four social partners who could decide to share some amount of money with the participants. Specifically, on each trial participants played a Dictator Game in role of the recipient, such that participants viewed how much the social partner of their choice (e.g., the Dictator) decided to share with them. Participants were told that partners could differ in their levels of generosity, and importantly they were told that the Dictators made their decisions previously and could thus not be affected by the participants' choices.

As said, half of the participants played either two social versions of the game or two individual versions of the game, but in one of the two games participants played, prior beliefs about either the slot machines or the social partners were induced. Specifically, in one of the games (that were administered in counterbalanced order), participants were informed about each slot machine's or social partner's 'generosity', which could be very high, high, low, or very low.

In the nonsocial task, participants were told that each of the algorithms that represented a slot machine was predetermined to have a specific (e.g., very high – very low) chance of generating relatively high sums of money. In the social task, participants prior beliefs about their partners' levels of generosity were induced as follows: As part of the experimental instructions, participants were explained that the pool of participants who made the Dictator decisions also completed a scale on which they had to fill in on a 5-point Likert scale how much they agreed with a number of items (see Appendix). To familiarize participants with this questionnaire, participants also completed it; were asked to compute their own score; and learnt what it meant to have an extremely high, high, low, or extremely low score on this task. Importantly, the questionnaire measured generosity, and to make sure participants understood this, they were asked to describe in one word which psychological construct the questionnaire measured. Before the start of the first trial, each partner was given a color code which indicated their measure on the generosity scale (see Figure 3.1) and the words ‘very high’, ‘high’, ‘low’ and ‘very low’ were displayed below each partner. The text disappeared at the start of the first trial, but the color code remained on the screen during the whole task.

Importantly, pay offs in all conditions were matched and were in fact generated by a Gaussian decay process. Specifically, the pay off from a bandit i is the result of a Gaussian random walk with standard deviation $\sigma_0 = 4$, and the mean defined as $\mu_{i,t+1} = \lambda\mu_{i,t} + (1 - \lambda)\,\theta + \nu$. In words, $\mu_{i,t}$ is the mean reward for a bandit i at trial t; the day was centered at 25 (i.e., $\theta$), the rate of decay $\lambda = 0.893$, and the diffusion term was set to $\nu = N(0, 2.8)$. We chose this specific strategy in order to make sure the mean pay off of all choice options was the same, but that they varied around the mean. Specific parameters for the Gaussian process were chosen to mimic previous experimental studies.

The only ‘control’ participants had about the amount of money they earned on each trial was to learn, by sampling, which of the four social partners or bandits was more ‘generous’ than the others and to keep selecting those specific partners or bandits. To incentivize participants to perform well on the task, three trials of each block were randomly selected and the average earnings on those trials were additionally paid out as a money bonus. In addition, to make sure the nonsocial and social versions of the task were as similar as possible, the remaining amount of the 10 Euros that participants, who played the nonsocial versions of the task, did not win on the selected trials (i.e., €2.50 in case they won €7.50 for example) was added to the money bonus of a different pool of participants who ostensibly took part in a similar experimental study.

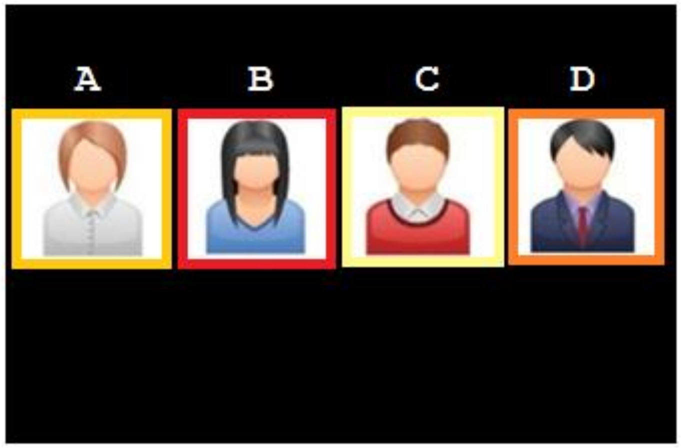


Figure 3.1 *A screenshot of the social task in which participants were induced with prior beliefs about their social partners. Color codes remained on the screen throughout the entire game; and indicated the questionnaire score of each partner (i.e., generosity levels). Colors more heading towards yellow indicate lower scores and color more heading towards red indicate higher scores.*

## ANALYSES

### *ANALYSES OF VARIANCE*

To investigate whether participants, in the games in which prior beliefs were manipulated, were affected by the belief manipulation, we first aggregated participants' trial-by-trial choices as the percentage of times each option was chosen. In a repeated measures ANOVA, this aggregated variable was used as the dependent measure; the prior belief (e.g., very high, high, low, very low) was the within-subject variable; and task version (e.g., social, nonsocial) was the between subject variable.

## *COMPUTATIONAL MODELS*

*Model 1: Differential updating of positive and negative prediction errors*

We first tested whether participants learned the value of their choice options through reinforcement learning without being affected by the presence of the priors. To this end, we used a Rescorla-Wagner learning rule (Rescorla & Wagner, 1972) to compute prediction errors that participants experienced at each given trial:

$$\delta(C, t) = r(t) - Q(C, t) \qquad (1)$$

in which the prediction error (δ) experienced from choosing option C at time point t is the difference between the received reward at time point t and the expected value of choice option C at time point t.

Prediction errors are then used to update the new expected value of choice option C at time t+1 (Q(C,t+1)) by weighting them and adding them to the expected value of option C at time t. Positive ($\delta(C, t)^{POS}$) and negative ($\delta C, t^{NEG}$) prediction errors are differentially updated ($\alpha^{POS}$ and $\alpha^{NEG}$) such that:

$$QC,t+1 = QC, t + \alpha\ POS * \delta\ C, t\ POS + \alpha\ NEG * \delta C, t\ NEG \qquad (2)$$

Next, as we now know the expected values of each choice option at each given time point, we can translate these expected values to action selection probabilities using a softmax selection rule, in which selection probabilities correspond to relative differences between choice options' expected values.

$$pC1, t = \exp[QC1,t / \tau] / (\exp[QC1,t / \tau] + \exp[QC2,t / \tau] + \exp[QC3,t / \tau] + \exp[QC4,t / \tau]$$

where the probability of selecting option 1 at time point 1 is the exponential of the expected value of choice 1 at that time point divided by a temperature ($\tau$) divided by the sum of the exponential of each choice option at that time point, each divided by the free parameter $\tau$.

*Model 2: Different prior beliefs*

Secondly, we tested whether participants' learning about their choice options was unaffected by the presence of prior information about their choice options, but rather that they had different initial expectations (at time 0) of, one the one hand, extremely high and high expectancy choice options and, on the other hand, extremely low and low expectancy choice options. To test this, prediction errors were computed using a Rescorla-Wagner learning rule (see Equation 1); and expected values of choice options were updated using a standard Q-learning rule:

$$QC,t+1 = QC, t + \alpha * \delta C, t \qquad (4)$$

where the existing expected value of choice option C (QC, t) is updated by the weighted ($\alpha$) prediction error ($\delta$ C, t) experienced at time point t. However, at time 0 a number (free parameter $\psi$) is added to the expected values of extremely high and high expectancy choice options, such that:

$$Q0, HIGH/EXTREMELY\ HIGH = 0 + \psi \qquad (5a)$$

$$Q0, LOW/EXTREMELY\ LOW = 0 \qquad (5b)$$

In addition, expected values are translated to selection probabilities by means of a softmax selection rule (see Equation 3).

*Model 3: Selection bias for high expectancy options*

Third, we tested the possibility that participants were initially unaffected by the prior information and that they learned the expected values of their choice options normally by trial-and-error, but that each time they had to make a decision, they had a selection bias to choose the extremely high and high expectancy choice options. More formally, prediction errors were learned using a Rescorla Wagner rule (see Equation 1); experienced prediction errors were weighted by a single learning rate and used to update existing expected values of chosen choice options (see Equation 4). However, before translating expected values into selection probabilities, a selection bias (β) was added to the expected values of high and extremely high expectancy choice options. The softmax selection procedure (see Equation 3) was then performed on these biased expected values (Q’). Importantly, the non-biased expected values (Q), and not the biased ones (Q’) were constantly updated with new prediction errors.

If C = high or extremely high, $Q'C,t = QC, t + \beta$

else $Q'C,t = QC, t + 0$

*Model 4: Differential updating for expectancy-consistent and expectancy-inconsistent prediction errors*

Finally, we tested whether participants were initially unaffected by the presence of priors, but that they updated expectancy-consistent versus expectancy-inconsistent rewards when learning about the ‘generosity’ of social partners and slot machine. First, prediction errors were computed using a Rescorla=Wagner learning rule (see Equation 1). However, and importantly so, expectancy-consistent (δ=) and inconsistent (δ~) prediction errors are weighted differentially such that, one the one hand, positive prediction errors from high expectancy options (δ=+) and negative prediction errors from low expectancy options (δ=-) have a different weight than, on the other hand, positive prediction errors from low expectancy options (δ~ -) and positive prediction errors from high expectancy options (δ ~ +). In mathematical terms:

QC,t+1 = QC, t + α CONSISTENT * δ C, t CONSISTENT + α INCONSISTENT * δC, t INCONSISTENT

Next, expected values of choice options were translated into selection probabilities by means of a softmax selection rule (see Equation 3).

### *MODEL FITTING, SELECTION AND COMPARISON*

To fit a model to participants' actual choices, we estimated the values of the free parameters by using the MATLAB fmincon function. In essence, this function randomly chooses as set of parameters and computes the log-likelihood of the model given those parameters. The log-likelihood of the model is computed by taking, for each trial, the log of the predicted selection probability of the option that the participant actually chose on that trial; and taking the sum of those log-probabilities across all trials. The fmincon function then slightly changes the value of the free parameters; computes the log-likelihood of the model again with the new set of parameters and evaluates if the log-likelihood has improved. The function iterates these steps until the log-likelihood of the model does not improve anymore and, thus, the best set of parameters has been found. In addition, multiple start values for the free parameters were used to avoid the fmincon function reporting the local rather than global minima. To evaluate the log-likelihoods, we calculated the Bayesian Information Criteria (BIC; Schwarz, 1978), which is a metric of model fit that rewards the most parsimonious model by adding a penalty for additional free parameters.

*ANALYSES OF VARIANCE*

The repeated measures ANOVA demonstrated that prior beliefs significantly ($F = 20.19$, $p < .001$) affected the percentage an option was chosen, and this effect was significantly ($F = 3.45$, $p = .021$) different between social and nonsocial task. Although the effect was significant in both social ($F = 7.48$, $p < .001$) and nonsocial ($F = 26.75$, $p < .001$) task, the effect size was stronger in the nonsocial ($\eta 2 = 0.43$) than social ($\eta 2 = 0.22$) task (see Figure 3.2).

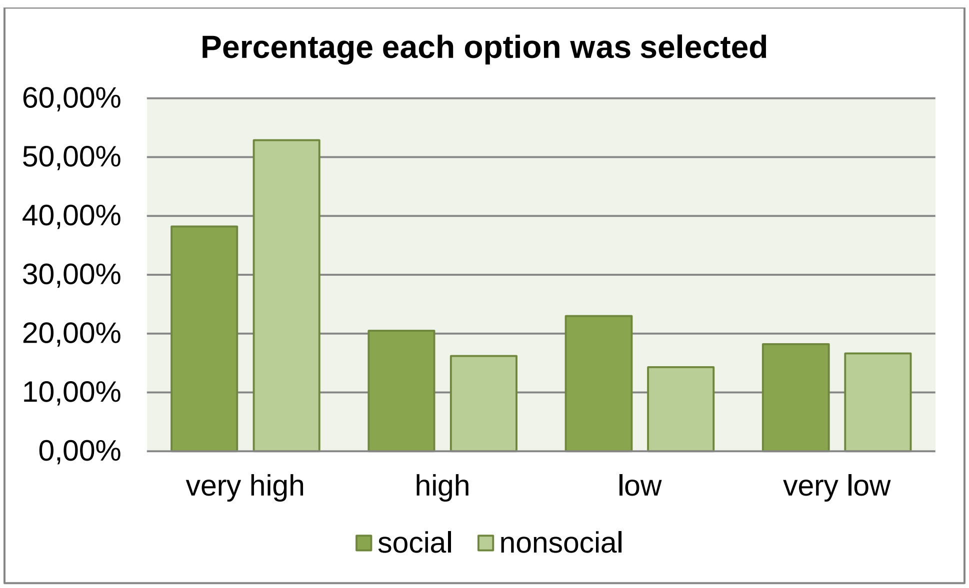


Figure 3.2 *Percentage of cases in which the very high, high, low and very low expectancy options were chosen in social and nonsocial condition.*

*MODELING RESULTS*

Results demonstrated that in both social and nonsocial (prior) conditions, model 4 provided the best fit to the data (see Table 3.1). In the social condition, the learning rate for expectancy-consistent prediction errors (M = .55) and expectancy-inconsistent prediction errors (M = .63) were not significantly different from each other (t = -1.12, p = .264). Also in the nonsocial condition, the learning rates for expectancy-consistent (M = 0.39) and expectancy-inconsistent (M = 0.44) prediction errors were not significantly different from each other (t = -0.60, p = .548). However, the expectancy-consistent learning rate was marginally significantly (t = 1.94, p = .060) higher in the social than nonsocial condition. Moreover, the expectancy-inconsistent learning rate was significantly (t = 2.31, p = .027) higher in the social than nonsocial condition (see Figure). The softmax temperature was not significantly different (t = -1.63, p = .111) between social (M = 1.66) and nonsocial (M = 2.07) condition (see Figure 3.3).

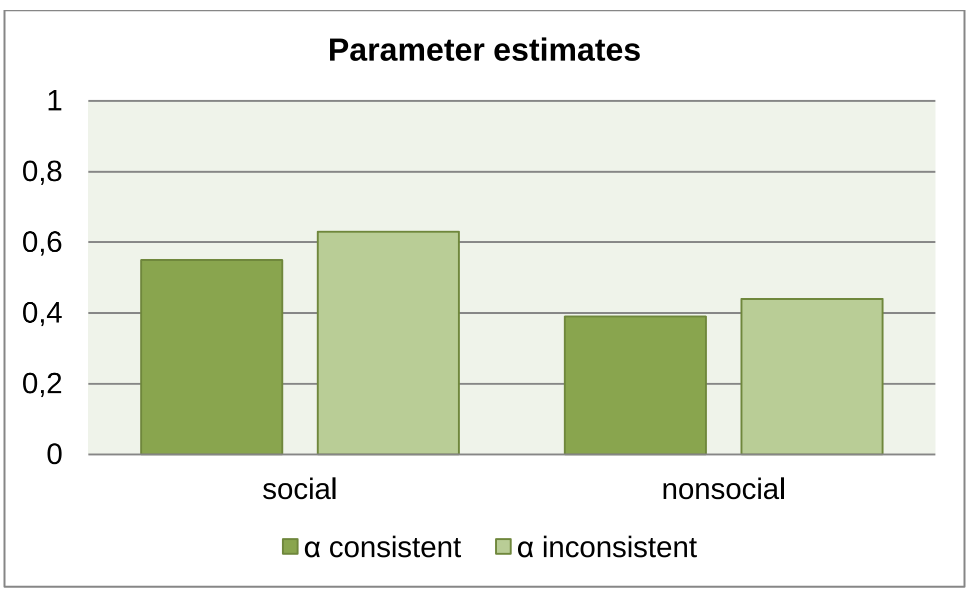


Figure 3.3 *Parameter estimates for belief-consistent and inconsistent learning rates in social and nonsocial condition separately.*

To investigate whether learning rates were better overall in social rather than nonsocial task also when no prior beliefs about choice options was induced, we only fitted Model 1 and a simplified version of Model 1 in which all observations were updated using the same single learning rate (Model 0) to participants' choices. Bayesian Information Criterion indices indicated that model 0 fitted the data in both social and nonsocial condition best (see Table 2). Parameter estimations indicated that average learning rates in the social condition (e.g., 0.56) were not significantly ($t = 0.17$, $p = .864$) different from average learning rates in the nonsocial condition (e.g., 0.55). In addition, also the softmax temperatures were not significantly ($t = -0.56$, $p = .578$) different between social (e.g., 1.65) and nonsocial (e.g., 1.75) condition.

| Social | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| BIC | 48715 | 48796 | 49165 | 48526 |
| Log-likelihood | 112.27 | 112.48 | 113.42 | 111.79 |

| Nonsocial | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| BIC | 42974 | 43011 | 43241 | 42857 |
| Log-likelihood | 97.52 | 97.61 | 98.20 | 97.22 |

Table 3.1: *Bayesian Information Criterion (BIC) and log-likelihoods for each of the four models in social and nonsocial condition separately.*

The present chapter aimed to investigate how prior beliefs affect the underlying mechanisms of stay/leave decision making; and to explore why social stay/leave decisions are less strongly affected by prior beliefs than individual stay/leave decisions are. To this end, we made use of a traditional and social version of the 4-armed bandit task, in which participants choose between four choice options (e.g., slot machines or social partners) and receive a monetary reward from their chosen option on each trial. Participants learned which options were most generous by sampling, and in half of the versions they also were induced with prior beliefs about each option's generosity.

We first demonstrated that also in the current task prior beliefs had an effect on participants' decisions, and that this effect was stronger when deciding between nonsocial resources rather than between social partners. By fitting several reinforcement learning models to participants' trial-by-trial decisions, we demonstrated that in both social and nonsocial task, participants differentially updated new observations based on whether they were consistent or inconsistent with their prior beliefs. Results were inconclusive as to how much weight was put on consistent and inconsistent observations in social and nonsocial task. However, it was demonstrated that participants had generally higher learning rates when making social rather than nonsocial stay/leave decisions. Interestingly, this difference in overall learning rates was lacking when no prior beliefs were induced.

Importantly, our findings are consistent with previous literature on the effects of prior beliefs on learning and decision making. First, we replicated our finding from the former chapter which demonstrates the validity of our claim that social stay/leave decisions are affected by prior beliefs less strongly than individual decisions. Second, our finding that belief-consistent and belief-inconsistent are differentially updated when prior beliefs are induced is in line with previous studies using a reinforcement learning framework to investigate the effects of prior beliefs on belief updating (Biele et al., 2011; Delgado et al., 2005; Doll et al., 2009; Fareri et al., 2012; Fouragnan et al., 2013; Li et al., 2011). Third, the finding that prior beliefs bias learning and decision making to be in line with those beliefs are consistent with a long line of findings that people typically gather, interpret and remember new observations in line with prior beliefs (e.g., confirmation bias; Plous, 1993).

More interestingly is however that general learning rates were higher for both belief-consistent and belief-inconsistent new observations in the social rather than nonsocial task; and that participants only had higher learning rates in the social task when prior information was available. Why would this be the case?

One potential explanation comes from the notion that people's behavior may be much more susceptible to change than the outcomes of a nonsocial resource are. That is, people's behavior may vary based on social context (i.e., one may behave differently at work versus at home); it may depend on the target of their behavior (i.e., a friend or a stranger); it may even depend on internal factors, such as mood but also the internal motivations that people have (i.e., trying to make a good impression). In comparison to social partners, nonsocial resources may typically be less susceptible to change; and it may be for this reason that our participants were more sensitive to the behavior of their social partners than the outcomes of nonsocial resources, when they had prior beliefs about them.

Related to this is the fact that we typically have prior expectations about our interaction partners (i.e., based on age, gender, skin color, nationality, facial characteristics, social group, social status, reputation) and know, from experience, that these expectations can be false. People may thus simply have learned to pay attention to actual behavior of our interaction partners even when we have prior beliefs about them; something that might not be the case in nonsocial learning contexts.

One limitation of the present study is that while our computational modeling analyses demonstrated that participants differentially updated belief consistent and belief-inconsistent new observations, t-tests indicated no difference in learning rates between these two learning rates. In this way, our modeling results are thus inconclusive and one may wonder whether indeed this model captures the mechanisms underlying the effects of prior beliefs on decision making. Two things can be said on this matter. One is that a typical problem in computational modeling is that this analysis technique merely indicates which of the tested models fits the data 'best'. However, there might be a better model 'out there' which we did not test and which captures the underlying mechanisms better than our currently 'winning' model. This is a typical problem of computational modeling, but other than trying to test all plausible models one can think of, there is no way to overcome this.

Even so, amongst a set of four models that could each plausibly explain how prior beliefs are integrated in stay/leave decision making, the model in which belief-consistent and belief-inconsistent observations did fit our data best. This thus means that it is reasonable to consider the effect of prior beliefs on decision making in this way. Importantly also, this model is consistent with other studies on the effects of prior beliefs on learning and decision making.

Finally, while we can speculate about why overall learning rates were higher in social than nonsocial condition, but only when priors were available, the present chapter provides no conclusive answer to why this is the case. We managed to provide some initial accounts of why people are more resistant to priors when learning about social partners rather than slot machines, but future research is still necessary to investigate why this is the case.

The present chapter demonstrated the usefulness of reinforcement learning frameworks to understand the underlying mechanisms of stay/leave decision making; and specifically to explore potential differences between individual and social stay/leave decision making. More importantly however, we demonstrated that prior beliefs affect subsequent learning such that new observations are differentially updated based on whether they are consistent or inconsistent with prior beliefs; and that people put more weight on new observations –regardless of whether they are consistent or inconsistent with prior beliefs – when making social rather than nonsocial decisions, but only when prior beliefs are present.

# Chapter 4

# *Social versus nonsocial stay/leave decisions: An fMRI study*

The present chapter aimed to investigate the underlying behavioral, computational and neural mechanisms of stay/leave decision making; and to investigate how individual and social stay/leave decision making processes relate to each other. Participants played a 4-armed bandit task and an adapted version of this task in which participants chose between four social partners and played a Dictator Game in the role of the recipient with the partner of their choice on each trial. A Reinforcement Learning model predicted decisions in both tasks above chance and equally well. Neural correlated of latent variables replicated earlier work on value-based learning and decision making. However, imaging analyses demonstrated increased caudate activation for social versus individual stay decisions. Moreover, in the social task leave decisions were associated with a stronger increase in signal in dorsal anterior cingulate activation compared to social decisions, whereas the reverse pattern was found in the individual stay/leave decision making task. Potential relations of these findings to a theorized need to belong are discussed.

An extensive body of evidence has identified a number of brain regions (i.e., several regions of the prefrontal cortex, striatum, anterior cingulate cortex, anterior insula) typically implicated in value-based learning (see Lee et al., 2012) and decision making (Rangel et al., 2008; Bartra et al., 2013; Rilling & Sanfey, 2008). Importantly however, these regions do not just contribute to individual value-based decision making (i..e, about foods, drinks, money), but also respond to social value (for a review see Fareri & Delgado) and are implicated in social learning and decision making (for a review see Rilling & Sanfey, 2008). To highlight, these regions have been implicated in representing the value of social approval and acceptance (Jones et al., 2011), the value of sharing rewards with close others (Fareri et al., 2012b), the value of donating to charity (Moll et al., 2006; Hare et al., 2010) and the value of getting trust reciprocated (Phan et al., 2010). Furthermore, these regions contribute to the social learning of trust (Delgado et al., 2005; Fareri et al., 2012a; Fouragnan et al., 2013) and social norms (Xiang et al., 2013). Altogether, these findings suggest that the same neural mechanisms underlie both social and nonsocial (value-based) decision making processes.

However, it has also been well-established that, on a behavioral level at least, social decision making is strongly affected by social factors, such as social norms (see Xiang, et al., 2014; Sanfey et al., 2014;), social closeness (see Akerlof, 1997), social emotions and social motivations (see Rilling & Sanfey, 2008): factors that are non-existent in nonsocial decision making processes. Even more, while in individual decisions, people only need to maximize their own interest; in social decisions they often have to balance self-interested and social motivations (e.g., transformation of motivation; see Yovetich & Rusbult, 1994). For example, in an individual decision making context, one would most likely never deliberately decrease to take only a part of the money that they are entitled to; but in a social context, people oftentimes forego a part of their personal endowments to share it with another person. Thus, while both individual and social value-based decisions share similar neural regions; behavioral outcomes of individual and social decisions are typically quite different.

One type of social decision making that is theorized to be based upon value-considerations is the decision to stay with or leave a social relationship partner. Specifically, social relationships were framed as exchange structures, in which people keep track of relationship rewards and costs (see Interdependence Theory and the Investment Model; Emerson, 1976; Kelley & Thibaut, 1978; Rusbult, 1980; 1983; Rusbult & Farrel, 1983; Rusbult & Johnson, 1986); and the intention to stay in a relationship (e.g., commitment) was theorized to be based upon the net gain of the relationship and the quality of the alternatives when leaving. Importantly, a bulk of self-report data on real-life (including romantic) relationships supports the idea that the decision to stay with or leave a social relationship partner is indeed based upon motives of value-maximization (see Cate et al., 2002; Le & Agnew, 2003; Le et al., 2010).

While social stay/leave decisions might thus be based upon general principles of value-based decision making, it seems implausible that social stay/leave decisions rely on (exactly) the same neural computations as individual stay/leave decisions (i.e., the decision to abandon a monetary investment) even if neural regions contributing to individual and social value-based decisions typically overlap. The goal of the present paper is therefore to investigate (1) whether the decision to stay with or leave a social relationship partner is behaviorally, computationally and neurally based upon general principles of value-based decision making; and (2) to explore how individual and social stay/leave decisions relate to each other.

## *Participants*

Twenty-six right-handed healthy students of the Radboud University in Nijmegen (the Netherlands) participated in the experiment (mean age: 23.04, range 19-30; 50% female). Participants were excluded from participation if they took any form of medication that could interfere with the BOLD response, if they ever had head trauma or an operation on their head, if they ever experienced psychological or neurological problems, if they had a history of drug abuse, if they had irremovable metal parts or active implants in their body, if they were epileptic, claustrophobic, pregnant or if they were younger than eighteen years of age. All gave informed consent under the ethical approval provided by an acknowledged Dutch Review Board. Participants received a twenty Euro standard participation fee and were additionally incentivized to perform well on the task by administration of a performance-dependent monetary bonus of maximally ten Euros.

## *Imaging procedure*

High-resolution T1-weighted structural scans were acquired on a Siemens 3.0 Tesla Skyra scanner using an MPRAGE sequence with an acceleration factor of 2 and an 8° flip angle; the FOV was 256 x 256 with 1.0 x 1.0 x 1.0 mm voxels. Four functional runs were then acquired using a 5-shot multi-echo planar GRAPPA sequence with acceleration factor 3 and a flip angle of 90°. The FOV was 224 x 224 mm and contained a 64 x 64 matrix of voxels with dimensions 3.5 x 3.5 x 3.0 mm. Slice thickness was thus 3.0 mm and the gap between slices was 0.51 mm (e.g., 17% of 3mm). Because we use a 5-shot multi-echo sequence, five echoes are acquired within each volume with varying TE's between the five echoes. The rationale for this is that TE is optimal when it equals T2*, but that T2* varies across the brain. When interested in areas across the whole brain, it is therefore difficult to choose one appropriate TE. A multi-echo sequence solves this problem by acquiring multiple echoes at different TE's within one volume. Within the first thirty pulses of the first functional run, the T2* of each voxel is measured and used to compute the appropriate TE for that voxel. These thirty volumes and the first five volumes (to account for T1 equilibrium effects) of the other three functional runs are discarded from analyses.

### *TASK*

While undergoing fMRI, participants played two experimental blocks of a task that were administered in counterbalanced order. In one of the blocks, participants played a standard 4-armed bandit task, and in the other block they played a modified (e.g., social) version of this task. The blocks consisted of one-hundred rounds each, with a brief scanning break after each fifty rounds and between the two blocks. The task was thus divided over four scan runs in total. Participants were told in advance that all the money they collected in the entire game would be divided by ten and paid out later. They thus understood that their decisions in the game were consequential to their earnings.

On each trial of the standard 4-armed bandit task, participants were first presented with four slot machines (4 seconds) after which they received a cue to choose one of the slot machines by pressing the according button on a button box with their right hand (max 3 seconds). If participants did not respond within 3 seconds, the trial ended and the participant received no money for that trial. If they did respond on time, participants waited for the outcome (e.g., for 4 seconds +/- a random jitter of 2 seconds), and were then showed the outcome of that trial (e.g., for 3 seconds). After an inter trial interval of three seconds +/- a random jitter of 1 second during which a fixation cross was displayed, a new trial would automatically start. Participants were told that probability of payoffs could differ between slot machines and over time.

The structure of the modified (e.g., social) version of the task was exactly the same as the version described above. However, participants now played a Dictator Game in the role of the recipient on each trial. Specifically, we told participants that we had endowed previous participants with 1 Euro on each round and that we had asked these previous participants repeatedly if, and if so how much, they wanted to share some of that Euro with an anonymous other participant (e.g., the participant of the current study) who would otherwise get nothing. Rather than choosing between slot machines, participants chose between four of those previous Dictators (e.g., social partners) and viewed how much money the Dictator had decided to share with them.

In reality, we used Gaussian decaying processes to generate the payoffs for each slot machine and social partner at each trial. That is, the payoff from a choice option i is the result of a Gaussian random walk with standard deviation $\sigma 0 = 4$, and the mean defined as $\mu i,t+1 = \lambda \mu i,t + (1 - \lambda)\ \theta + \nu$. In the equation, $\mu i,t$ is the mean reward for option i at trial t; the decay was centered at 25 (i.e., $\theta$), the rate of decay $\lambda = 0.893$, and the diffusion term was set to $\nu = N(0, 2.8)$. We chose this specific strategy in order to make the environment dynamic, so that participants needed to explore it. Specific parameters for the Gaussian process were chosen to mimic previous experimental studies (Daw et al., 2006).

Payoffs in the social and nonsocial version of the game were thus matched. In addition, participants were told that the remaining part of the 1 Euro that the Dictator kept would be paid out to that Dictator; and the remaining part of the 1 Euro that a slot machine did not pay out was added to one of the Dictator's money bonus. In this way, the social and nonsocial tasks are also similar as to where the remaining part of each 1 Euro would go to.

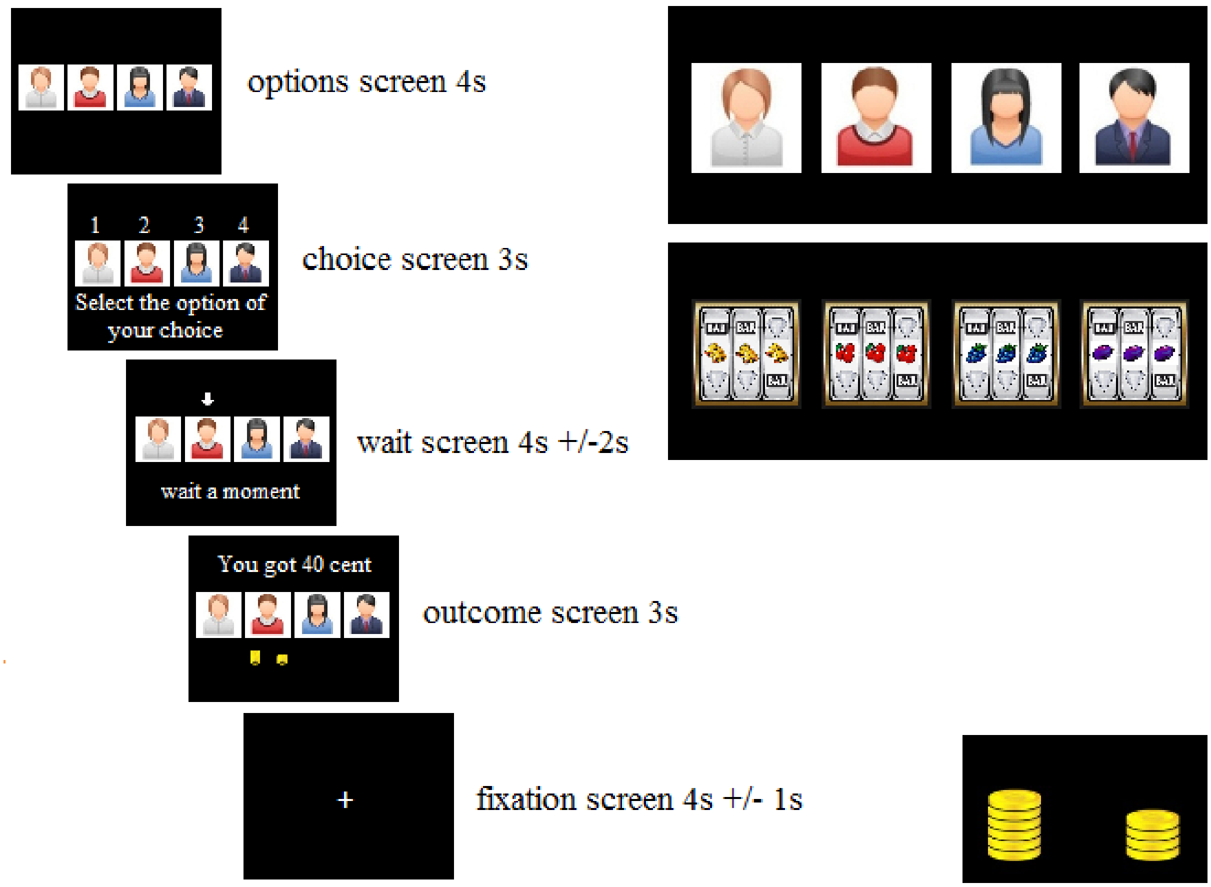


FIGURE 4.1 *On each trial, participants first saw their four choice options (e.g., the 'options-screen'); and were then asked to select option 1, 2, 3 or 4 by pressing the corresponding button on the button box (e.g., 'the choice screen'); they next waited for the outcome (e.g., 'wait-screen') and finally saw how much money they received on that trial (e.g., 'outcome-screen'). All trials were separated from each other by a fixation cross (e.g., 'fixation-screen'). Choice options could be four different social partners or four different slot machines. Monetary outcomes were also visually represented by means of two piles of coins: one representing the partner's money and the other representing the participant's money.*

## *MIXED MODEL ANALYSES*

Data were analyzed using the statistical software package R (R_Development_Core _Team, 2008). The lmerTest function (Kuznetsova, et al., 1978) was used to test whether trial-by-trial decisions to stay or switch were predicted by task (e.g., social or nonsocial) and (centered and scaled) reward; while controlling for block (e.g., first or second) and order (e.g., social-nonsocial or nonsocial-social). To account for the possibility that participant have difference baseline tendencies to stay or switch, we included a fixed intercept and a random participant-specific adjustment to that intercept, to the model. In addition, as the strength of the effect of each (within-subject) predictor could differ between participants, random slopes of all within-subject factors were included to the model (see Barr, 2013; Barr et al., 2013). P-values were calculated based on Satterthwaite's approximations.

## *REINFORCEMENT LEARNING MODELING ANALYSES*

To predict participants' choices  on a trial-by-trial basis, we modeled participants' choices (e.g., choose option 1, 2, 3 or 4) as a function of their previous choices and rewards, I used a temporal-difference learning algorithm (Rescorla & Wagner, 1972; Sutton & Barto, 1998) with separate learning rates for positive and negative prediction errors (see Bayer & Glimcher, 2005; Cazé & van der Meer, 2013; Seymour et al., 2007; Yacubian et al., 2006). Specifically, each time an option was selected, the expected value (Qt) of that option (C1-4) was updated with the prediction error (δt), which is the difference between expected value (Qt) and obtained reward ($r_t$) from that option. In addition, prediction errors were weighted - with a different learning rate for positive ($\alpha^{POS}$) and negative ($\alpha^{NEG}$) prediction errors - before added to the expected value of an option. Moreover, expected values of each of the four choice options at each trial were translated to selection probabilities using a softmax selection rule (with free parameter $\tau$), such that options with a higher expected value had a higher chance of being selected. To fit a model to participants' choices, we estimated the values of the free parameters ($\alpha^{POS}$, $\alpha^{NEG}$, $\tau$) by using the MATLAB fmincon function which computes the log-likelihood of a model given a set of randomly chosen parameters. The function updates those parameters constantly, until the maximum negative log-likelihood is reached and, thus, the best fitting set of parameters is found. Multiple starting values for the free parameters were used to avoid the fmincon function reporting the local rather than global minima.

Prediction error:

$\delta t = rt - Q(A, t)$

Value updating:

If $\delta t \geq 0$: $Q(A, t+1) = Q(A,t) + \alpha^{POS} * \delta t$

If $\delta t < 0$: $Q(A, t+1) = Q(A,t) + \alpha^{NEG} * \delta t$

Softmax selection rule:

$pC1, t = \exp[QC1,t / \tau] / (\exp[QC1,t / \tau] + \exp[QC2,t / \tau] + \exp[QC3,t / \tau] + \exp[QC4,t / \tau]$

## *DESCRIPTIVES*

We first explored any behavioral difference in stay/leave decision making overall using t-tests and found that the average reward preceding a stay (32.51 cents) decision was significantly ($t = 38.52$, $p < .001$) higher than the average reward preceding leave (25.39 cents) decisions; that the expected value of a chosen option was significantly ($t = 34.51$, $p < .001$) higher when participants decided to stay (e.g., 31.21 cents) rather than when they decided to leave (e.g., 23.90 cents); and that the value difference between chosen and not chosen options was significantly ($t = 13.66$, $p < .001$) larger when participants decided to stay (e.g., 7.79 cents) rather than when they decided to leave (e.g., 4.72 cents).

On a behavioral level, we found hardly any differences between social and nonsocial condition. That is, the percentage of trials on which participants decided to stay rather than leave was equal ($t = 0.46$, $p = .647$) in social (53.79%) and nonsocial (52.28%) condition. Also, the average reward preceding stay decisions did not significantly ($t = -1.07$, $p = .290$) differ between social stay (32.37 cents) and nonsocial stay (32.66 cents) decisions; the average reward preceding leave decisions did not significantly differ ($t = -0.55$, $p = .585$) between social leave (25.32 cents) and nonsocial leave (25.46 cents) decisions; and the average rewards obtained were equal ($t = -0.3$, $p = .773$) between social (28.84 cents) and nonsocial (29.06 cents) condition. Furthermore, the value differences did not differ between social and nonsocial conditions for when participants decided to stay ($t = 1.50$, $p = .140$) or leave ($t = 1.88$, $p = .066$). In addition, the difference between chosen and not chosen options did not differ ($t = 1.37$, $p = .174$) overall between social (e.g., 6.51 cents) and nonsocial (e.g., 5.99 cents) condition.

However, some differences between social and nonsocial condition were found. That is, the expected value of chosen options was significantly (-2.34, $p = .024$) lower when participants decided to stay in a social (e.g., 30.89 cents) than nonsocial (e.g., 31.54 cents) condition. Furthermore, the expected value of chosen options was significantly ($t = -2.27$, $p = .028$) lower when participants decided to leave social partners (e.g., 23.56 cents) than when they decided to leave slot machines (e.g., 24.24 cents). Overall, the expected values of chosen options did not significantly ($t = -2.18$, $p = .340$) differ between social (e.g., 27.23 cents) and nonsocial (e.g., 27.89 cents) condition.

### *MIXED MODEL RESULTS*

Our mixed model analyses demonstrated that rewards significantly predicted stay/leave decisions ($z = -10.22$, $p < .001$), but there was no effect of condition ($z = 1.28$, $p = .201$). The effects of block ($z = 5.67$, $p < .001$) and order ($z = -2.64$, $p = .008$) are significant.

### *COMPUTATIONAL MODELING ANALYSES*

The likelihood ratio of our temporal difference learning model predicted participants' actual choices in both social (LL = 95.89) and nonsocial (LL = 98.58) task better than chance ($p < .001$) and equally well. Parameter estimations indicate that participants learned significantly faster from negative ($\alpha NEG = 0.95$) rather than positive ($\alpha POS = 0.65$) prediction errors in both social ($t = -6.653$, $p < .001$) and nonsocial ($t = -5.758$, $p < .001$) task. There were no differences in parameter estimations between social and nonsocial task for positive learning rates ($t = -0.004$, $p = .997$), negative learning rates ($t = 0.346$, $p = .730$) or softmax temperatures ($t = 0.457$, $p = .649$).

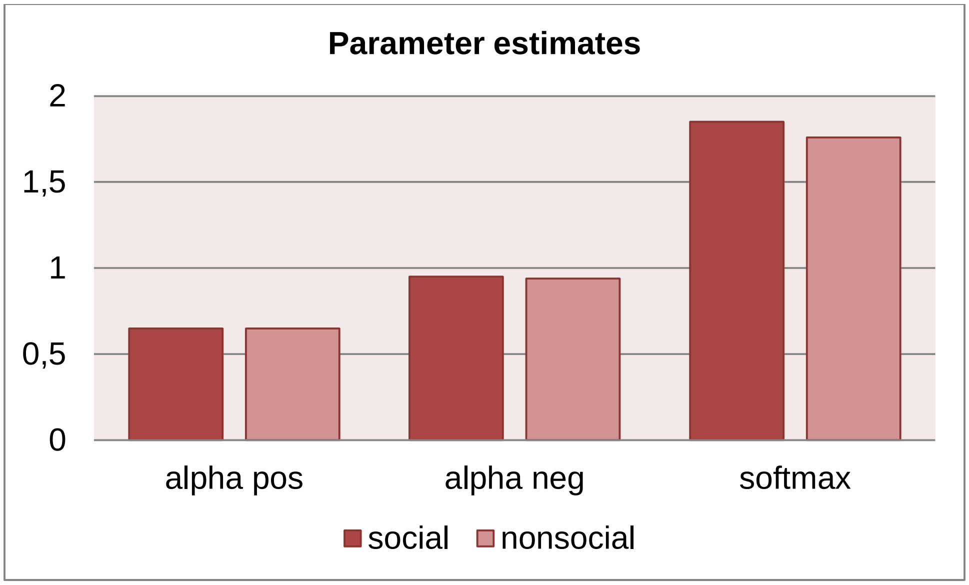


FIGURE 4.2 *Parameter estimations of the reinforcement learning model for social and nonsocial block. Learning rates for negative prediction errors are significantly higher than those for positive prediction errors. There are no differences between social and nonsocial condition.*

## IMAGING ANALYSES

### *PREPROCESSING*

First, as multi-echo data collection results in multiple scans per TR, these multiple scans were first combined to one scan per TR. As part of the combination process, scans are already corrected for motion. The rest of the data preprocessing was performed using SPM8 (http://www.fil.ion.ucl.ac.uk/spm/software/spm8). Images were corrected for slice time acquisition, and each participant's average high resolution structural scan was overlaid to their functional images. These co-registered images were then segmented in grey and white matter and cerebro-spinal fluid; and spatially normalized to the MNI template by applying a 12-parameter affine transformation and 4th Degree B-Spline interpolation. Finally, the images were smoothed using a 7 mm full width at half maximum Gaussian kernel and high pass filtered in the temporal domain (filter width of 800s to not lose any variance related to the social or nonsocial condition).

### *EXPLORATORY ANALYSES*

To identify the neural correlates of prediction errors, we regressed the trial-by-trial prediction errors against whole brain activation using a parametric General Linear Model (GLM). The same analyses were performed to identify the neural correlates of the expected values of chosen options and the inverse value difference between chosen and the mean of the not chosen options. To explore whether the brain showed differential activation for these correlates between social and nonsocial (and nonsocial versus social) task, we performed factorial GLMs to contrast activation between the two task versions. Even more, we contrasted activation across the whole brain for stay versus leave (and the reverse); social stay versus social nonsocial stay (and the reverse); and social leave versus nonsocial leave (and the reverse) decisions. For all these analyses, we reported whole brain activation if it survived the $p < .001$ uncorrected threshold and was significant at the $p < .05$ FWE corrected threshold.

### *REGION OF INTEREST ANALYSES (ROIS)*

Given the well-established role of the ventral striatum in the encoding of prediction errors, we performed a ROI on this region (e.g., a 10mm sphere around the coordinates from

Pessiglione et al., 2006; [-10, 12, -8]), and reported activation in this region that survived the $p < .05$ uncorrected threshold. Furthermore, given the strong priors in the literature that activation in the ventromedial prefrontal cortex / medial orbitofrontal cortex represents subjective value, we reported activation in this region when it survived the $p < .05$ uncorrected threshold. Moreover, because the dorsal anterior cingulate cortex was found to track the inverse value difference between chosen and not chosen options in a stay/leave decision making context, we compared the mean time course in this region (e.g., a 10mm sphere around the coordinates taken from Kolling et al., 2013; [-4, 32, 20]) for stay versus leave and social versus nonsocial task separately. All ROI analyses were performed using the Marsbar toolbox within SPM8.

## IMAGING RESULTS

### *RESULTS: NEURAL CORRELATES OF PREDICTION ERRORS*

Across tasks, we found several clusters of activation that correlated with the size of the prediction errors (see Table 4.1 and Figure 4.3) at the window that participants received their trial-by-trial rewards. An ROI analysis on the ventral striatum revealed significant activation in this region correlating with prediction errors. No differential activation was found for task specific correlates of prediction errors.

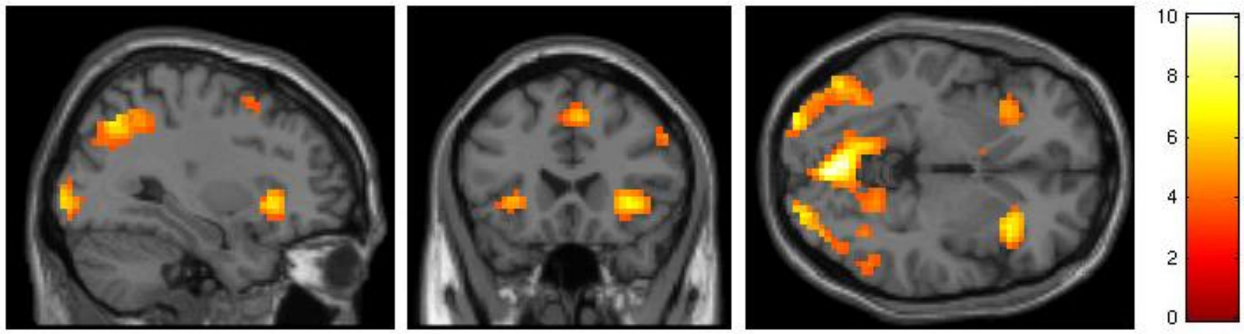


FIGURE 4.3 *Neural activation correlating with prediction errors*

| Brain area | # voxels | p | z | x | y | z |
|---|---|---|---|---|---|---|
| Right inferior parietal gyrus | 275 | < .001 | 5.82 | 48 | -35 | 46 |
| Right inferior temporal gyrus | 276 | .002 | 5.29 | 48 | -52 | -18 |
| Right anterior insula | 79 | .004 | 5.13 | 34 | 21 | -4 |
| Right middle frontal gyrus | 184 | .009 | 4.99 | 41 | 38 | 14 |
| Left lingual gyrus | 577 | <.001 | 6.23 | -1 | -74 | 0 |
| Left inferior occipital gyrus | 299 | <.001 | 5.72 | -46 | -70 | -10 |

TABLE 4.1 *Brain activation correlating with trial-by-trial prediction errors above the p < .001 uncorrected threshold and significant above the p < .05 FWE corrected threshold.*

RESULTS: NEURAL CORRELATES OF EXPECTED VALUE

Above the p < .001 uncorrected threshold, no significantly activated clusters correlated with the expected values of the chosen options across the whole brain at the windows that participants viewed their choice options. However, a cluster of activation appeared in the medial orbitofrontal cortex (491 voxels with peak at [-1, 24, -7]) that correlated with the expected value of the chosen options above the $p < .05$ uncorrected threshold (see Figure 4.4). No differential activation was found for social versus nonsocial representations of expected value.

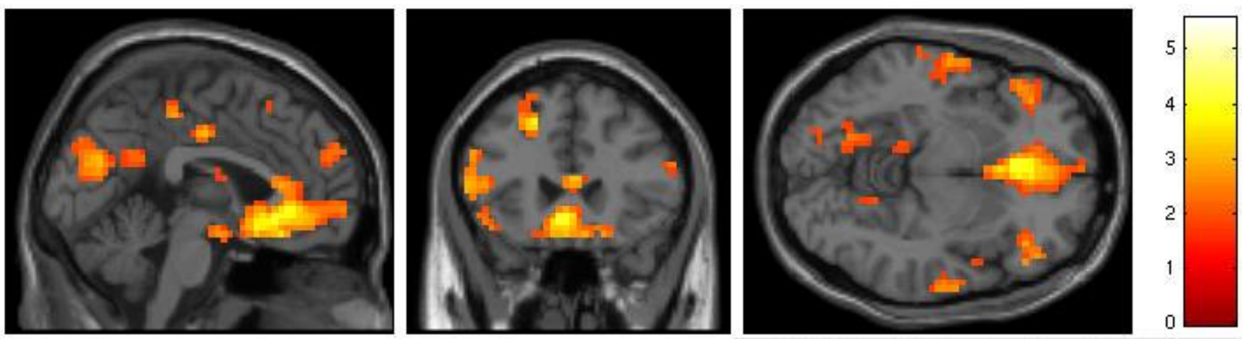


FIGURE 4.4 *Neural activation correlating with the expected values of chosen options that survived the p < .05 uncorrected threshold*

## *Results: Neural correlates of value differences*

A number of brain regions (including the dorsal anterior cingulate cortex) was significant above the $p < .05$ FWE corrected threshold (see Table 5.2 and figure 5.4). Contrasting this activation for social versus nonsocial task, revealed no significant clusters of activation. Interestingly however, a mean fitted time course analysis in the dorsal anterior cingulate cortex demonstrated that, in the social task, the BOLD response in the dACC was significantly ($t = -6.75$, $p < .001$) higher when participants decided to leave rather than stay. Conversely, in the nonsocial task, the BOLD response in the same area was significantly ($t = 4.05$, $p < .001$) higher when participants decided to stay rather than leave (see Figure 4.6).

| Brain area | # voxels | p | z | x | y | z |
|---|---|---|---|---|---|---|
| Right inferior temporal gyrus | 1099 | < .001 | 6.87 | 6 | 21 | 46 |
| Right inferior parietal gyrus | 112 | < .001 | 6.09 | 34 | -49 | 46 |
| Right inferior orbitofrontal gyrus | 76 | < .001 | 6.08 | 30 | 24 | -7 |
| Right thalamus | 31 | < .001 | 5.96 | 20 | -32 | 0 |
| Inferior fontal operculum | 33 | < .001 | 5.59 | 41 | 10 | 32 |
| Right cingulate gyrus | 22 | .001 | 5.43 | 6 | 21 | 46 |
| Left insula | 29 | 29 | 5.38 | -29 | 24 | 0 |
| Right middle frontal gyrus | 10 | .006 | 5.08 | 41 | 38 | 14 |

TABLE 4.2 *Brain activation correlating with trial-by-trial inverse value difference between chosen and not chosen options that survived the p < .001 uncorrected threshold and was significant above the p < .05 FWE corrected threshold.*

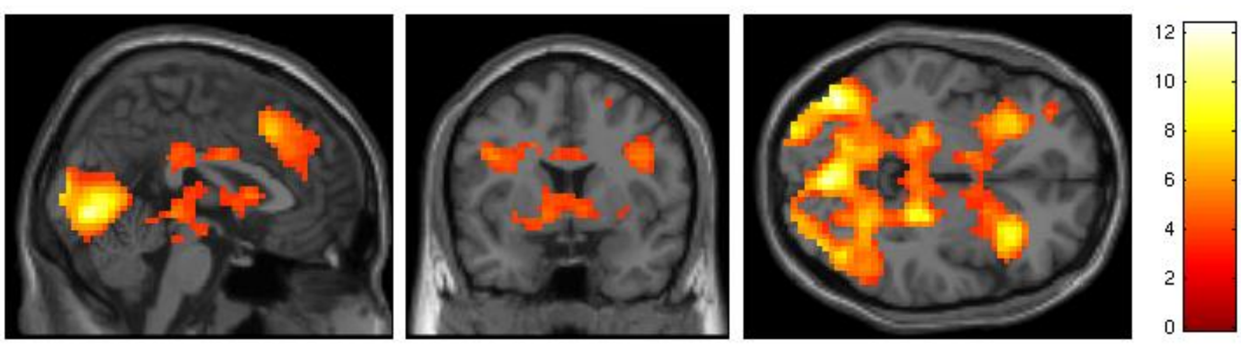


FIGURE 4.5 *Brain activation correlating with inverse value difference between chosen and not chosen options at p < .001 uncorrected threshold*

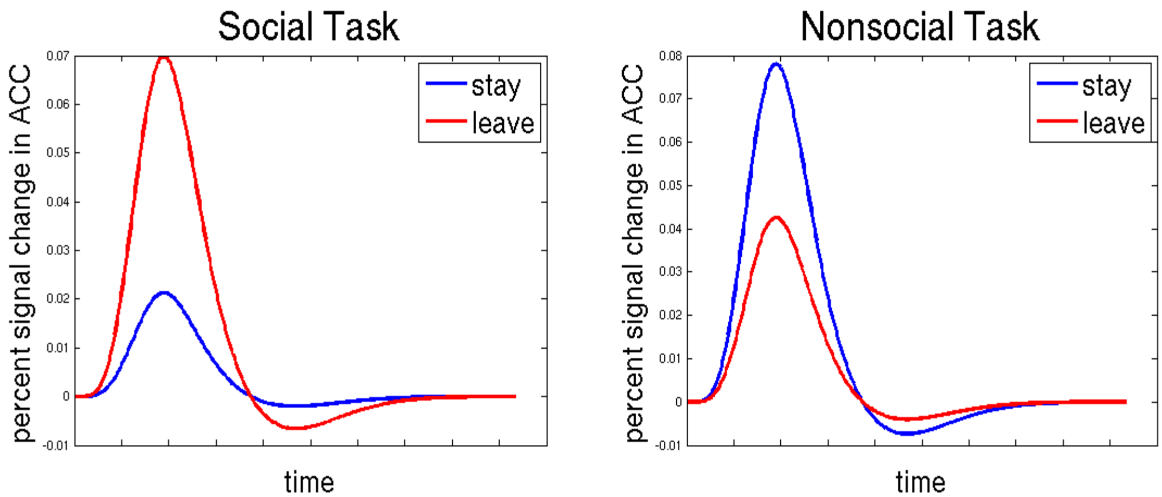


FIGURE 4.6 *Time course for anterior cingulate gyrus activation as a function of stay versus leave decisions*

*RESULTS: STAY VERSUS LEAVE DECISIONS*

Our analyses demonstrated no differential activation for stay versus leave decisions. However, when contrasting social versus nonsocial stay decisions, this revealed a significant cluster of activation in bilateral caudate (94 voxels with peak at [-8, 18, -4, peak z = 5.06] see Figure 4.7). No clusters were significantly activated for the reverse contrast.

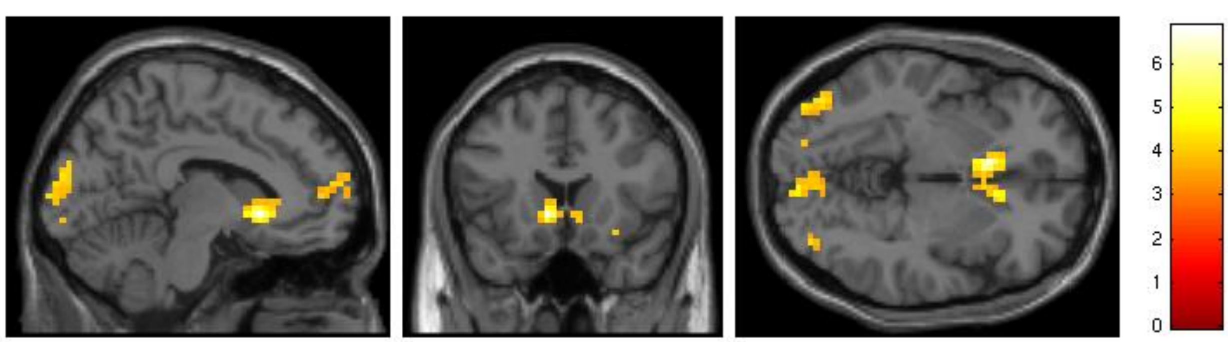

*Figure 4.7 Neural regions that become significantly more activated for social stay versus nonsocial stay decisions.*

*RESULTS: NEURAL CORRELATES OF LEAVE VERSUS STAY DECISIONS*

Differential activation was found for leave versus stay decisions in the left inferior parietal gyrus / post-central gyrus ($p = .040$ FWE corrected peak-level, 239 voxels with peak at [-57, - 21, 46, peak $z = 4.46$] see Figure 4.8). Contrasting decisions to leave in the social versus nonsocial condition, and vice versa, revealed no significantly activated clusters above the $p < .001$ uncorrected threshold.

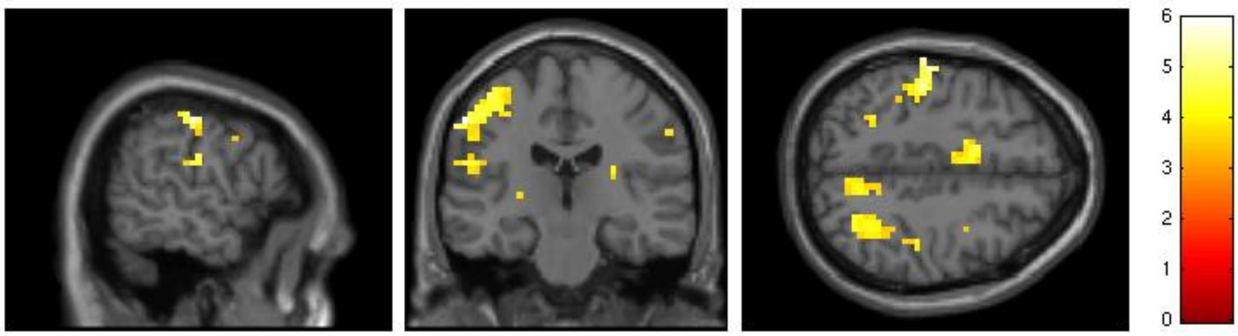


FIGURE 4.8 *Neural regions that are significantly more activated for leave versus stay decisions*

## DISCUSSION

The goal of the present study was to (1) investigate whether social and individual stay/leave decisions share the same mechanisms as value-based decisions on the behavioral, computational and neural level; and (2) to explore in which way, if any, social stay/leave decisions differ from individual stay/leave decisions. To this end, participants played a social and nonsocial version of the 4-armed bandit task in which they chose between slot machines that paid out money in the nonsocial task; and in which they chose between social partners who shared money with them in the social task.

On a behavioral level, participants' choices in both social and nonsocial task appeared to be based upon value-considerations. That is, participants' stay/leave decisions were, in both tasks, predicted by reward magnitude, such that participants' likelihood of staying was larger after receiving a larger rather than smaller reward on the previous trial. In addition, temporal difference learning models predicted participants' choices equally well in both social and nonsocial task. Moreover, on a neural level, regions typically implicated in value-based decision making were also activated for important latent variables underlying value-based decisions such as prediction errors, expected value of chosen options and inverse value difference between chosen and not chosen options.

However, important but subtle differences appeared when contrasting neural activation between social and nonsocial task for actual stay and leave decisions. That is, increased differential activation was found in the bilateral caudate when contrasting social versus individual stay decisions; and percentage signal change in the dorsal ACC was higher for leave than stay decisions in the social task, but higher for stay rather than leave decisions in the nonsocial task.

Previous studies have well-established the role of the striatum (including the bilateral caudate) in the representation of decision and outcome value. The finding that social stay decisions engage more activation in this reward-related region, clearly suggests that it was more rewarding for participants to stay with their social partners than when they stayed with slot machines. Importantly, this finding cannot be explained by any behavioral differences in reward value for social versus individual stay decisions. In fact, the mean reward after which participants decided to stay with social partners was even slightly *lower* than the mean reward after which they stayed with slot machines. Quite possibly, the intrinsic added subjective value to staying with social partners specifically, allowed them to stay with partners even when objective outcomes were lower. We can thus state that the decision to stay with a social partner was valuable above and beyond the objective monetary value of staying.

Although debate exists about the exact function of the dACC, most theorized functions of the dACC in both human and non-human primates, suggest that the dACC is implicated in signaling (opportunity) costs associated with a given decision option. That is, it is consistently found that dACC activation increases when the value difference between two choice options decrease (and thus when opportunity costs become higher; Kolling et al., 2013; Pochon et al., 2008); it was stated that dACC tracks the value of leaving (and thus the opportunity cost of staying) in an individual stay/leave decision making task (Hayden, et al., 2011; Kolling et al., 2013, but see Shenhav et al., 2014); was found to vary with choice complexity (Shenhav et al., 2014) and in non-human primates, dACC activation has been implicated in cost-benefit trade-offs (Croxson et al., 2009; Kennerley, et al., 2012). In line with this interpretation of the dACC that it signals the cost associated with making a specific decision, the pattern of findings in this region suggests that staying with a slot machine was more costly than leaving one; and that leaving a social partner was more costly than staying with one.

Why would the decision to stay with a social partner be more valuable above and beyond the objective value of staying? And why would the decision to leave a social partner specifically be more costly than staying with him or her? Interestingly, the answer to both questions could be that people have a fundamental need to belong (Baumeister & Leary, 1995): An intrinsic motivation to initiate and maintain connections with others that explains why people readily form social attachments and resist against breaking them; and why having social attachments is associated with positive affect and wellbeing, whereas lacking them is associated with negative affect and well-being.

Thus, in line with this theorized need to belong, the current findings indeed indicate a neural preference to stay with social partners and a neural aversion against breaking social connections. That is, the mere act of staying with a social partner engaged more reward-related activation that staying with slot machines. Moreover, as the decision to leave social partner appears to be more costly than staying in social relationships, we can infer that staying with a given social partner while there may be better partners out there is less severe than breaking a social connection. In addition, the fact that we find the opposite pattern of activation for costs associated with staying and leaving in the nonsocial task, suggests that this aversion against leaving is specific for social stay/leave decisions.

Some questions still remain however. One is whether the current task was able to capture real-life social stay/leave decision making processes. That is, the 'interactions' participants had with the social partners were rather one-sided; and the 'social' rewards were in fact monetary in nature. Even more, participants could freely switch between social partners, something that is not typically the case in all types of social relationships. Importantly however, these factors are both a limitation in terms of ecological validity as well as an important strength of the present study. That is, even when the social tie between participants and social partners was minimal we still found neural evidence that breaking such minimal tie was more costly and staying with a social partner was more rewarding than leaving versus staying was in the nonsocial condition. If the effects are already this strong in such as minimal social paradigm, then only supports the validity of our findings. Even more, the fact that 'social' rewards in our study were objectively exactly the same as the nonsocial rewards indicates that any differences between social and nonsocial condition cannot be explained by the nature or size of the rewards; and can only be explained by a subjective intrinsic additional value or cost associated with staying or leaving in the social task. Even so, however, it is important to validate the present results to more realistic types of social stay/leave decision making.

Also, our interpretation of the function of the dACC has not yet been studied extensively. Although previous findings on the role of the dACC support our claim, further research is necessary to validate this interpretation. Even so, none of the other existing theorized functions of the dACC can fully support our data. That is, while the finding that leave decisions is consistent with one theorized function of the dACC that it tracks the value of leaving (Kolling et al., 2013), why would leaving a social partner be more difficult or more complex than staying with them? Even more, the finding that stay decisions engaged more dACC activation is directly opposite to Kolling et al's (2013) suggestion; and again why would leaving a slot machine be more difficult or more complex than staying with it?

Finally, even if both individual and social stay/leave decisions were both based upon value-considerations, it is surprising that the behavioral differences between social and individual stay/leave decision making were rather minimal. However, this also indicates the added value of investigating neural differences between individual and social types of decision making. That is, based upon behavior alone, it would seem that staying with or leaving a slot machine is the same as staying with versus leaving a social partner, but by looking at neural activation associated with each decision we can demonstrate the existence of social preferences specifically.

## CONCLUSION

To conclude, the present study demonstrates that the decision to stay with or leave a social partner is based upon general principles of value-based learning and decision making on both the behavioural, computational and neural level, but that there is an intrinsic neural value associated with maintaining social connections and an intrinsic cost with terminating them that go beyond objective value-considerations. In addition, the present study demonstrates the added value of directly comparing social and nonsocial decision making to better understand the underlying processes of social decision making specifically.

# Chapter 5

## *General Discussion*

## General Aim

The overall aim of the present dissertation was to investigate the underlying mechanisms of stay/leave decision making. Specifically, I focused on stay/leave decisions from both individual and social perspectives and investigated (a) how positive and negative experiences shape the likelihood of staying versus leaving; (b) how prior expectations shape the likelihood of staying versus leaving; and (c) how individual and social stay/leave decisions may relate to each other. To investigate these questions, I used a multidisciplinary approach which combined knowledge and tools from the fields of Psychology, Economics and Neuroscience.

## Scientific Approach: Advantages & Challenges

### *Advantages*

An important aspect of this work is that the current findings would have been difficult to uncover without combining knowledge and tools from Psychology, Economics and Neuroscience. Psychological theories provided the insight that (social) stay/leave decision making might be value-based, and that decision likelihoods can be shaped by the history of positive and negative consequences of previous choices. Economic models and games, in turn, then allowed me to test whether value-maximization motives and general reward-learning mechanisms could predict stay/leave decision-making. Finally, the use of functional neuroimaging then demonstrated subtle but highly important differences between the processing underlying individual and social stay/leave decision-making, which are behaviorally indistinguishable. In turn, interpretation of these neural differences was heavily reliant on psychological theories (e.g., the need to belong).

### *Challenges*

The interdisciplinary approach thus has clear and important strengths, but naturally also introduces challenges. Firstly, the breadth and depth of knowledge across multiple fields that has to be taken into account when studying stay/leave decisions from different perspectives is so large that one is forced to set strict boundaries. In addition to the factors studied here there are of course other aspects that may influence stay/leave decision making or differentiate between individual and social stay/leave decision making processes. However, while different factors may alter the decision outcome (e.g., stay or leave), the (neural) mechanisms or pathways leading to the decision will likely be similar across variations in the type of stay/leave contexts. To gain a more unified understanding of stay/leave decision making, I therefore decided to investigate the underlying fundamental mechanisms of individual and social stay/leave decision making.

Secondly, when combining knowledge and tools from different fields, it is very difficult to satisfy the strict requirements of each field. That is, a psychologist could value the inclusion or control of factors that could influence stay/leave decision making outcomes and the ecological validity of a task; an economist values the ability to model and predict participants' choices; and a neuroscientist wants to learn how the brain works. Importantly, these different 'desires' have important effects on the choice of experimental questions and design. Doing interdisciplinary research will therefore always require a compromise between fields.

Taken together therefore, by doing interdisciplinary research one must incorporate a large variety of knowledge and tools to ask the most useful and precise research questions - which requires a both breadth and depth in terms of expertise - and at the same time deliberately and selectively choose from the set of traditions, knowledge and tools from each field.

## SUMMARY OF THE FINDINGS

### *HOW SOCIAL AND NONSOCIAL REWARDS AFFECT STAY/LEAVE DECISION MAKING: THE INFLUENCE OF ACTUAL AND EXPECTED REWARDS*

In the first empirical chapter, I demonstrated that individual and social stay/leave decisions are based upon value-maximization motives. That is, in the first study I demonstrated that the higher the actual probability of an agent's success was, the longer participants decided to stay with both social and nonsocial agents. The same pattern was found in the second, such that participants stayed longer with both social and nonsocial agents, the higher the prior expectations were about these agents. However, the effects of prior expectations on stay/leave decision making was much stronger in the social versus nonsocial condition. These findings suggest that participants relied less strongly on their prior beliefs when making decisions about their social partners than when they made the same decisions about nonsocial agents.

## *Social versus nonsocial reinforcement learning: Resisting against the effect of priors*

The second empirical chapter investigated stay/leave decisions from an exploitation/exploration perspective and demonstrated that learning the value of both social and nonsocial agents was predicted by reinforcement learning models. Moreover, prior beliefs about social and nonsocial agents again affected decision-making in line with prior beliefs, with the effect again stronger when making individual rather than social decisions. Modeling results demonstrated that expectancy-consistent and expectancy-inconsistent new experiences were differentially updated; and that general learning rates were higher in a social versus nonsocial context, but *only* when prior expectations were induced.

## *Social versus nonsocial stay/leave decisions: An fMRI study*

The third empirical chapter demonstrated that brain regions typically implicated in reward-based decision making are also implicated in both social and nonsocial stay/leave decisions, but that subtle differences between the two types of stay/leave decisions also exist. Specifically, activation in striatal regions was larger for decisions to stay with a social agent than for decisions to stay with a nonsocial agent; and the pattern of activation in the anterior cingulate cortex was reversed for stay versus leave decisions between social and nonsocial context. These results suggest that deciding to stay with a social partner is rewarding above and beyond objective 'relationship outcomes'; and that the decision to leave a social partner *specifically* is more costly than the potential cost of missing out on better partners when deciding to stay.

## CONCLUSIONS

### *HOW DO OUR EXPERIENCES SHAPE STAY/LEAVE DECISION MAKING OVER TIME?*

Previous psychological theories claimed that *relationship* maintenance is based upon value-considerations; and that the likelihood of an *animal* repeating a decision or not is based upon temporal difference learning. Economists have framed stay/leave decisions as the decision to exploit an option with the highest known expected value versus the decision to explore potentially alternative decisions, and provided economic models to compute the likelihood of exploitation and exploration on a trial-by-trial basis. Neuroscientists have demonstrated an important role of the striatum in reward-learning. One research question was therefore how the likelihood of staying versus leaving is shaped by experiences, and I demonstrated that reinforcement learning models, based on theories of animal learning and economic models, could predict both individual and social stay/leave decision making over time.

### *HOW DO PRIOR BELIEFS SHAPE STAY/LEAVE DECISION MAKING?*

Previous psychological theories on how expectations influence subsequent behavior made opposing predictions regarding stay/leave decision-making. I demonstrated that prior beliefs affect stay/leave decision-making such that decision-makers hold on to their prior beliefs. Moreover, I demonstrated that individual stay/leave decision-making is more strongly affected by prior beliefs than is social stay/leave decision-making.

### *HOW DO SOCIAL VERSUS NONSOCIAL STAY/LEAVE DECISION MAKING RELATE TO EACH OTHER?*

Psychological theories have likened the decision to stay with or leave a social partner to an economic choice; economists reasoned that socially valuable options must also be valuable to the self; and neuroscientists demonstrated that both social and individual value, learning, and decision-making share the same neural regions. Taken together, the three fields thus suggest that social stay/leave decision-making is similar to nonsocial stay/leave decision-making. While I demonstrate that the same principles underlie both types of decision-making, I also show that the decision to stay with or leave a social partner is in fact different from individual stay/leave decisions. Specifically, decisions to stay with social partners engaged more reward-related activation in the brain; and decisions to leave a social partner specifically appeared to be more costly than staying with them (and potentially missing out on better partners), while decisions to stay appeared more costly than decisions to leave in an individual stay/leave decision making task.

### *WHAT DO THE PRESENT FINDINGS MEAN FOR STAY/LEAVE DECISION MAKING IN REAL LIFE?*

While the tasks used throughout this entire research project were chosen to investigate *fundamental* mechanisms of stay/leave decision making, they are arguably not terribly representative of actual real-life stay/leave decisions (i.e., deciding to sell one's house or quit one's job, deciding to terminate a romantic relationship). For the individual stay/leave decisions, the stakes in real life are obviously higher than in the experimental task used, with for example sentimental concerns perhaps arising when deciding to sell the house one grew up in. Furthermore, for the social versions of the tasks used, the 'interactions' between partners were one-sided in that participants could not directly impact the behavior of their partners, and the rewards gained were monetary in nature. It is therefore important for future work to extend the current findings into more ecologically valid stay/leave decision making scenarios. As the current findings are fundamental, they are also likely to underlie real-life stay/leave decisions, but they can be affected by higher order motivations that will start playing a role in more realistic stay/leave decision making problems.

### *WHY IS LEARNING ABOUT SOCIAL PARTNERS MORE RESISTANT TO THE INFLUENCE OF PRIORS THAN NONSOCIAL VALUE LEARNING*?

In the second empirical chapter, I used a computational modeling approach to investigate why prior beliefs have a weaker effect on social as compared to individual stay/leave decisions. Unfortunately however, while this approach provided some insights (e.g., when prior beliefs are present, overall learning rates are higher for social versus individual stay/leave decision making), a clear answer to our question was not evident. Future research will be necessary to find an answer to this question.

### *HOW CAN WE INCREASE THE RESISTANCE OF STAY/LEAVE DECISION MAKING TO THE EFFECT OF PRIORS?*

Both previous research as well as the current project demonstrates the maladaptive effect of prior beliefs on learning and decision-making when these prior beliefs are false. It is therefore important to investigate how stay/leave decision-making competence can be increased, or how the influence of prior beliefs on decision-making can be diminished. Previous research suggests that encoding of prediction errors (which are essential to reinforcement learning) is diminished when prior beliefs are present. Key to guarding people against the influence of their prior beliefs could therefore be to boost neural activation to prediction errors. Although highly speculative, I expect this could be achieved by emotional upregulation of decision outcomes. However, future research is necessary to investigate this and other options.

### *HOW IS THE VALUE OF STAYING VERSUS LEAVING COMPUTED?*

By focusing on the fundamental mechanisms of stay/leave decision making in the current dissertation project, I demonstrated that both individual and social stay/leave decisions depend on value-considerations; and that the value of choice options may depend on social or nonsocial context. However, the next important but challenging step is to investigate how the combination of all factors previously linked to individual and social decision making together shape the value of staying and the value of leaving.

Whether you consider quitting your job, selling your house, or end a romantic relationship, the decision to stay with a current option or to leave it for a potentially better alternative is based upon which option has the highest expected value to you. But how to determine which is more valuable? This dissertation project demonstrates that your decision depends on the one hand on your prior beliefs about each option and, on the other hand, on your positive and negative experiences with the current option. Importantly also, the present project indicates that staying with or leaving a social relationship partner is not exactly the same as quitting your job. That is, although we're led by prior beliefs about our partners, we appear to take into account actual relationship outcomes as well when deciding to stay or leave, a factor specific to social stay/leave decision making. Even more, when deciding to stay with or leave a social relationship partner, the decision to stay is valuable above and beyond the objective relationship outcomes; and the brain enhances the likelihood of staying by assigning a greater cost to decisions to leave than to decisions to leave.

# Chapter 6

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# *Chapter 7*

# *Appendix*

Please consider the statements below and enter the number of your answer on the empty lines after each statement.

1 = strongly disagree

2 = disagree

3 = neither agree nor disagree

4 = agree

5 = strongly agree

1. When I make decisions, I try to take into account the wishes of others ...
2. I have donated goods or clothes to charity ...
3. I help out fellow students / colleagues when they ask for it ...
4. I usually hold the door for people walking behind me ...
5. I sometimes buy small presents for my loved ones for no reason other than to make them happy ...
6. I do not want to be an organ donor ...
7. I usually do not allow people to go ahead of me in a line (e.g., in the supermarket, public transport, copying machine etcetera) ...
8. I do what is best for me, regardless of what is considered “fair” by others ...
9. I try to show my friends and family that I love them ...
10. I feel annoyed when others ask for my help ...
11. When it comes to my personal relationship with others, I am not a very generous person ...

12. I am never too busy to help a friend ...

13. I have never donated blood ...

14. I don't like it when charities come at my door to beg for money ...

15. I try to treat others the way I would like to be treated myself ...

16. I usually don't tip waiters/waitresses in bars or restaurants ...

Now calculate your own score on this scale. Important is that you get acquainted with the meaning of relatively high or low scores. To calculate your score do the following:

1. Reverse-score your answers on the items: 6, 7, 8, 10, 11, 13, 14 and 16. This means that (for these items only!):

- if you wrote down 1, change it to 5
- if you wrote down 2, change it to 4
- if you wrote down 3, leave it as it is
- if you wrote down 4, change it to 2
- if you wrote down 5, change it to 1

2. Add your scores from the items 1, 2, 3, 4, 5, 9, 12 and 15. Which number do you get? ...

3. Add your (reverse-scored!) scores on the items 6, 7,8, 10, 11, 13, 14 and 16.
Which number do you get? ...

4. Add the numbers from step 2 and step 3. Which number do you get? ...

What do you think the questionnaire captures? In other words, what does it measure? Please use as few words as possible (preferably one).

The questionnaire measures ....................................................................................

Determine how high you score on this measure.

| | |
|---|---|
| 64 points or higher: | Very high score |
| Between 48 and 64 points: | High score |
| Between 32 and 48 points: | Low score |
| 31 points or lower: | Very low score |

# Chapter 8

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*The End*